Journal of Soft Computing in Civil Engineering 7-2 (2023) 115-137

Contents lists available at SCCE

Journal of Soft Computing in Civil Engineering

Journal homepage: www.jsoftcivil.com

Prediction of Compressive Strength of Corncob Ash Concrete for Environmental Sustainability Using an Artificial Neural Network: A Soft Computing Techniques

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https://doi.org/10.22115/SCCE.2023.347663.1471

ARTICLE INFO

Article history:
Received: 17 June 2022
Revised: 12 December 2022
Accepted: 31 January 2023

Keywords:
Soft-computing techniques;
Levenberg-Marquardt;
Agriculture waste;
Construction materials;
Pozzolanic material.

ABSTRACT

Agricultural waste materials are increasingly being used as partial replacements for cement in concrete. Several experimental studies are available to evaluate the mechanical properties of plastic waste reinforced concrete but there are limited evaluations on agricultural waste material. In this study, an attempt is made to investigate the compressive strength of Corn Cob Ash (CCA) concrete at different replacement levels by implementing an Artificial Neural Network (ANN). As the percentage of CCA increases, workability, density and compressive strength decreases, hence the developed ANN model consists of 3 input parameters (cement content, CCA content, and curing ages) in the input layer, 4 hidden neurons in the hidden layer and 3 output parameters (slump, density, and compressive strength) in the output layer. Training is done by adopting Levenberg-Marquardt back-propagation algorithm by considering 80% of experimental data with log-sigmoid activation function for both hidden and output layers. The developed model has a high correlation coefficient of 0.999 for both the training and testing data sets. It has low MSE and MAPE values of 2.2768×10^{-5} and 1.25 for training data respectively and 3.0463×10^{-5} and 1.37 for testing data respectively. Hence, it is concluded that the developed model predicts the output at an average rate of 98% accuracy. The predicted 2.5% replaced CCA concrete shows the best performance at all curing ages. Therefore, this percentage level is considered as an optimum replacement level which does not much affect the hardened properties of concrete.

How to cite this article: Abhishek R, Gowda BSK, Naveen DC, Naresh K, Sundarakannan R, Arumugaprabu V, Varsha A. Prediction of compressive strength of corncob ash concrete for environmental sustainability using an artificial neural network: a soft computing techniques. J Soft Comput Civ Eng 2023;7(2):115–137. https://doi.org/10.22115/scce.2023.347663.1471

1. Introduction

In recent years many industrially-related byproducts such as silica fume, fly ash and carbon nanotubes are being incorporated to enhance the properties of cement paste or concrete [1]. But in many countries, large amounts of agricultural waste materials such as bagasse, banana stalks, rice husk, bamboo, corncob, etc., are discarded as waste. Their disposal is causing serious environmental problems. Therefore, efficient utilization of these agricultural waste materials as a partial replacement for concrete is a good approach. Several researchers reported that the CCA could be used as a partial replacement in concrete (Fig 1) that exhibited the best pozzolanic property at its later ages [2–7].

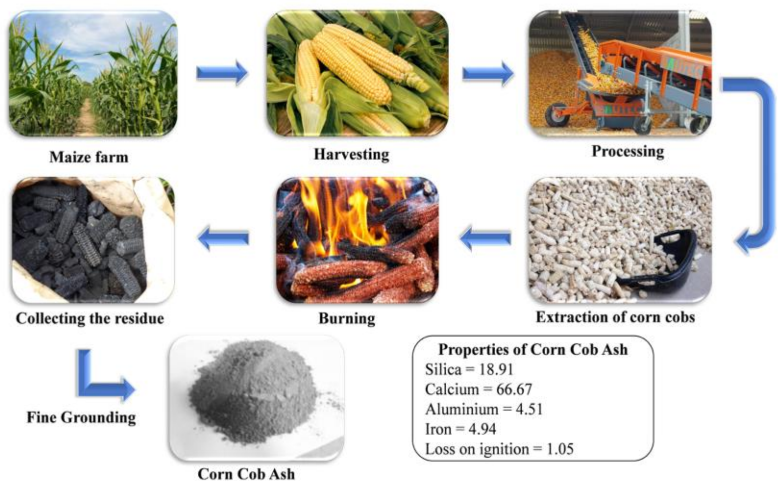

Fig. 1. Stepwise procedure for the production of corn cob ash.

The Extraction process of CCA is shown in Fig 1. The main difficulty in using CCA as a substitute for cement in concrete is that it reduces the compressive strength along with the reduction of fresh and hardened properties of concrete. Therefore, various research works were carried out to determine the mechanical properties of concrete at different percentage replacements in order to find out the best optimum results [2–5]. The effect of agricultural waste material like corn cob ash (CCA) on the mechanical properties of concrete was studied by Patel et al.,[2]. The results of this study indicate that concrete workability decreases as the replacement percentage increases and the initial and final setting time also increase with the increase in percentage level. It was found that compressive strength is lower at an early age, but increases significantly at an older age due to the pozzolanic activity of CCA [5,7]. Therefore, the compressive strength of high-performance concrete was investigated by Aliyu et al., [3] by replacing CCA at different weight percentages (5%, 10%, 15%, and 20%) of cement in M-50 grade concrete. The results of this study indicated that there was a decrease in strength at 3 and 7 days and greater improvement in strength is observed after 28, 56, and 90 days. Moreover, as the percentage of replacement increases, a reduction in strength was reported.

The density of CCA is lower when compared to cement in concrete, therefore the addition of CCA into concrete beyond 15% replacement makes concrete lighter [4]. Usually, the concrete samples with 10% of CCA replacement provide the best results without much affecting the concrete strength properties [5]. Adesanya and Raheem [7] based on their research work stated that 2% and 4% of CCA replacement provide higher strength compared to the control mix at later ages. Serbănoiu et all [8] investigated the concrete properties at 2.5% and 5% CCA replacement and obtained the best compressive strength values at 2.5% CCA replacement. Therefore, from these previous studies on CCA concrete, we can conclude that strength can be predicted at various replacement levels, but it is difficult to quantify the smaller variations in strength by using some small percentage variations of CCA in approximate fractions. Developing experiments that account for such small variations could be difficult. Fortunately, these types of problems can be overcome by implementing soft computing techniques in concrete strength prediction.

Usually, concrete strengths are determined by casting and testing specimens under compressive load but recent advances in computer software and technologies provide a new way to predict concrete strengths based on the constituent materials of concrete. The water-cement ratio, cement content, quality and quantity of aggregate materials used, type and amount of admixtures used, quality control during the production of concrete and many other factors influence the strength development of concrete. Therefore, many researchers implemented advanced software packages to determine the concrete strength based on its constituent materials [9–14]. The implementation of such techniques saves cost and practical time, and it is also possible to determine the concrete properties with lesser effort [15]. The implementation of these types of techniques is collectively called soft computing techniques. These are used to make automated processes that partially or completely replace human efforts.

The compressive strength of concrete can also be predicted by soft computing techniques like regression analysis [16], Supervised machine learning (SML) techniques, gene expression programming [17] and Group Method of Data Handling (GMDH) [18]. The Decision tree and Random Forest Machine Learning Techniques are also providing a promising way to determine the compressive strength of concrete rather than ANN but the Accuracy and flexibility offered by ANN are quite impressive. Few researchers previously implemented the ANN in predicting the compressive strength of concrete. An estimation of waste concrete's compressive strength was conducted by Heidari et al., [19] using backpropagation neural networks. Charhate et al., [20] compared the ANN approach with the Multi linear regression approach in predicting the concrete properties. When it comes to slump and compressive strength, ANN performs better and yields more accurate predictions than MLR models. Keshavarz et al., [21] are also tried to compare the ANN model with the Adaptive Neuro-Fuzzy Inference System (ANFIS) model. The ANN and ANFIS models are both successful at predicting concrete compressive strength. Asteris and Mokos [12] predicted the compressive strength with a deviation of ± 20% from the developed ANN model through MATLAB by utilizing both UPV and rebound hammer experimental results and concluded that the ANN approach with log-sigmoid and hyperbolic transfer function is a useful tool for the researchers and engineers to interpret the relationship between NDT and compressive strength values. Kulkarni et al., [13] have investigated the compressive strength of Recycled Aggregate Concrete (RAC) and Fly ash (Class F) embedded concrete using a three-layered Feed-Forward neural network. The ANN models were developed by using 'log-sigmoid' and 'linear' transfer functions with the help of MATLAB 2016 software. They reported that the developed ANN model provides good results in predicting the compressive strength of concrete within an acceptable performance. The compressive and flexural strengths of concrete were investigated by Solanki and Gangwal [14] by implementing ANN through MATLAB. It was reported that the developed ANN model predicts the strength very close to actual strength values with a deviation of 2% error rate. Paulson et al., [22] implemented ANN to predict the compressive strength of silica fume concrete. The weight of cement, silica fumes, fine aggregate, coarse aggregate and water in kilograms were used as five different input parameters. The deviation obtained between experimental and ANN predicted results is less than 1%. Based on these low deviations, they concluded that the ANN can be used for further studies without any experimental implementations within the acceptable range.

Deep Convolutional Neural Network (DCNN) models were implemented by Jang et al., [9] to investigate the compressive strength of concrete. About 150 to 200 digital microscope images of the concrete samples were collected before the compressive strength test and these images were used as inputs to determine the compressive strength results through CAFFE version 1.0. Chopra et al., [10] performed a comparative analysis of the compressive strength of concrete with and without replacement of fly ash as a substitute for cement based on two different techniques such as ANN and Genetic Programming (GP). The data required for analysis were collected from the experiments conducted at different curing age periods of 28, 56 and 91 days; and also 1442 data from the RMC plant for testing the model. The errors involved between actual and experimental values are determined by the statistical approach R^2 and RMSE. The ANN model which was trained by the Levenberg Marquardt algorithm provides better results compared to GP for both experimental and in-situ data. An Evolutionary Artificial Neural Network (EANN) was implemented by Nikoo et al., [11] to determine the strength of concrete. A Neuro Solution ver 5.0 software was used for the network learning and training processes. The optimized ANN model is compared with Multiple Linear Regression (MLR) models to check the accuracy level. The predicted compressive strength of concrete from the EANN model is more precise, highly flexible and accurate compared to MLR models. Many researchers used ANN and fuzzy models of different types for the prediction of compressive strength attributes of cement concrete in the field of geopolymers [23–27].

In the present study, an attempt is made to develop an ANN model to predict the compressive strength attributes of CCA embedded concrete for 2.5%, 7.5% and 12.5% of CCA replacement with cement using ANN approach. The density and slump variations are also studied at different concrete curing ages. However, the conventional experimental techniques are time-consuming and require a lot of manpower. Therefore, there is a need to implement artificial intelligence (AI) based modeling approaches to reduce the cost and time [28]. This helps researchers to predict the strength variations without much difficulty at small percentage replacements levels of CCA and at different curing age periods.

2. Methods

2.1. ANN and its mechanism

Humans are intellectual creatures in this universe, whose nervous system consists of cells called neurons and they are interconnected by axons and dendrites. Accordingly, an ANN is defined as an assemblage of interconnected simple processing units or nodes similar to the biological function of neurons in humans. The performance capability of a neural network depends on the connectivity between the neurons and their connected strength, which are often called weights and are obtained during the learning process of the training data (Appendix 1).

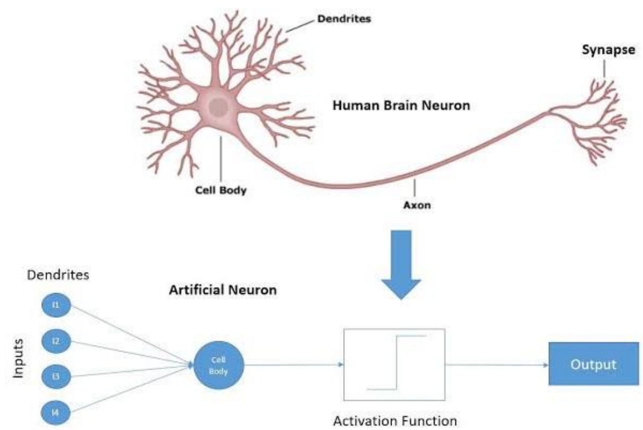

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Fig. 2. An ANN which resembles the biological neuron.

A simple ANN, like a biological neuron, also consists of three important layers which are input, hidden and output layers that resemble the functioning of the dendrite, cell body and axons of biological neurons respectively (Fig 2). The input layer receives input values and the number of input nodes depends on the number of input variables associated with the problem domain or experimental data.

Each input node in the input layer is connected to hidden neurons in the hidden layer through scaled weights. The multiplied weights for each input are the neural network's regression coefficients, which are pre-determined numbers stored in the program. The transformation of input data takes place within the hidden layer through summation and activation functions that resemble the cell body in the biological neuron. The number of hidden layers and hidden neurons in the network depends on the amount of input and output variables associated with the problem. The inputs are summed using a simple addition function called the summation function and passed through a transfer function to meet the required threshold value. The behavior of each neuron is determined based on the type of transfer function used in the neural network. The output layer gives the response of the ANN network with the input variable. The information flows in the forward direction from the input to the output layer through several hidden layers, so it is called a Multilayered Feed-Forward neural network.

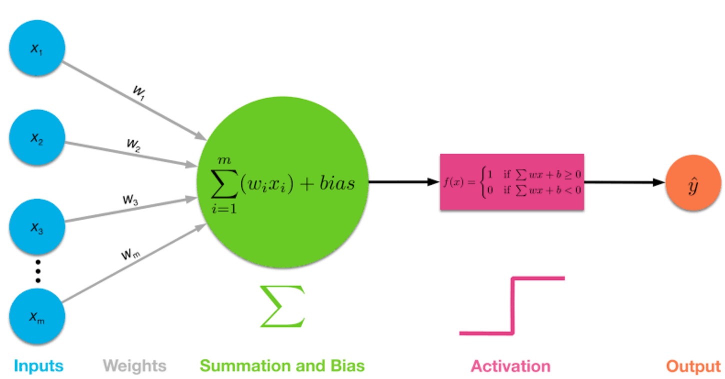

Fig. 3. An illustrative ANN with sigmoid activation function [22].

A simple ANN is represented in Fig 3. It includes a sigmoidal activation function between the input and output layers. Generally, a linear transfer function is used between the hidden layer and the output layer. A linear function does not interpret the output values and it returns the same value as the output obtained from the summation function.

Let $X_1, X_2, X_3, \ldots, X_n$ be the given inputs to the network. Before entering the computational layer the inputs must be multiplied by appropriate weights $W_1, W_2, W_3, \ldots, W_n$ respectively and a bias is also added to it, it is represented in Equation 1.

$$I = \underbrace{W_1X_1 + W_2X_2 + W_3X_3 + \cdots + W_nX_n + bias}_{Weighted\ input} \quad (1)$$

In general,

$$I = \sum_{i=1}^{n} W_nX_n + b_j \quad (2)$$

Equation 2 represents the general summation function that computes the sum of weighted inputs with their bias values. A bias neuron is also added in the hidden layer, which provides the bias variables associated with the network. Where 'I' is the output of the summation function and it becomes an input to the activation function which is given in Equation 3.

$$Y = \emptyset\left(\sum_{i=1}^{n} W_nX_n + b_j\right) \quad (3)$$

i.e.,

$$Y = \emptyset(I) \quad (4)$$

Where Ø is the transfer function or Activation function that produces the output Y. For any system that has input and output values, the above-given relationship (Equation 4) maps the outputs. A sigmoid transfer function is a continuous transfer function where the output of the function varies between 0 and 1. It is often used to predict the output as a function of the probability given in Equation 5.

$$\emptyset(I) = \frac{1}{1+e^{-x}} \quad (5)$$

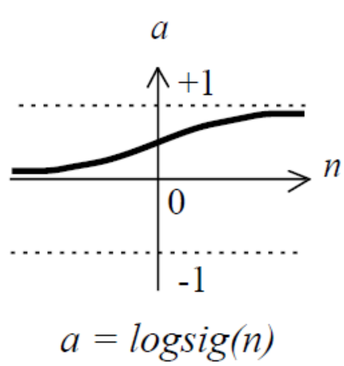

Fig. 4. Log-sigmoid transformation function.

The efficiency of neural network depends on the proper selection of weights and the number of hidden neurons in the hidden layers. The presence of more than one hidden layer improves prediction accuracy [29]. However, the number of hidden layers should be kept minimum to avoid the problem of overfitting and also to minimize time consumption.

The main objective of the training process is to minimize the error rate between the target and network outputs. The developed ANN model provides an output for any input value, so it must be validated to check the efficiency of the model, and how well it can predict the outputs [30]. The Validation of the model can be done by using various statistical parameters, some of them are:

Mean Square Error Function (MSE)

In Regression analysis, errors can be quantified using mean squared errors between predicted value x_i and observed value y_i. MSE is the average of the squared difference between predicted and experimental values. The equation required to predict the MSE value is represented in equation 6 where n is the total number of data.

$$MSE = \frac{1}{n}\sum_{i=1}^{n}(x_i - y_i)^2 \tag{6}$$

A lower MSE value close to zero represents a more efficient model in the prediction process. If it is zero, it represents that no error exists between the target and predicted output values.

Pearson Correlation Coefficient (R^2)

The correlation coefficient represents the linear relationship between predicted and target values. A better fit can be obtained when R-value is closer to unity. Therefore, a high R^2 value is required during the testing and training process.

$$R^2 = 1 - \left(\frac{\sum_{i=1}^{n}(x_i - y_i)^2}{\sum_{i=1}^{n}(x_i - \bar{x})^2}\right) \tag{7}$$

Equation 7 represents the mathematical representation of the correlation between two data sets, where x_i, y_i and $\bar{x}$ are the predicted value, target value and mean of predicted value, respectively.

Mean Absolute Percentage Error (MAPE)

The amount of errors between target and predicted values is determined in terms of absolute percentage error which is shown mathematically in equation 8. The lower the mean percentage error the better the prediction efficiency of the network.

$$MAPE = \frac{1}{n}\sum_{i=1}^{n}\left|\frac{x_i - y_i}{x_i}\right| \tag{8}$$

Where x_i and y_i are the actual and predicted values respectively.

2.2. Experimental data

In the present study, an ANN model is developed and trained based on experimental data of CCA embedded concrete (Table 1) designed, casted and cured as per Beauro of Indian Standards (BIS) norms. All the data required for the development of the ANN model are collected from the standardized tests conducted on fresh (as per BIS: 1199-1959) and hardened state (as per BIS: 516-1959) of CCA concrete by using a computerized compression testing machine of 2000 kN capacity. Here the compressive strength was measured at 7, 14, 21, 28, 35, 42 and 56 days of curing ages. Mix design is carried out for M30 grade concrete and CCA is used as partial replacement of cement in different proportions (0, 5, 10 and 15 percent by weight of cement which are designated as M1, M2, M3, and M4 respectively).

Here, partial replacement of different proportions of cement of different curing ages is carried out by CCA; so that water content, W/C ratio, fine and coarse aggregate contents remain constant for all the mix ratios. The methodology adopted to use ANN for the prediction of fresh and hardened properties of CCA substituted cement concrete is shown in Fig 5.

The density of CCA is comparatively less than cement and CCA absorbs more amount of water. Therefore, concrete density decreases by increasing replacement percentage along with the reduction in slump value. Here, cement content and CCA content at different curing ages are considered as three different inputs to determine the compressive strength, density and slump as three outputs.

Table 1
The CCA replaced cement concrete mix design test data for prediction process.

Concrete Mix ID	CCA Replacement (%)	Cement Content (kg/m^3)	CCA (kg/m^3)	Slump (cm)	Density of concrete cube (kg/m^3)	Age in Days	Compressive Strength (MPa)	Remark
M1-D7	00	426.0	00.0	21.50	2420.88	07	23.40	T
M1-D14	00	426.0	00.0	21.50	2454.00	14	27.00	T
M1-D21	00	426.0	00.0	21.50	2487.77	21	30.60	T
M1-D28	00	426.0	00.0	21.50	2502.00	28	36.00	T
M1-D35	00	426.0	00.0	21.50	2547.50	35	37.44	Test
M1-D42	00	426.0	00.0	21.50	2571.25	42	38.88	T
M1-D56	00	426.0	00.0	21.50	2594.07	56	39.96	T
M2-D7	05	404.7	21.3	15.25	2461.60	07	21.36	T
M2-D14	05	404.7	21.3	15.25	2499.40	14	24.63	Test
M2-D21	05	404.7	21.3	15.25	2530.07	21	27.23	T
M2-D28	05	404.7	21.3	15.25	2564.70	28	32.04	T
M2-D32	05	404.7	21.3	15.25	2587.90	35	33.32	Test
M2-D42	05	404.7	21.3	15.25	2572.12	42	34.60	T
M2-D56	05	404.7	21.3	15.25	2606.50	56	35.56	T
M3-D7	10	383.4	42.6	07.00	2368.29	07	19.43	T
M3-D14	10	383.4	42.6	07.00	2431.11	14	20.12	T
M3-D21	10	383.4	42.6	07.00	2466.67	21	22.87	T
M3-D28	10	383.4	42.6	07.00	2495.30	28	26.90	T
M3-D35	10	383.4	42.6	07.00	2565.60	35	27.97	T
M3-D42	10	383.4	42.6	07.00	2532.48	42	29.06	Test
M3-D56	10	383.4	42.6	07.00	2543.70	56	29.85	T
M4-D7	15	362.1	63.9	05.80	2308.70	07	16.43	T
M4-D14	15	362.1	63.9	05.80	2357.00	14	17.00	T
M4-D21	15	362.1	63.9	05.80	3376.29	21	19.24	T
M4-D28	15	362.1	63.9	05.80	2382.80	28	22.64	Test
M4-D35	15	362.1	63.9	05.80	2457.77	35	23.54	T
M4-D42	15	362.1	63.9	05.80	2432.29	42	24.43	T
M4-D56	15	362.1	63.9	05.80	2487.11	56	25.13	T
Note:	1. The mix designation ‘M1’, ‘M2’, ‘M3’ and ‘M4’ represents 0, 5, 10 and 15 % CCA replaced concrete mix respectively and ‘D’ designation with number suffix represents its corresponding curing age. 2. T = Training.							

2.3. Performance of ANN model

In the present work, the ANN model was developed by using MATLAB R2015a, version 8.5 software. The software is user-friendly and finds applications in research works, project works, and engineering applications as well as science and economics fields. MATLAB was developed in early 1970 by Cleve Moler, chairman of computer science at the University of New Mexico [31]. MATLAB is an acronym for "matrix laboratory". It is a programming language for technical computing and it creates a numerical computing environment developed by MathWorks. Around 4 million people worldwide are using MATLAB software in various fields [32]. In the present study MATLAB is used for mathematical computing. It has Predefined algorithms that make the analysis much easier so that no more recompilation of programs is required. It provides an innovative and interactive way of solving problems. Files and variables can be easily tracked within the workspace. Therefore, MATLAB is one of the user-friendly software in the field of ANN application. In the present study, several steps were followed to develop an efficient ANN model for compressive strength prediction of CCA embedded concrete as given in Fig 5 [33].

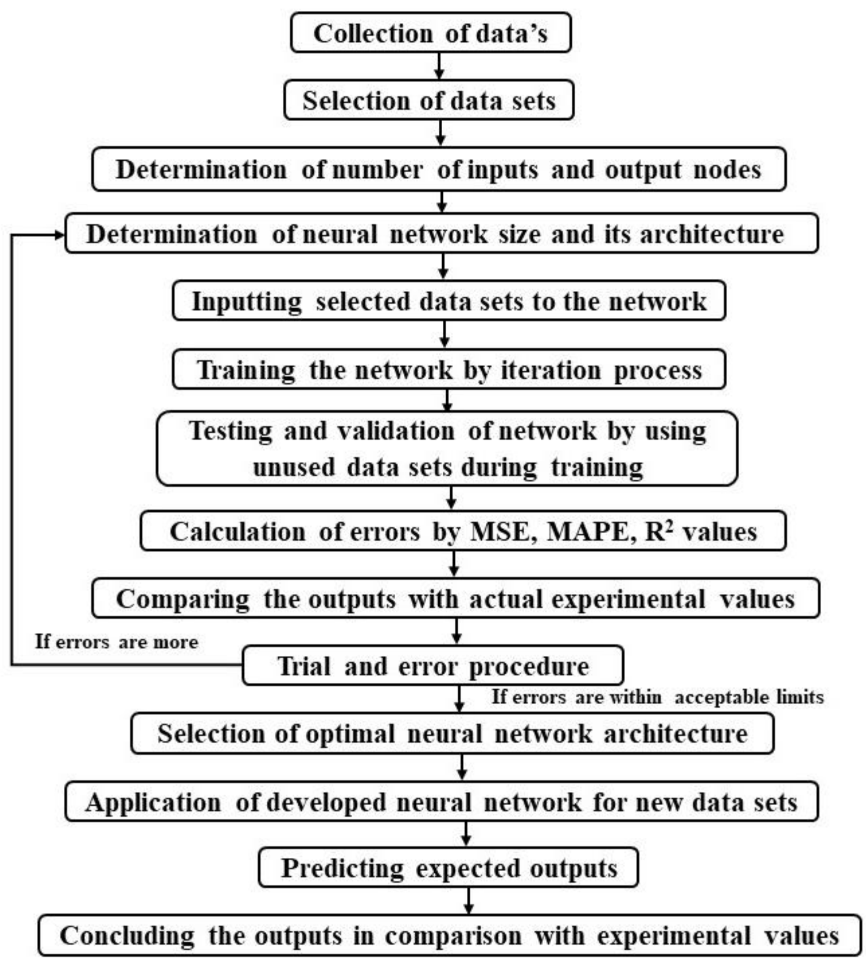

Fig. 5. Flowchart for developing an ANN model to predict the compressive strength of corncob ash concrete.

2.3.1. Selection of data

The fresh and hardened properties of concrete such as cement content, CCA content and curing age are considered as three different inputs to the ANN network. 7, 14, 21, 28, 35, 42 and 56th day compressive strengths and corresponding slump and cube density values are considered as target outputs. Out of 28 available data sets, about 80% of data are selected for training (T – as mentioned in Table 1) and 20% of data sets are randomly selected for testing (Test – as mentioned in Table 1) i.e., 23 data sets are used for the training process and remaining 5 for testing the ANN model. All these data are arranged to fit the ANN matrix size of 3 x 23. It consists of three parameters of 23 samples belonging to four different types of concrete mix tested at different curing ages. Each column in the matrix represents a separate material property. Target values are necessary to train and validate the ANN model. The efficiency of the developed model is determined by comparing the actual target values with the predicted values. The difference obtained should be minimum in order to endorse that the developed ANN model as an efficient model.

2.3.2. Neural network size and architecture

ANN is an efficient approach for the estimation process to analyze a large number of data sets at a high accuracy rate. In this study, a model with a single hidden layer is used to predict the experimental values. The final architecture is characterized as 3-4-3-3. It means, 03 inputs in the input layers, 04 hidden neurons in the hidden layer and 03 output neurons in the output layer and finally, 03 outputs are predicted by the developed network which are slump, density and compressive strength values of CCA concrete at different percentage replacements of CCA. The architecture of the ANN model is shown in Fig 6.

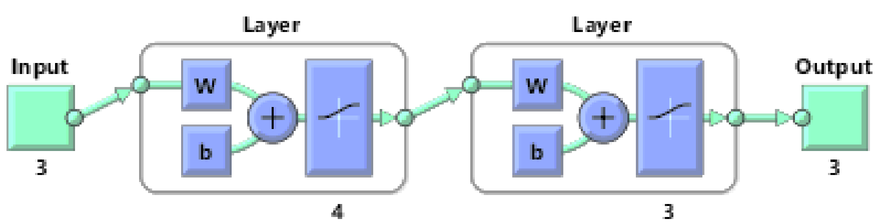

Fig. 6. Neural network architecture (3-4-3-3).

2.4. Training the network

The training is done by using 80% of experimental data samples. Here, an MSE value of 2.2768x10^{-5} and a correlation R-value of 0.99932 were obtained for the trained ANN model. These final results are obtained after several attempts of the training iteration process performed by changing the number of hidden neurons in the hidden layer and changing other network parameters such as goal, epochs and learning rate. The performance of the network is determined based on the number of errors accumulated in the predicted values. The model that gives the least amount of error is considered as the best-trained model. Training is performed for 2000 epochs, which means the network can iterate up to 2000 cycles to check the adequacy of the model. Currently, the training is stopped at the 184th epoch. Plots for training status and performance are shown in Fig 7 and 8 respectively.

The best performance obtained at the end of training is shown in Fig 8 which shows the variations in MSE values at each epoch. Training is stopped once the lowest MSE value is obtained from the network. The low MSE value indicates the robustness of the neuron layer [18]. The regression plot of the training data is shown in Fig 9. It shows the best fit of the data at the end of the iteration process during training i.e., it represents a linear relationship between the target inputs and predicted outputs.

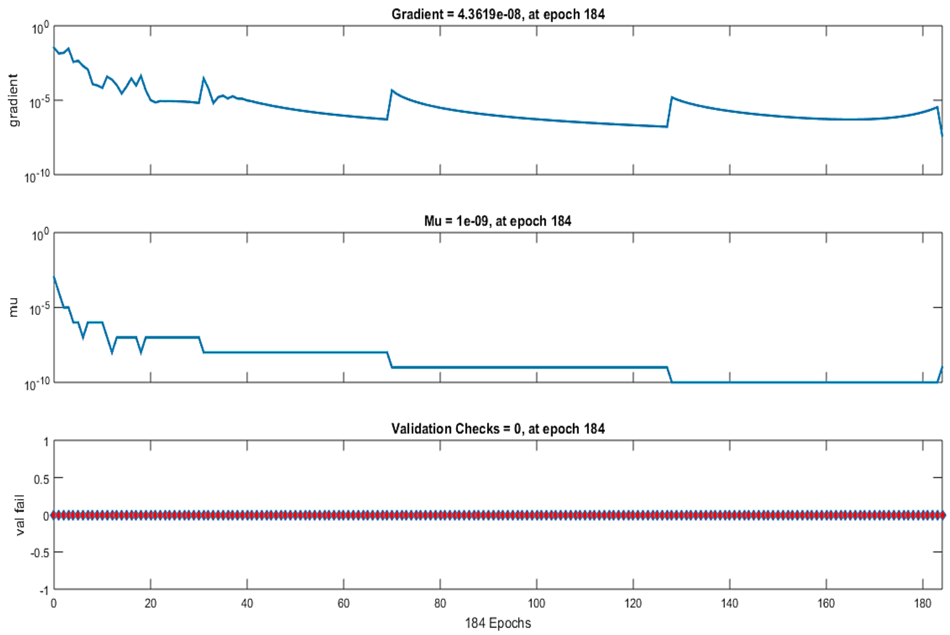

Fig. 7. Illustrative training status of the network.

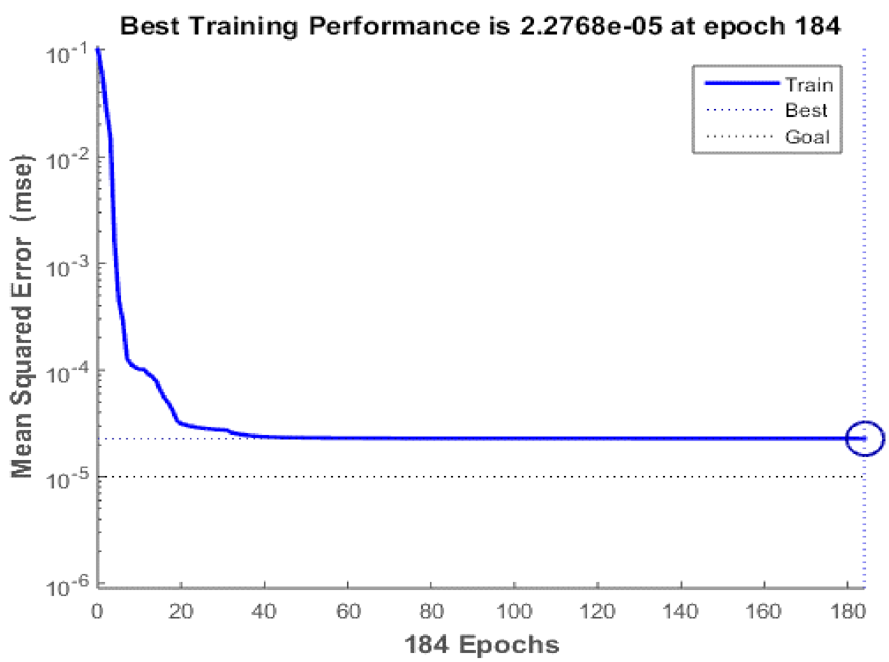

Fig. 8. Performance plot of the training network.

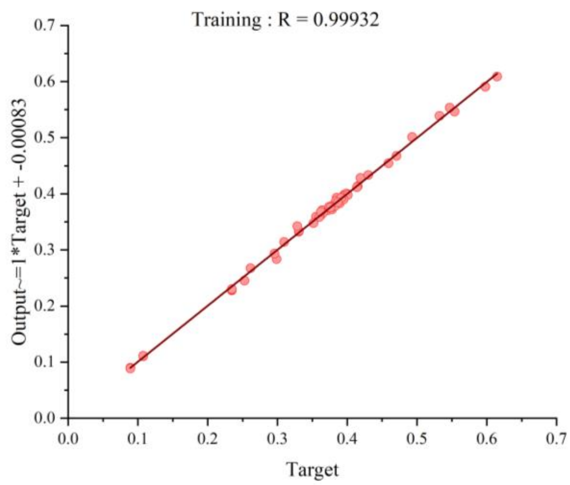

Fig. 9. Regression plot for training data sets.

2.5. Testing and validation

Testing and validation are done by utilizing the remaining 20% of experimental data samples from Table 1. MSE and correlation R-values were obtained during testing. This indicates that the best validation performance is obtained at these values for the given network.

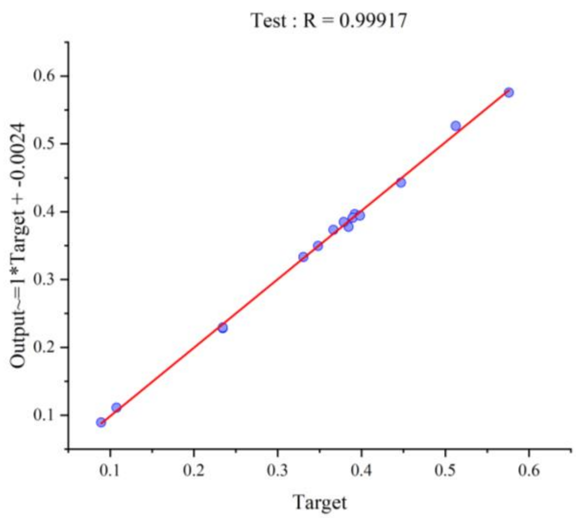

Fig. 10. Regression plot for testing data sets.

The data sets which were not used during the training process are now used to test the model and a good performance is obtained with MSE value of 3.04632 x 10^{-5} and an R-value of 0.99917.

The R-value indicates the linear relationship between the target values and the network outputs, so the training process is repeated until the correlation coefficient R values close to unity. Here, the end of the 184th epoch, R values of training, testing and validation reach near to unity, therefore, a high correlation is obtained between the target and the predicted outputs. The regression plot of the test process is shown in Fig 10. This clearly shows that a strong positive linear relationship exists between target and predicted output values. The analysis results are finally saved after obtaining satisfactory results from the developed ANN model for future analysis.

3. Results and discussions

The compressive strength of concrete coupons is conventionally determined at the age of the 28th day after curing the specimens. It becomes a difficult task to determine the strengths at different ages and practically it is Laborious. Hence the implementation of ANN provides an easy and economical way to predict the compressive strength of concrete at different ages in an acceptable mathematical way. Therefore, in this work, an attempt has been made to predict the compressive strength attributes of CCA embedded concrete for different percentages of CCA replacements, tested at different curing ages. Here the variations in slump and densities of CCA embedded concrete coupons are also studied.

3.1 Validation of ANN model

The obtained results are almost close to the experimental values with a maximum error of 3.438% accumulated in predicting the slump values, 2.087% error in determining density values and a maximum error of 5.054% in predicting compressive strength values. The overall mean absolute percentage error (MAPE) for the generated outputs with 4 hidden neurons was 1.256%.

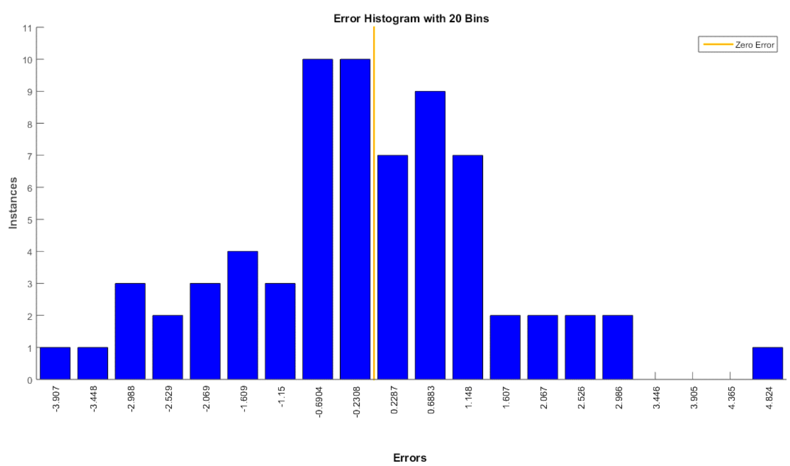

Fig. 11. Error Histogram for training data sets.

Figure 11 shows the error histogram. The percentage errors are grouped into 20 bins. The error bins are nearer to the zero line, therefore, it is clear that the developed model predicts significant output values within the range of acceptable errors. Therefore, this model is finalized for testing and validation. The experimental results and predicted outputs from the ANN model are given in Table 2.

Table 2
Comparision of experimental and ANN predicted outputs of test data set.

Mix ID	Slump (cm)			Density (kg/m^3)			Compressive strength (MPa)		
	Exp.	ANN	% error	Exp.	ANN	% error	Exp.	ANN	% error
M1-D35	21.50	21.66	0.764	2547.50	2576.81	1.151	37.44	37.42	0.065
M2-D14	15.25	14.84	2.662	2499.40	2455.81	1.745	24.63	25.01	1.540
M3-D42	07.00	07.22	3.181	2532.48	2541.82	0.369	29.06	28.79	0.944
M4-D28	05.80	05.80	0.013	2382.80	2427.32	1.869	22.64	22.73	0.380
M2-D35	15.25	14.90	2.280	2587.90	2563.87	0.929	33.32	34.21	2.686

Note:- Exp. = Experimental data
ANN = Predicted output values from the developed ANN model

The absolute percentage errors are also within the acceptable range, so it can be realized that the developed model predicts outputs close to the experimental values. The maximum absolute percentage error involved in predicting slump value is 3.181%; for density, it is 1.869% and for compressive strength, it is 2.686%. The overall MAPE is 1.371%. Therefore, it is decided that the developed ANN model predicts the output with an average accuracy rate of 98%. Figures 12, 13 and 14 show the graphical representation of variations in predicted outputs of the slump, density and compressive strength attributes with their corresponding experimental results respectively.

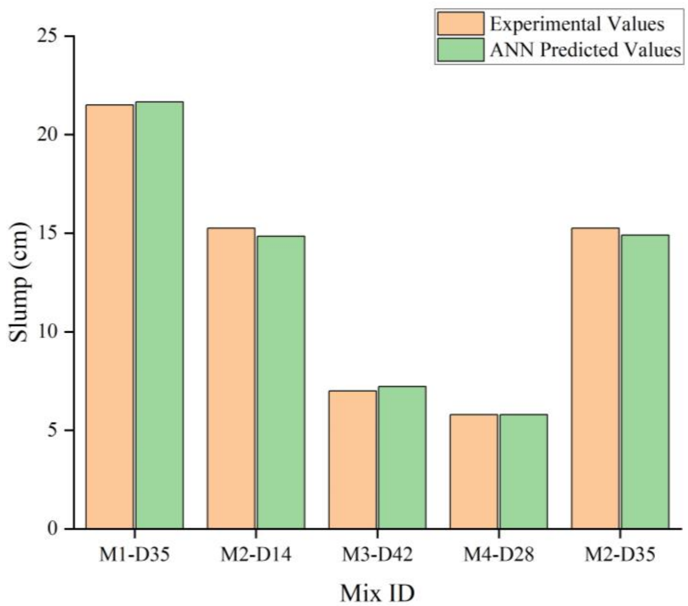

Fig. 12. Variations in slump values of experimental and predicted test output.

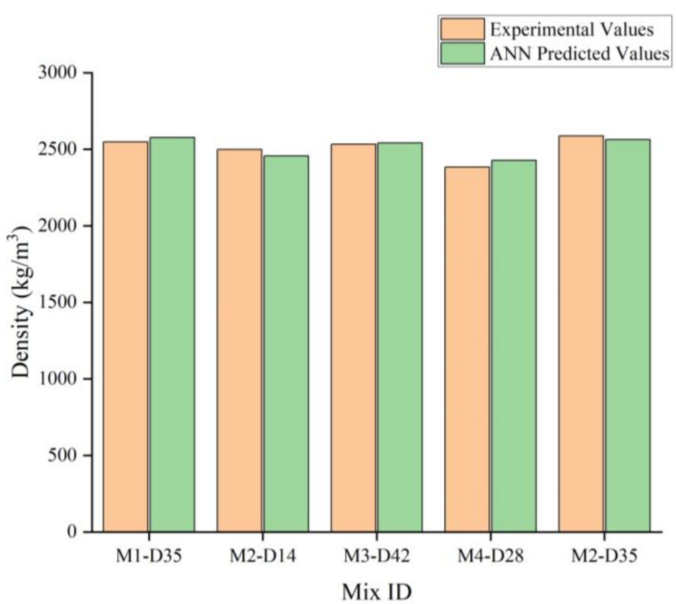

Fig. 13. Variation in density values of experimental and predicted test output.

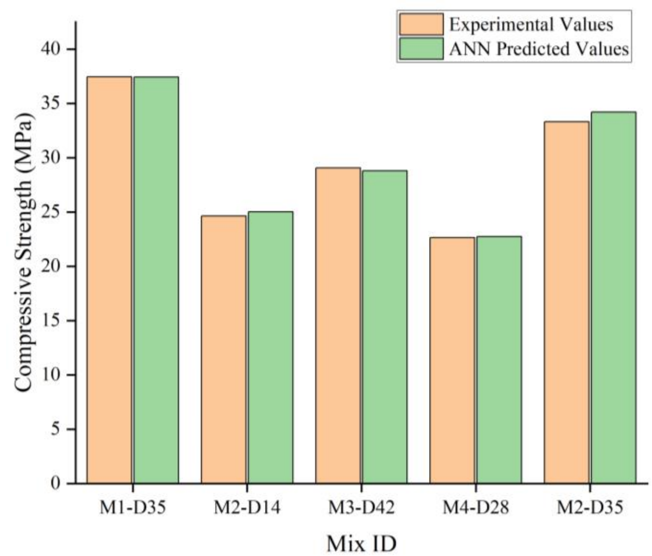

Fig. 14. Variations in compressive strength values of experimental and predicted test output.

The developed ANN model is capable of predicting the outputs with the least amount of errors. Therefore, this model was finalized to predict the compressive strengths at different desired percentages of CCA at different curing ages. Experimental results show strength values for 5%, 10% and 15% replacement of CCA. Therefore, the strength properties at intermediate percentages such as 2.5%, 7.5% and 12.5% CCA replacement were found with the help of developed ANN model in order to find out the best optimum percentage replacement of CCA for cement in concrete. For our convenience, the mix designations M5, M6 and M7 are considered for individual percentage replacements of 2.5, 7.5 and 12.5%, respectively. The strength parameters for each replacement of CCA were estimated for 3, 7, 14, 21, 28, 35, 42, 56, 90, 100, 180, 270 and 365 days.

Table 4
Average slump values of predicted outputs.

Mix	CCA %	Slump in cm	Reduction in slump with respect to mix 1 (%)
M1	00.0	21.50	00.00
M5	02.5	19.18	10.77
M2	05.0	15.25	29.07
M6	07.5	10.48	51.25
M3	10.0	07.00	67.44
M7	12.5	05.69	73.53
M4	15.0	05.80	73.02

The slump value collected from the experiment results for 0% CCA is 21.5 cm, for 5% CCA replacement it is 15.25 cm and for 10 % and 15% CCA replacement it is found to be 7 cm and 5.8 cm respectively. The developed ANN model provides the slump value for each day when the compressive strength is to be determined. These slump values obtained from the ANN model for the particular mix are almost similar but slightly vary in fractional digits at different ages, so the average of the slump values was considered for further analysis to interpret the results. The average slump values for predicted results are tabulated in Table 4.

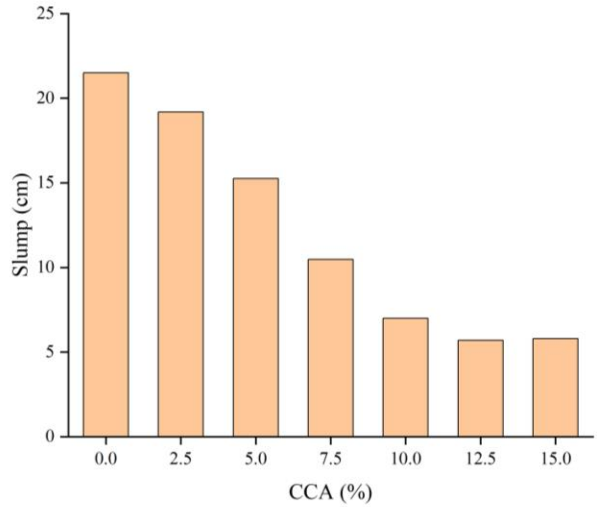

Fig. 15. Slump variation for different CCA replacement predicted by ANN.

Fig 15 represents the variation in slump values for various percentage replacements of CCA. It clearly shows that as the percentage of CCA increases the workability of concrete decreases. It is due to the high water absorption characteristics of CCA. The control mix had the highest slump value of 21.5 cm. The 12.5 % CCA replaced concrete shows lowest slump value of 5.69 cm. The slump value for 2.5% CCA replaced concrete showed the maximum slump that is very close to the control mix (0% CCA), Therefore, it is considered as more workable concrete compared to other mixes.

Fig 16 represents the percentage reduction in slump values for each percentage variation of CCA. This graph represents that as the percentage of CCA increases there is an increase in in percentage reduction of slump compared to the control mix.

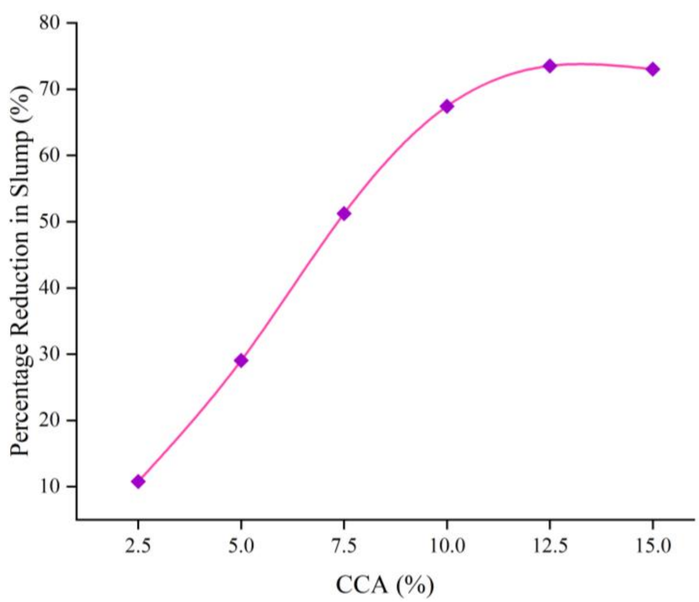

Fig. 16. Percentage reduction in slump for different percentage replacement of CCA.

There is about 10% reduction in slump for 2.5% replacement of CCA concrete compared to control mix (0% CCA) and for 12.5% and 15% replacement, reduction is more than about 70% with respect to control mix concrete. The experimental and predicted density for each mix at different curing ages are tabulated in Table 5 and Fig. 17 indicates the density values ranging from 0% to 15% replacement of CCA.

Table 5
Densities of CCA replaced test coupons predicted by ANN at different ages.

Curing Days	Density(kg/m^3) at percentage replacement						
	control mix (0% CCA)	2.5% CCA	05% CCA	7.5% CCA	10% CCA	12.5% CCA	15% CCA
03	2377.96	2391.25	2396.07	2394.09	2391.73	2393.30	2315.76
07	2420.88	2419.56	2461.60	2416.38	2368.29	2410.80	2308.70
14	2454.00	2458.51	2499.40	2447.06	2431.11	2434.88	2357.00
21	2487.77	2495.87	2530.07	2478.08	2466.67	2460.82	2376.29
28	2502.00	2552.93	2564.70	2530.75	2495.30	2509.98	2382.80
35	2547.50	2573.76	2587.90	2548.62	2565.60	2525.53	2457.77
42	2571.25	2584.39	2572.12	2557.01	2532.48	2532.11	2432.29
56	2594.07	2597.17	2606.50	2567.05	2543.70	2539.90	2487.11
90	2615.33	2607.99	2594.35	2575.67	2558.23	2546.53	2470.68
100	2616.46	2609.02	2595.30	2576.53	2558.97	2547.17	2472.82
180	2618.41	2610.99	2597.35	2578.52	2560.64	2548.51	2485.47
270	2618.68	2611.48	2598.14	2579.44	2561.36	2548.99	2496.60
365	2618.90	2611.95	2598.93	2580.38	2562.12	2549.47	2506.19

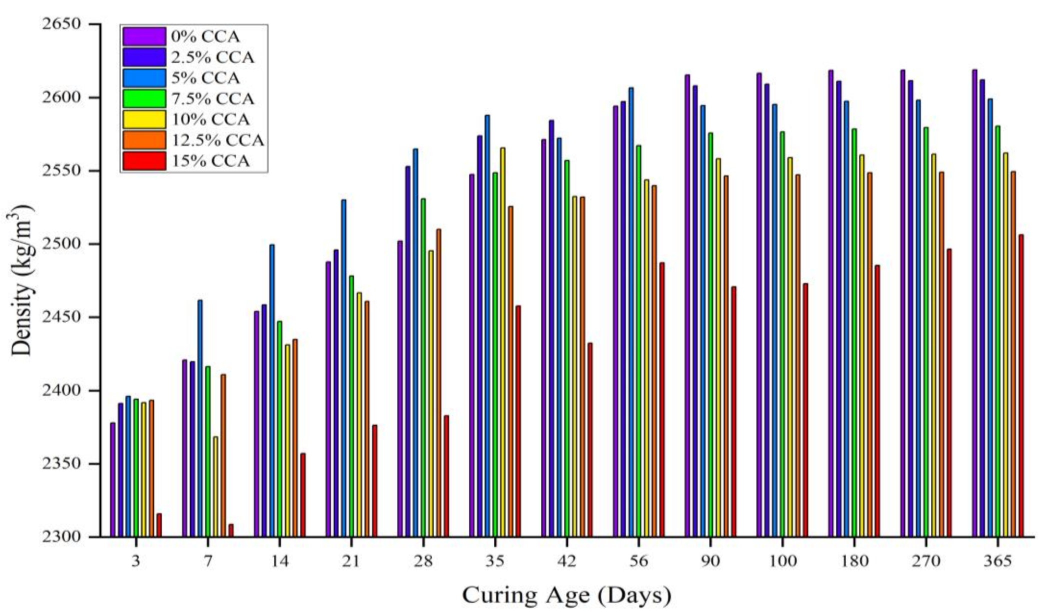

Fig. 17. Variation in densities of different % CCA replaced concrete cubes at different curing ages predicted by ANN.

The experimental and predicted compressive strengths for each mix at different curing ages are tabulated in Table 6. The compressive strength for 0%, 2.5%, 7.5% and 12.5% for 3-day curing age periods are 20.38, 21.17, 18.62 and 16.37 MPa respectively. It was recorded as 23.40, 23.38, 22.59 and 19.23 MPa for corresponding percentage variation of CCA for 7 days curing age period. While for 28 days, it is 36.00, 34.65, 29.54 and 25.08 MPa respectively. Whereas for 90 days concrete achieved strength of 40.55, 39.25, 33.41 and 28.12 MPa for each percentage variation of CCA respectively.

Table 6
Predicted compressive strength at various percentage replacements of CCA.

Curing days	Compressive strength (MPa)						
	control mix (0% CCA)	2.5% CCA	05% CCA	7.5% CCA	10% CCA	12.5% CCA	15% CCA
03	20.83	21.17	20.33	18.62	17.09	16.37	14.97
07	23.40	23.38	21.36	20.24	19.43	17.54	16.43
14	27.00	26.56	24.63	22.59	20.12	19.23	17.00
21	30.60	29.73	27.23	25.08	22.87	21.16	19.24
28	36.00	34.65	32.04	29.54	26.90	25.08	22.64
35	37.44	36.42	33.32	31.07	27.97	26.37	23.54
42	38.88	37.30	34.60	31.79	29.06	26.91	24.43
56	39.96	38.36	35.56	32.65	29.85	27.56	25.13
90	40.55	39.25	36.82	33.41	30.21	28.12	25.60
100	40.64	39.34	36.91	33.49	30.28	28.18	25.68
180	40.81	39.54	37.14	33.74	30.48	28.32	26.02
270	40.85	39.62	37.28	33.90	30.61	28.40	26.29
365	40.89	39.70	37.42	34.08	30.74	28.47	26.52

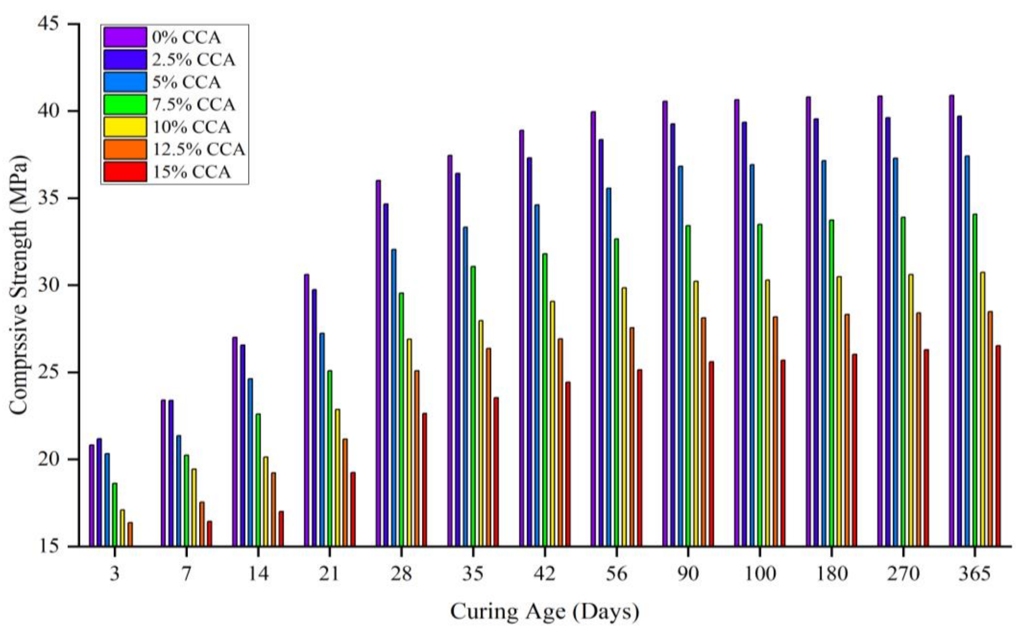

Fig. 18. Predicted compressive strength variations at different curing ages.

The compressive strength of 2.5% and 5% CCA replacement showed very appreciable results and is very close to the control mix, so this replacement level can be used for desired suitable application without much loss in the concrete strength. Fig 18 graphically represents the reduction in compressive strength for different mixes. It clearly shows that as the percentage of CCA increases, the compressive strength reduces as compared to the control mix.

Table 7
Percentage reduction in compressive strength compared to control mix.

Curing age (days)	2.5% CCA	05% CCA	7.5% CCA	10% CCA	12.5% CCA	15% CCA
03	1.64	02.41	10.61	17.96	21.42	28.14
07	0.09	08.72	13.51	16.97	25.05	29.79
14	1.63	08.78	16.34	25.49	28.78	37.04
21	2.85	11.02	18.04	25.27	30.85	37.13
28	3.75	11.00	17.95	25.28	30.34	37.12
35	2.73	11.01	17.02	25.30	29.57	37.13
42	4.07	11.01	18.24	25.26	30.79	37.17
56	4.01	11.02	18.30	25.31	31.04	37.12
90	3.21	09.20	17.61	25.50	30.66	36.87
100	3.20	09.18	17.60	25.50	30.66	36.82
180	3.12	09.00	17.33	25.32	30.61	36.25
270	3.02	08.74	17.02	25.07	30.48	35.65
365	2.92	08.49	16.66	24.83	30.38	35.15

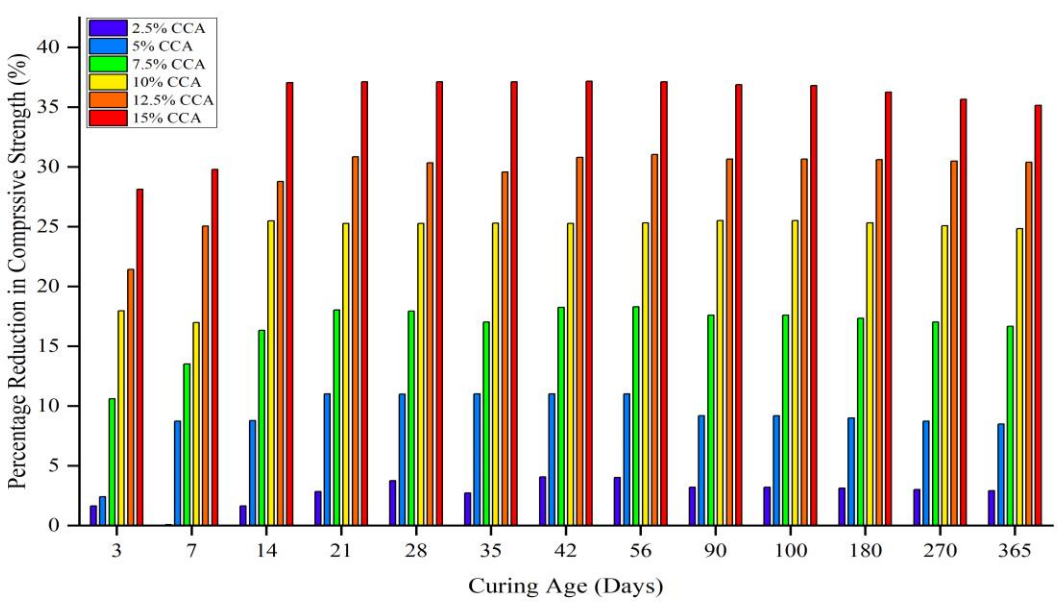

Fig. 19. Reductions in compressive strength with varying curing age periods.

The percentage reduction in strength with respect to the control mix is tabulated in table 7 and its graphical representation is shown in Fig 19. The percentage reduction in strength of 2.5% CCA replacement is less as compared to other different mixes. Hence 2.5% of CCA replacement is considered as optimum dosage in terms of strength consideration.

4. Conclusions

In the present study, a multilayer feed-forward neural network with 4 numbers of hidden neurons is developed based on available 0%, 5%, 10% and 15% CCA replaced cement concrete experimental data. Compressive strength attributes for 2.5%, 7.5% and 12.5% CCA replacements at 3, 7, 14, 21, 25, 28, 42, 56, 90, 100, 180, 270 and 365 days of curing ages were predicted by using the developed ANN model.

The developed ANN model has a high correlation value of 0.99932 and 0.99917 for the training data and testing data, respectively. This indicates a strong linear relationship that exists between the target and the predicted outputs. It also showed low MSE values of 2.2768×10^{-5} and 3.0463×10^{-5} for the training and testing data set respectively. This represents that the developed model is more effective in predicting the desired outputs [34–36]. The maximum absolute percentage errors of 5.05 and 3.18 were observed in the training and testing data sets, respectively and MAPE values of 1.25 and 1.37 were obtained for the training and testing data sets, respectively. Therefore, it can be concluded that the developed model predicts the output with an average accuracy of 98%.

With the application of the developed ANN model, compressive strength results with relatively low percentage errors can be expected without conducting any additional experiments in a short period. The slump results show that the workability of concrete decreases as the percentage of CCA increases [37,38]. Currently, the workability of 2.5% replaced CCA is relatively nearer to the control mix without much loss in workability. The densities of coupons with 2.5% and 5% replacement of CCA do not show much variation in comparison with the control mix and also they are slightly higher than that of the control mix. But as the percentage replacement of CCA increases, the density of concrete decreases. For 2.5% and 5% CCA replaced concrete, compressive strength reaches its target strength of 30 MPa at its 28 days of curing. But beyond 12.5% CCA replaced concretes failed to achieve it. Hence 2.5% and 5% CCA replaced concretes are suitable for structural applications from the point of strength consideration.

Compressive strength, slump and density of coupons decrease as the percentage replacement of CCA increases. The results specified that 2.5% replacement gives a peak value of compressive strength for all curing ages in M30 grade concrete. Therefore, 2.5% is recommended as the optimum dosage of CCA (an agricultural waste) replacement for the given concrete mix. For predicting the compressive strength of CCA embedded concrete at various replacement levels based on available experimental data, ANN is an efficient method; as it saves time, manpower, material and costs in carrying out complex and labor-intensive practical experiments. As a result of savings in concrete constituents, it helps to reduce CO_2 emissions to the environment and preserves natural resources. Therefore, adaptation of soft computing techniques like ANN helps less experienced engineers to carry out the prediction process without much difficulty along with environmental sustainability.

Appendix 1

Input Weight (IW_{11}) and bias (b_1) value for first hidden layer.

$$IW_{11} = \begin{bmatrix} 9.2618 & 0.1735 & -3.141 \\ -11.2837 & -1.2438 & 32.0195 \\ -77.3811 & -2.1779 & -0.0299 \\ -77.155 & 25.1598 & -0.1634 \end{bmatrix}_{4\times 3}$$

$$b_1 = \begin{bmatrix} -9.8388 \\ -4.4079 \\ 48.1807 \\ 16.0323 \end{bmatrix}_{4\times 1}$$

The input weight and bias matrix depends on the number of input variables and the number of neurons in the hidden layer. There are three inputs (Cement content, CCA, days) and four hidden neurons therefore input weight matrix will be 4x3 matrix and bias will be 4x1 matrix.

Layer Weight (LW_{21}) and bias (b_2) for output layer.

$$LW_{21} = \begin{bmatrix} -0.3393 & -0.0012 & -2.0511 & 1.7725 \\ -6.213 & 0.0346 & -0.0555 & -0.5599 \\ -50.2446 & 0.2862 & -0.9695 & -1.1596 \end{bmatrix}_{3\,X\,4}$$

$$b_2 = \begin{bmatrix} -0.542 \\ -0.4244 \\ 0.3029 \end{bmatrix}_{3\,X\,1}$$

The second layer weights and bias matrix depends on the number of hidden neurons in that layer and the number of inputs from the previous layer. Therefore, in the present study four inputs from first layer to second layer and it consist of three hidden neurons therefore the weight and bias matrix of the second layer becomes 3x4 and 3x1 matrix respectively. By using these weight and bias matrices, it is possible to develop an Excel program to predict the ANN outputs by adopting approaches described in section 2.1 (equation 1 to 5).

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