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Comparison of machine learning algorithms to evaluate strength of concrete with marble powder

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Abstract. In this paper, functionality of soft computing algorithms such as Group method of data handling (GMDH), Random forest (RF), Random tree (RT), Linear regression (LR), M5P, and artificial neural network (ANN) have been looked out to predict the compressive strength of concrete mixed with marble powder. Assessment of result suggests that, the overall performance of ANN based model gives preferable results over the different applied algorithms for the estimate of compressive strength of concrete. The results of coefficient of correlation were maximum in ANN model (0.9139) accompanied through RT with coefficient of correlation (CC) value 0.8241 and minimum root mean square error (RMSE) value of ANN (4.5611) followed by RT with RMSE (5.4246). Similarly, other evaluating parameters like, Willmott's index and Nash-sutcliffe coefficient value of ANN was 0.9458 and 0.7502 followed by RT model (0.8763 and 0.6628). The end result showed that, for both subsets i.e., training and testing subset, ANN has the potential to estimate the compressive strength of concrete. Also, the results of sensitivity suggest that the water-cement ratio has a massive impact in estimating the compressive strength of concrete with marble powder with ANN based model in evaluation with the different parameters for this data set.

Keywords: artificial neural network; coefficient of correlation; compressive strength; marble powder; Nash-Sutcliffe coefficient; root mean square error; Willmott's index

1. Introduction

In the construction industry concrete is most generally utilized material acquired by allowing a careful mix proportion of cement, sand, gravel water, and other coarse aggregates (Zongjin 2011). Concrete with broad properties can be procured fitting measure of alterations in the degrees of the fundamental constituents (Darwin *et al*. 2016). Most of the constituents are easily available in surroundings such as fine aggregates, coarse aggregate and water except cement. For upgrading the engineering properties of concrete, financial and environmental contemplations play a critical part in the additional cementing material utilization as well as better designing and execution properties (Talah *et al*. 2015). Industrial wastes are increasing due to industrialization and urbanization. Also manufacturing of cement emits carbon dioxide which has hazardous impact in the environment. It provides a good amount of help to the environment if industrial waste will become the part of concrete constituent (Khater *et al*. 2020). Marble powder is one such waste

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from marble industry that can be utilized as a partial substitution of cement and sand (Sharma *et al*. 2020, Zhang *et al*. 2020). In the manufacturing of marble, little amount of mica, silica, iron oxide, feldspar, fluorine and organic matters may be found (Uygunotlu *et al*. 2014). For technical issues such as performance of concrete mix can be improved by using waste marble (Kelestemur *et al*. 2014). Large amount of marble was generated from the cutting process in marble industry, which exploits the environment (Aliabdo *et al*. 2014). Consumption of marble waste in concrete mix reduces the number of pollutants in the atmosphere (Singh and Madan 2017). Previously researches have been done using marble waste and found out the strength properties of concrete. As concrete strength properties have non-linear behavior it becomes difficult to predict the result for compressive strength (Mukherjee and Biswas 1997, Amlashi *et al*. 2020).

Nowadays, researchers are addressing these issues by using soft computing techniques (Thakur *et al*. 2021, Sobhani *et al*. 2010, Madandoust *et al*. 2012, Rabia *et al*. 2021, Upadhya *et al*. 2021) Concrete's compressive strength are mainly depending on quantity of cement, aggregates, water, admixtures and wastes used in concrete mix. These variables can act as an input parameter and help to predict the outcome. Conventional methods for forecasting the outcomes are chiefly depend upon the linear and non-linear regression techniques. But over the last few years, the prediction for mechanical properties of concrete is done by artificial intelligence techniques such as artificial neural network (ANN), Linear Regression (LR), Group Method of Data Handling (GMDH), Random Forest (RF), and Random Tree (RT) etc. Most of the research work can be found for the forecasting of mechanical properties of concrete mix. Sobhani *et al*. (2010) considering concrete constituents as input factors, regression, neural networks (NNT) and ANFIS models are created to anticipate the compressive strength of no-slump concrete. By looking at the outcomes it shows that NNT and ANFIS models are achievable in anticipating the 28-day's compressive strength for no-slump concrete than the proposed traditional regression models. Madandoust *et al*. (2012), apply GMDH type of neural network and ANFIS modeling for the forecast of compressive strength of concrete with cementitious material. In the study, for designing GMDH type of neural network, genetic algorithm was deployed. Parameters like length to diameter ratio, core diameter etc. was considered as input to predict the output strength. Chopra *et al*. (2018), study have been done to foresee compressive strength of concrete by utilizing AI procedures such as decision tree, random forest and neural network. By comparing the results of these techniques, it was found that neural network model predicts the compressive strength of concrete mix with high accuracy. Ayat *et al*. (2018) the investigation was directed to consider the affectability of the created model to certain fundamental variables influencing the compressive strength of concrete. It uncovered that the proposed ANNs model demonstrated a superior as a feasible and profoundly effective tool for simulating the Lime filler (LF) concrete compressive strength forecast. Hassan *et al*. (2019), compare the dependability of using the multiple linear regressions (MLR) model and the artificial neural networks (ANN) model to predict the concrete compressive strength using metakaolin (MK) and silica fume (SF) admixtures materials and parameters which includes concrete specimen age, water, fine aggregate, metakaolin, cement, coarse aggregate, silica fume, and superplasticizer. Relating to these input parameters in the ANN model, the concrete compressive strength containing MK and SF, are predicted. The results from the training, validation, and testing stages from making use of the ANN model showed that neural networks (NN) have strong potential use for the prediction of the compressive strength of concrete. By using classification algorithms such as M5P Tree models, Multilayer Perceptron, and Linear Regression, Deepa *et al*. (2010) estimates the compressive strength of high performance concrete. The outcomes indicate that tree-based models do exceptionally well in anticipating the concrete mix compressive strength. Ghazanfari *et al*. (2017) predicting mechanical properties, and identifying nonlinear patterns along with optimizing concrete mixtures using MLP and GMDH artificial neural networks. The results indicated that the performance of GMDH model, suggests acceptable accuracy of this model in evaluation of compressive strength and slump.

Last few decades, soft computing techniques are widely used in various engineering fields. As per best knowledge, no one compares the performance of these soft computing techniques for the prediction of compressive strength of concrete mix with waste marble powder. In the present study, different soft computing techniques have been used such as Group method of data handling (GMDH), Random Forest (RF), Random Tree (RT), and Linear Regression (LR), M5P, and Artificial neural network (ANN). Comparison of results has been done to find out the best method of modeling for the prediction of compressive strength of concrete mix.

1.1 Overview of Group Method of Data Handling (*GMDH*)

Group method of data handling is inductive mathematical approach for a complex model system. Artificial intelligence problems can be solved by GMDH technique because it is helpful for short or long term output prediction of a complex structure. It was first introduced in 1976 by Ivakhnenko. Pattern recognition for complex structure is the main application of GMDH model. This technique can be used in different fields for optimizing the data. This will be help, for find the interrelationship between the data. Group method of data handling gives the possible approach for finding the best model to a complex structure. There are number of hidden layers in GMDH model where errors at each level are basic criteria for developing another layer (Ghazanfari *et al*. 2017). Madandoust *et al*. (2012), assess the in-situ strength of concrete. Model is developed by GMDH and ANFIS by taking input parameters such as size of aggregate, age of concrete, strength of core, and length-diameter ratio to get the output of strength of concrete. In result, it was found that both GMDH and ANFIS have the ability for forecasting the cube strength. Ghazanfari *et al*. (2017), in this study two neural network techniques were approached, one is multilayer perceptron and second, group method of data handling, for the accurate forecasting output of concrete workability and compressive strength of cube. In the investigation it was found that, GMDH model suggest accurate prediction for the output of cube strength as well as the slump value for a concrete mix.)

For the output prediction say z, input variable is used $A = (a_1, a_2, a_3, a_4, \ldots\ldots, a_N)$ as nearer possible output z. In this study N numbers of observations are used.

$$z_i = f(a_1, a_2, a_3, a_4, \ldots\ldots, a_N) \qquad (i = 1, 2, 3, \ldots\ldots, N) \tag{1}$$

For the prediction of outcome, GMDH based model can be used for any input vector $A = (a_{i1}, a_{i2}, a_{i3}, a_{i4}, \ldots\ldots, a_{iN})$ i.e.

$$\hat{z_i} = \hat{f}(a_{i1}, a_{i2}, a_{i3}, a_{i4}, \ldots\ldots, a_{iN}) \qquad (i = 1, 2, 3, \ldots\ldots, N) \tag{2}$$

The difference between square of the actual and predicted values is to be minimum, for this GMDH based model is to be determined

$$\sum_{i=1}^{N} [\hat{f}(a_{i1}, a_{i2}, a_{i3}, \ldots\ldots, a_{iN}) - y_{iN}]^2 \rightarrow min \tag{3}$$

There is complicated relation between input and output variables

$$z = y_0 + \sum_{1}^{N} y_i\, a_i + \sum_{1}^{N}\sum_{1}^{N} y_{ij} a_i a_j + \sum_{1}^{N}\sum_{1}^{N}\sum_{1}^{N} y_{ijk}\, a_i a_j a_k + \cdots \ldots \tag{4}$$

The system consists of mathematical equation and represented by quadratic polynomial equation consists of two variables as shown in Eq. (5).

$$\hat{z} = G(a_i, a_j) = y_0 + y_1 a_i + y_2 a_j + y_3 a_i a_j + y_4 a_i^2 + y_5 a_j^2 \tag{5}$$

To find out the difference between actual and predicted data, y_i coefficient is calculated (see Eq. (5)) by the regression techniques, calculated $\hat{z}$, for minimizing the input variables a_i, a_j. Quadratic coefficient H_i is obtained to fit in the output in the full data set of input and output data, i.e.

$$F = \frac{\sum_{i=1}^{N} (z_i - H_i)^2}{N} \rightarrow min \tag{6}$$

Justification of the coefficient of equations is given by method of least square.

$$Yy = Z \tag{7}$$

$$y = \{y_0, y_1, y_2, y_3, y_4, y_5\} \tag{8}$$

$$Z = \{z_1, z_2, z_3, \ldots \ldots, z_N\}^T \tag{9}$$

$$Y = \begin{bmatrix} 1 & a_{1s} & a_{1t} & a_{1s}\, a_{1t} & a_{1s}^2 & a_{1t}^2 \\ 1 & a_{2s} & a_{1t} & a_{2s}\, a_{2t} & a_{2s}^2 & a_{2t}^2 \\ \cdots & \cdots & \cdots & \cdots & \cdots & \cdots \\ 1 & a_{Ns} & a_{Nt} & a_{Ns}\, a_{Nt} & a_{Ns}^2 & a_{Nt}^2 \end{bmatrix} \tag{10}$$

$$Y = (Y^T Y)^{-1} Y^T Z \tag{11}$$

Matlab is used to prepare the GMDH model. Neurons are selected for each input used in first layer. In next layer only neurons are used which is adequate.

1.2 Overview of Random Forest (RF)

Random forest is another technique that is used in this paper for the prediction of the compressive strength from the given dataset. Many researchers used this model technique for the prediction of the outcome (Chopra *et al.* 2018). In random forest model, numbers of trees are constructed from the provided dataset of inputs and output. These sets of trees are known as forest. For the desired output prediction, total dataset is divided into training and testing dataset. Training dataset consists of randomly selected 70% of the observations which is known as bagging and testing dataset consists of remaining 30% of the total dataset for the testing and validation of the data. Each tree will grow with the combination of input variables for the accurate prediction of the outcome.

1.3 Overview of Random Tree (RT)

Tree based models can handle the missing data variables and are good at nonlinear relationships findings. It will also be helpful for interpretation of the outcomes. Random tree is a modeling technique where data is divided randomly between training and testing datasets. Without pruning random tree algorithm constructs a tree with k number of random features at each node. Random tree is formed by selecting set of possible trees randomly. Random selection for trees has fair chance for each set of tree to be sampled i.e., uniform distribution of trees. Weka software is used in this study for the random tree based modeling.

1.4 Overview of Linear Regression (LR)

Linear regression is a part of regression analysis model where relationship between two or more dependent and independent variables are modeled with linear equations (Sobhani *et al*. 2010). The main aim of linear regression model is to find out the linear line which predicts the best suited relation between dependent and independent variables. It can only be possible by reducing the sum of the squares of vertical line from the designed line. Linear regression model consists or dependent variable and independent variable for example d and z respectively from the given dataset. It forms a simple mathematical equation to find the best numeric prediction. It also helps to find out the correlation coefficient which can describe the variations in the dataset. More the value is nearer to 1, more the data is reliable. (Deepa *et al*. 2010).

$$Y^T d = c_0 + c_1 z_1 + c_2 z_2 + C_3 z_3 + C_4 z_4 + C_5 z_5 + C_6 z_6 + \cdots\cdots\cdots\cdots \tag{12}$$

1.5 Overview of Artificial Neural Network (ANN)

Artificial neural network (ANN) is used for processing the information. It typically consists of processing units tied in a complex structure, in other words, we can say that it behaves like a human brain. In artificial neural network, inputs behave as neurons that are interconnected to find out the best output prediction. Artificial neural network technique work in different layers such as input layer, hidden layer and output layer as shown in Fig. 1. There are number of neurons present in hidden layer which when connected with input layer forms a complex structure. The data is divided into two datasets, namely training dataset and the testing dataset. Artificial neural network technique is applied on the training data set and for validation, testing data set is used. Training dataset helps in enhancing the performance of the structure whereas testing dataset is employed for the quality and the effectiveness of the network. Results for complex problems are rapidly and accurately solved by the artificial neural network technique.

1.6 Overview of M5P

Quinlan in 1992, introduces a supervised algorithm known as M5P. M5P can solve classification as well as regression analysis. M5P works in 3 steps. First step includes design of decision tree by dividing samples into sub samples and develop the branches. In second step,

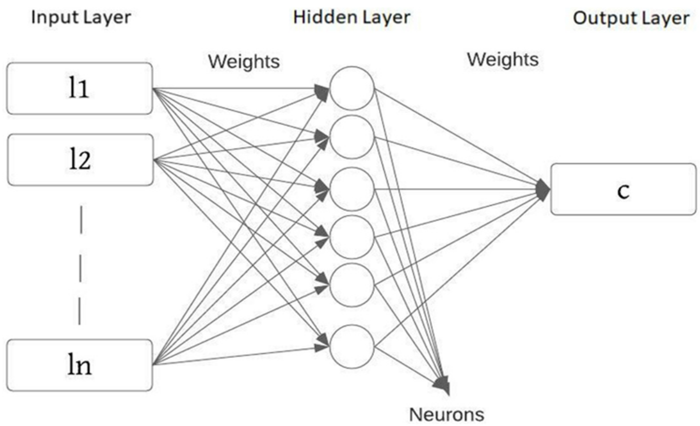

Fig. 1 Artificial Neural Network Model Structure

pruning of the data samples has been done from individual leaf. Prunning of decision tree are done either by converting inner node into a leaf or with the help of calculating tree score. Tree score can be calculated by using sum of squared residuals and number of leaf used or terminal nodes. In this prunning process surplus trees are destroyed or they can be substituted by sub-trees. In comparison to regression trees, model trees predict better results with good accuracy (Deepa *et al*. 2010).

2. Methodology and dataset

2.1 Dataset

In total data of 49 readings were collected from the previous studies as shown in Table 1. Dataset was divided randomly between two groups i.e., training and testing dataset. Training

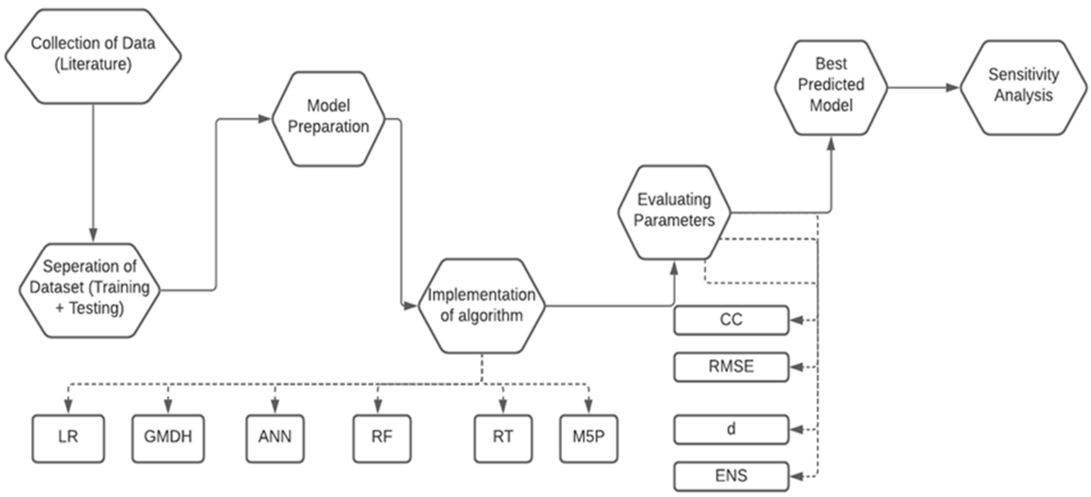

Fig. 2 Flow chart of methodology

Table 1 Detail of dataset

S.no	Authors name	Year	Total data set
1	Alyamac and Ince (2009)	2009	10
2	Topcu *et al*. (2009)	2009	1
3	Ergun (2011)	2011	7
4	Sounthararajan and Sivakumar (2013)	2013	4
5	Soliman (2013)	2013	6
6	Vaidevi (2013)	2013	3
7	Chavhan and Bhole (2014)	2014	11
8	Sakalkalel *et al*. (2014)	2014	3
9	Talah *et al*. (2015)	2015	1
10	Dhiman and Bhardwaj (2015)	2015	3
	Total		**49**

Table 2 Features of data set

Statistics	Training data set					Output parameter
	C (kg/m^3)	*FA* (kg/m^3)	*CA* (kg/m^3)	*w/c*	*MP* (kg/m^3)	*CS* (MPa)
Minimum	255.0000	0.0000	578.0000	0.3000	0.0000	21.3200
Maximum	500.0000	1157.0000	1721.4000	0.7000	860.0000	59.0000
Mean	375.1162	723.0859	1025.3904	0.4847	98.0479	34.5700
Standard deviation	57.3369	310.7109	359.0789	0.0771	158.1681	9.5899
Kurtosis	-0.1479	-0.7909	-0.8142	2.4122	16.4845	0.4082
Skewness	-0.0295	-0.1488	0.2663	1.0014	3.6212	0.9616
			Testing data set			
Minimum	240.0000	312.3000	578.0000	0.3000	0.0000	20.3000
Maximum	500.0000	1157.0000	1721.4000	0.6300	316.4700	64.5000
Mean	360.8953	596.1767	1227.9933	0.4900	75.6687	36.7673
Standard deviation	77.7888	288.0042	391.5690	0.0909	100.0508	9.8888
Kurtosis	-0.9845	-0.8002	-0.7826	0.0518	1.4482	4.0810
Skewness	-0.1589	0.6669	-0.2316	-0.1472	1.5757	1.3715

dataset contains 70% data from the total observations and testing dataset contains 30% observations from the total dataset. Cement (C), fine aggregates (FA), coarse aggregates (CA), w/c, and Marble powder (MP) are used as an input parameters for the prediction of the output data which is compressive strength (CS) in MPa. Statistics features of input parameters to attain the output are listed in Table 2. Input parameter i.e., Cement (C), Fine aggregates (FA), Coarse aggregates (CA), w/c, and marble powder (MP) ranges from 240-500 kg/m^3, 0-1157 kg/m^3, 578-1721.4 kg/m^3, 0.3-0.7, and 0-860 kg/m^3 respectively to get the output of compressive strength for a range of 20.3 -64.5MPa were used. A flow chart is also plotted in Fig. 2 for the better understanding of the methodology.

2.2 Model evaluation and comparison

Assessment of different parameters utilized for estimating the compressive strength of concrete, various techniques were chosen, for example, coefficient of correlation (CC), root mean square error (R.M.S.E), Willmott's index (d) and Nash- Sutcliffe coefficient (ENS)

1. $$CC = \frac{N\sum_{i=1}^{N} EF - \sum_{i=1}^{N} E \sum_{i=1}^{N} F}{\sqrt{N\left(\sum_{i=1}^{N} E^2\right) - \left(\sum_{i=1}^{N} E^2\right)}\sqrt{N\left(\sum_{i=1}^{N} F^2\right) - \left(\sum_{i=1}^{N} F^2\right)}} \quad (13)$$

2. $$R.M.S.E. = \sqrt{\frac{1}{N}}\left(\sum_{i=1}^{N}(F-E)^2\right) \quad (14)$$

3. $$d = 1 - \frac{\sum_{i=1}^{N}(F-E)^2}{\sum_{i=1}^{N}(|F-\bar{E}| + (|E-\bar{E}|)^2} \quad (15)$$

4. $$ENS = 1 - \frac{\sum_{i=1}^{N}(F-E)^2}{\sum_{i=1}^{N}(E-\bar{E})^2} \quad (16)$$

E = Observed values
$\bar{E}$ = Average of observed value
F = Predicted values
N = Number of observations

3. Result and discussion

3.1 Assessment of GMDH based model

GMDH (Group method of data handling) is algorithm for computer based mathematical modeling. In this investigation, Table 3 shows the results of coefficient and constants used for transferring the function of GMDH based model. The values of performance evaluation parameters for GMDH based model technique for the prediction of compressive strength using both (training and testing) stages as shown in Table 4. Results of Table 4 indicate that the GMDH based model is suitable for predicting the compressive strength of the cement concrete when mixed with marble powder with the coefficient of correlation CC is 0.8309, R.M.S.E. is 5.2908, d is 0.9022 and ENS is 0.6864 for training dataset and the coefficient of correlation is 0.7493, R.M.S.E. is 7.1468, d is 0.8008 and ENS is 0.4390 for testing dataset. Scatter plot among actual and predicted values using GMDH technique is plotted for both stages as shown in Fig. 3. These figure shows that the most of the points lay close to the line of perfect agreement and confirms that the GMDH model is suitable for predicting the compressive strength with marble powder. The line of perfect agreement shows the ideal relationship between actual and predicted values, the values nearer to the perfect agreement line will result towards more accuracy.

Table 3 Results of transfer function of GMDH Model for adjusting the parameters

Layer	Neurons	B_0	B_1	B_2	B_3	B_4	B_5
1	1	138.9361	-0.60021	0.10157	0.000821	-6.22E-05	-0.00016
	2	386.0749	-1.38057	-462.826	0.001276	149.4429	0.9453
	3	209.3636	0.026196	-0.27646	-7.82E-05	9.49E-05	3.87E-05
	4	33.26598	0.006213	-0.19336	-8.88E-06	0.000209	0.000253
	5	41.97698	-0.02138	0.172713	1.00E-05	-1.29E-05	-0.00016
2	1	119.2473	-12.8144	7.025084	0.31709	0.036025	-0.25881
	2	32.28865	-3.16855	2.028216	0.118545	0.053908	-0.13914
	3	-15.1931	0.471396	1.486299	-0.01673	-0.04945	0.051788
	4	244.4383	-12.1795	-1.39101	0.171444	0.02895	0.014256
	5	21.62369	-1.84108	1.605911	0.139922	0.110239	-0.23545
3	1	-6.21582	1.348836	0.081058	0.079932	0.094106	-0.18204

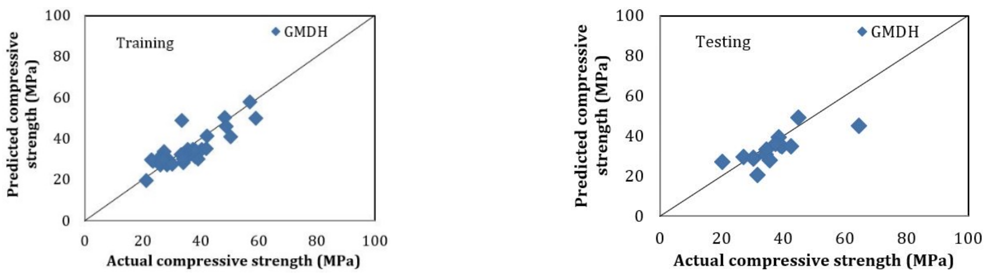

Fig. 3 Scatter graph shows actual and predicted value of compressive strength using GMDH

3.2 Assessment of Random Forest and Random Tree based model

The RF and RT model technique for the 28-days of compressive strength as shown in Table 4 for both testing and training stages. From Table 4 it has been found that the performance of RT based model is better than the RF based model for predicting the compressive strength of concrete mixed with marble powder with the value of CC is 1 & 0.8241, RMSE values as 0.0243 & 5.4246, values as 1 & 0.8763 and ENS values as 1 & 0.6628 for training and testing stages respectively. Figs. 4 and 5 shows the scatter graph plotted among actual and predicted values using RF and RT based models. It shows that the execution of RT based model is better for the prediction of compressive strength of concrete mixed with marble powder. The results show that the RT-based model predicts a greater compressive strength with less scatter and a better agreement between actual and predicted values.

3.3 Assessment of Linear Regression (LR) based model

LR based model predict the relationship between two variables or factors. The results of Table 4 shows the linear regression model technique for the 28-days of compressive strength for both training and testing dataset Fig. 6 is the graphical representation of actual versus predicted compressive strength with coefficient of correlation CC is 0.4396, R.M.S.E. is 8.4858, d is 0.5488

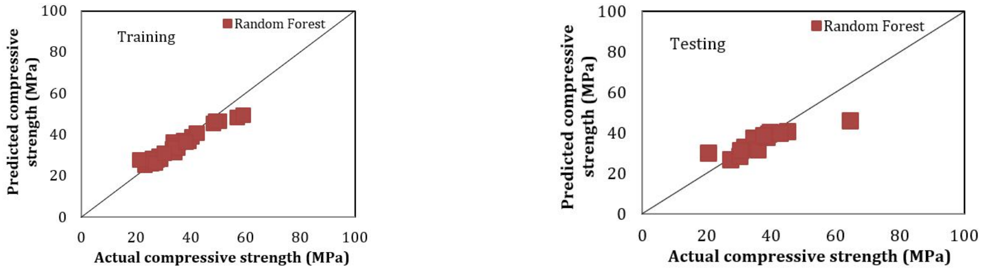

Fig. 4 Scatter graph shows actual and predicted value of compressive strength using Random Forest

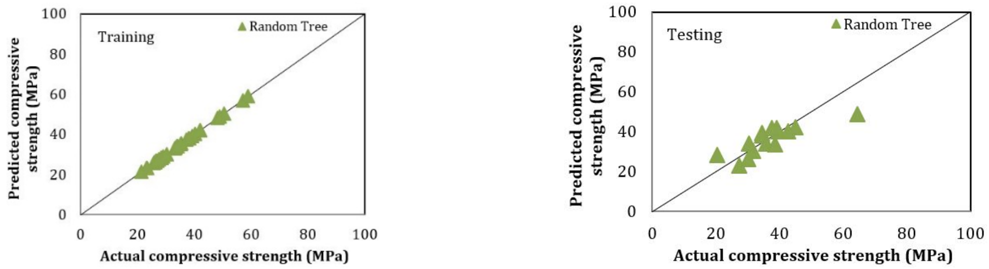

Fig. 5 Scatter graph shows actual and predicted value of compressive strength using Random Tree

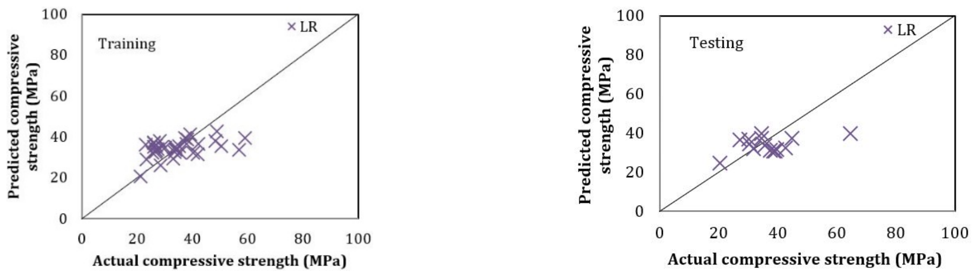

Fig. 6 Scatter graph shows actual and predicted value of compressive strength using Linear Regression

and ENS is 0.1933, and for training dataset and coefficient of correlation is 0.4466, R.M.S.E. is 8.8358, d is 0.5215 and ENS is 0.1144 for testing dataset as listed in Table 4. The findings reveal that with significant scatter, the LR-based model predicts a lower compressive strength and does not establish a better agreement between actual and predicted values because of less CC value less than 0.8.

$$\begin{aligned} \mathrm{CS} = \ & 84.33136 + 0.01613 \times \mathrm{C} - 0.03521 \times \mathrm{FA} - 0.02929 \\ & \times \mathrm{CA} \ + 9.08984 \times \frac{\mathrm{w}}{\mathrm{c}} - 0.04817 \times \mathrm{MP} \end{aligned} \tag{17}$$

3.4 Assessment of ANN based model

ANN is a computational model in machine learning. In this investigation the numbers of hidden layers are used with 25 neurons with learning rate 0.2, momentum 0.1 and training time 2000. To forecast the compressive strength property of concrete with marble powder five different

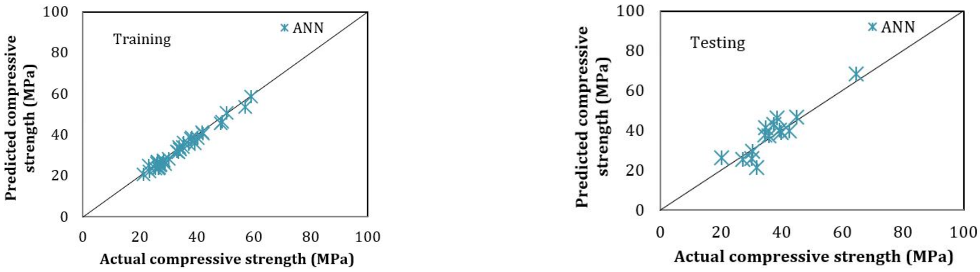

Fig. 7 Scatter graph shows actual and predicted value of compressive strength using ANN

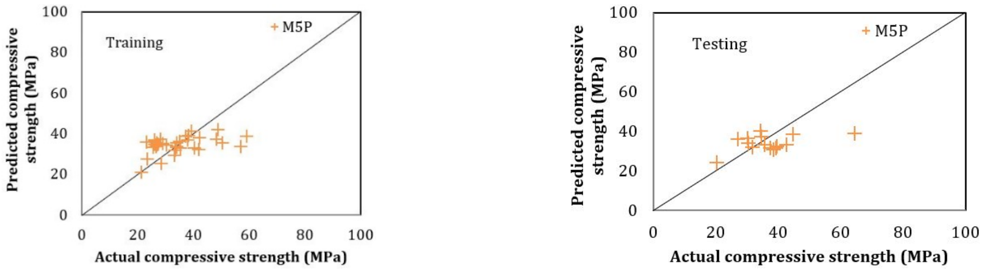

Fig. 8 Scatter graph shows actual and predicted value of compressive strength using M5P

performance assessment parameters were mainly used by using both (training and testing) stages. Table 4 indicates that ANN based model gives appropriate results to predict the compressive strength of concrete with marble powder with the training and testing values of CC as 0.9902 & 0.9139, RMSE values as 1.7941 & 4.5611, d value as 0.9809 & 0.9458 and ENS value as 0.9639 & 0.7502 respectively. The scatter graphs are plotted among actual and predicted values using ANN based model for both the stages as shown in Fig. 7. In this figure, it reveals that the most of the points lie close to the line of the perfect agreement and approves that the ANN based model is suitable for the prediction of the compressive strength of concrete mixed with marble powder. The results show that the ANN-based model predicts a greater compressive strength with less scatter and a better agreement between actual and predicted values.

3.5 Assessment of M5P based model

M5P based model predict the relationship between two variables or factors. The results of Table 4 show the M5P model technique for the 28-days of compressive strength for both training and testing dataset Fig. 8 is the graphical representation of actual versus predicted compressive strength with coefficient of correlation CC is 0.4334, R.M.S.E. is 8.5144, d is 0.5312 and ENS is 0.1878, and for training dataset and coefficient of correlation is 0.4694, R.M.S.E. is 8.8649, d is 0.5333 and ENS is 0.1389 for testing dataset as listed in Table 4. The results show that, the M5P-based model predicts a lower compressive strength and does not improve the agreement between actual and projected values with less CC value (0.4334).

3.6 Inter comparison of soft computing based models

To predict the compressive strength of concrete mixed with marble powder using soft

Table 4 Performances of GMDH, Random Forest, Random Tree, Linear Regression and ANN

Approaches	CC	R.M.S.E.	d	ENS
		Training data set		
GMDH	0.8309	5.2908	0.9022	0.6864
Random Forest	0.9784	2.9535	0.9677	0.9023
Random Tree	1.0000	0.0243	1.0000	1.0000
Linear Regression	0.4396	8.4858	0.5488	0.1933
ANN	0.9902	1.7941	0.9809	0.9639
M5P	0.4334	8.5144	0.5312	0.1878
		Testing data set		
GMDH	0.7493	7.1468	0.8008	0.4390
Random Forest	0.8556	5.7900	0.8358	0.6311
Random Tree	0.8241	5.4246	0.8763	0.6628
Linear Regression	0.4466	8.8358	0.5215	0.1144
ANN	0.9139	4.5611	0.9458	0.7502
M5P	0.4694	8.8649	0.5333	0.1389

computing techniques is simple and time saving than experiment observation. The performance of all the models listed in Table 4 for both stages i.e., Training and Testing. Fig. 9, presents the results of training and testing dataset for GMDH, random forest, random tree, linear regression, M5P and ANN model, which shows that predicted output of compressive strength is so close to actual values of compressive strength in ANN and random tree based models. Figs. 9(a)-(c) shows the comparison of the results formed by techniques used to predict the outcome. As in Table 4, Coefficient of correlation is best in ANN based model (0.9139) followed by random tree based model (0.8241). Also, Willmott’s index (d), Nash-Sutcliffe coefficient (ENS) are 0.9458 and 0.7502 respectively for ANN based model and 0.8763 and 0.6628 for random tree based model. The value of correlation coefficient is not considered as a good fit if its value is less than 0.8 so GMDH, linear regression and M5P is not a good fit for the testing dataset as they have correlation coefficient less than 0.8 i.e., 0.7493,0.4466 and 0.4694 respectively. Also as shown in fig. 9(d) relative error is minimum in ANN and random tree based model techniques compared to GMDH, random forest, linear regression and M5P based models.

4. Sensitivity investigation

Sensitivity investigation is carried out to examine the most significant parameter to evaluate the performance of best suited model for predicting the compressive strength of concrete with marble powder among all input parameters. Outcomes of sensitivity investigation using ANN based model as listed in Table 5 below. In Table 5, the performance of each model is evaluated in terms coefficient of correlation, mean absolute error and root mean square error as considered in comparison with the other input parameters. For this examination, the best model's performance has been chosen. Table 5 shows that the water-cement ratio (w/c) has a substantial influence on the compressive strength of concrete containing marble powder when compared to the other parameters in this data set. Furthermore, removing w/c raises the RMSE value (7.9521). The

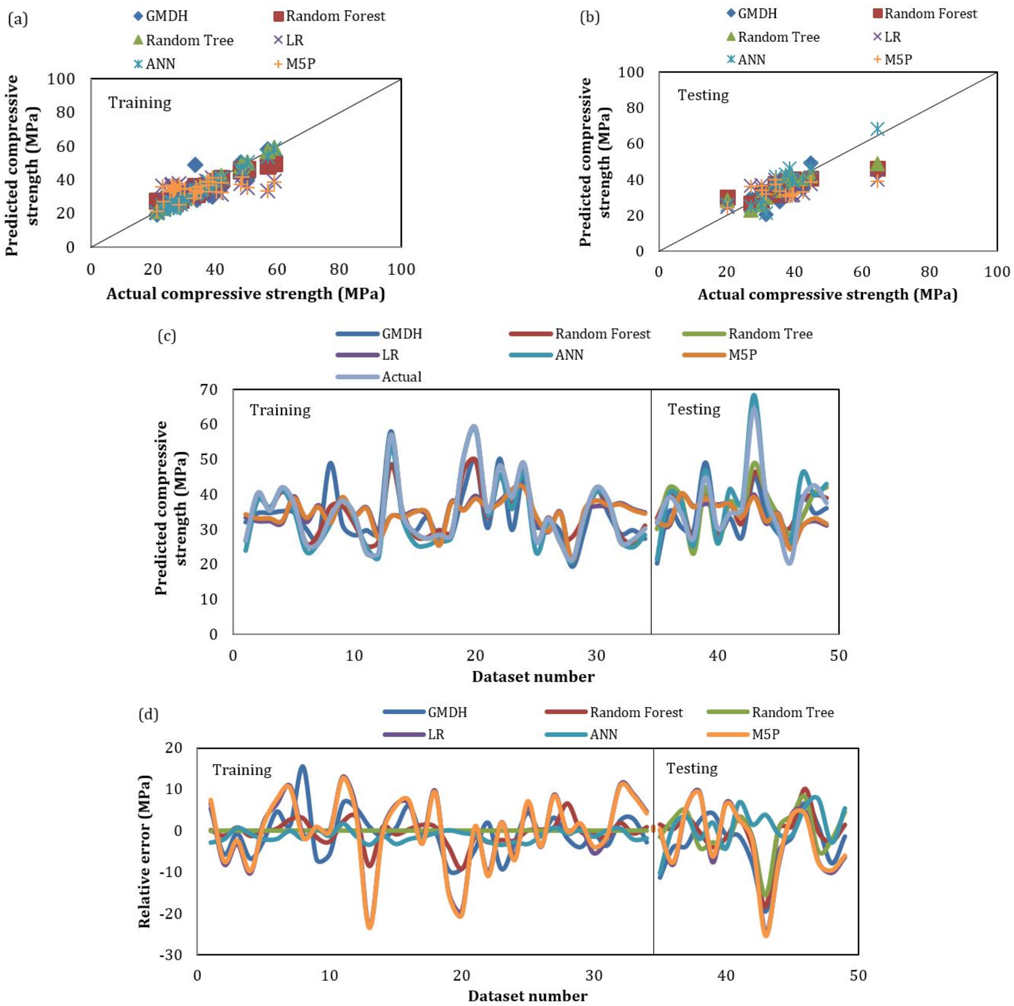

Fig. 9 Comparison between GMDH, RF, RT, LR, M5P and ANN predicted and actual values

Table 5 Sensitivity result analysis using ANN based model

Input combination					Removed	Output	ANN based model		
Cement (C) kg/m^3	Fine aggregate (FA) kg/m^3	Coarse aggregate (CA) kg/m^3	Water-cement ratio (w/c)	Marble powder (MP) kg/m^3		Compressive strength (MPa)	CC	MAE	RMSE
					-		0.9139	3.9306	4.7751
					Cement		0.7644	4.7542	6.9149
					FA		0.7012	5.448	6.8703
					CA		0.6877	5.3071	7.2553
					w/c		0.5673	5.5726	7.9521
					MP		0.7171	5.0406	6.7523

reason for the rise in compressive strength with w/c is the hydration process. Concrete stops growing stronger as it dries. The characteristics of such a concrete would be lower than wet concrete. In concrete, the reaction of water with the cement is responsible for the strength and durability of concrete.

5. Conclusions

The precise valuation of compressive strength property of the concrete plays an important role in improving the strength of the concrete with marble powder. In this study the soft computing techniques were used to evaluate the prediction of compressive strength of the concrete by applying different techniques i.e., ANN, GMDH, RF, RT, M5P and LR. Based on these models, compressive strength property of concrete mixed with marble powder was analyzed. Evaluation of models was checked by applying performance measures like CC, RMSE, d and ENS. Results acquired in this examination are summed up as follows:

(1) According to the assessment of results, it has been found that the performance of ANN based model is better than the other applied approaches for forecasting the compressive strength of concrete with marble powder.
(2) From this study the other major outcome shows that the working of ANN model is more preferable than other applied models for the forecasting of compressive strength property of concrete with marble powder.
(3) Among all algorithms, ANN predicts better results with highest CC, d, and ENS values 0.9139, 0.9458, and 0.7502 respectively and lower RMSE value i.e., 4.5611.
(4) Results of sensitivity indicates that the water-cement ratio (w/c) has a substantial influence in predicting the compressive strength of concrete with marble powder with ANN based model in comparison with the other parameters for this data set with minimum CC value i.e., 0.5673 and maximum error (7.9521).
(5) Scatter diagram shows that the ANN has minimum error band width, and it is good fit for predicting the output.

Data availability statement

All data, models, and code generated or used during the study appear in the submitted article.

Conflict of interest statement

There is no interest in conflict by the authors with anyone whosoever is connected to this research paper.

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