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RESEARCH

Efficient compressive strength prediction of concrete incorporating industrial wastes using deep neural network

Kumar Shubham[1] · M.K. Diptikanta Rout[1] · Abdhesh Kumar Sinha[1]

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Abstract
The prediction of concrete compressive strength based on mixing proportions using statistical and machine learning techniques has gained significant attention due to its relevance in the industrial context. However, most existing models have been developed with limited experimental data. In this study, a neural-based prediction model is proposed that employs both deep neural network (DNN) and artificial neural network (ANN) approaches to accurately forecast the compressive strength of high-strength concrete using eight input parameters. To ensure the robustness of the present model, a comprehensive dataset comprising over 1000 building site records has been used. For the development of the ANN model, MATLAB's ANN Tool is utilized and experimented with three different algorithms namely, Levenberg–Marquardt (LM), Bayesian regularization (BR), and scaled conjugate gradient (SCG). Additionally, the DNN model using Python coding is implemented. The prediction accuracy of the models is evaluated by analyzing the root mean square error (RMSE) and coefficient of determination (R^2), while also employing Taylor diagram to assess their performance. The results demonstrated that the DNN model achieved remarkable accuracy in predicting the compressive strength of concrete incorporating industrial waste, yielding an R^2 value of 0.972. Furthermore, a sensitivity analysis revealed that the cement content, amount of blast furnace slag, and age of concrete were identified as the most influential parameters affecting the compressive strength. This research contributes to the field by providing an effective prediction model for high-strength concrete compressive strength, leveraging the power of neural networks, and incorporating a comprehensive dataset.

Keywords Compressive strength · ANN · DNN · Sensitivity analysis

Introduction

Property of concrete to withstand compressive strength, it is an exceptional material for use in the construction industry. As a result of this, the concrete industry is searching for ways to include alternative materials in the production of concrete to reduce the negative effect that it has on the environment and to encourage sustainable development (Nazeer et al., 2023). As per the environmental report, approximately 3.5 billion tons of cement was used in the construction industry, and it will grow 25% more in the next decade (Meng et al., 2022). As a result, this huge use of cement produced carbon dioxide (CO_2) in the environment which will create adverse effects. Concrete is a remarkable building material due to its resistance to compressive stress (Rout et al., 2015). Consequently, the concrete industry is looking for methods to include alternative materials in concrete manufacturing to promote sustainable growth (Rout et al., 2023). The wastes such as silica fume (SF), metakaolin (MK), fly ash (FA), rice husk ash (RHA), ground granulated blast furnace slag (GGBFS), construction and demolition (CD) waste, and crumb rubber (CR) act as supplementary cementitious materials (SCMs) which can be used as a substitute for cement in the production of concrete (Gill & Siddique, 2018; Kumar, 2017; Singh et al., 2018). Compressive strength is the most typical measure of the technical qualities and performance of concrete after it has been allowed to cure for 28 days (Kaveh & Iranmanesh, 1998; Rout et al., 2021). Compressive strength after 28 days of aging is the criterion that is used most often when defining structural concrete. It is well-established that compressive strength is associated with other mechanical parameters such as flexural and tensile strength (Diptikanta Rout et al., 2023; Ziyad Sami

✉ Kumar Shubham
2018rsce013@nitjsr.ac.in

[1] Department of Civil Engineering, National Institute of Technology, Jamshedpur, India

et al., 2023). In addition, it is important to keep in mind that the ratio of water to cement, denoted as w/c, is one of the most important factors in determining the ultimate strength of concrete. Yet, for a given water-to-cement ratio, the strength of the concrete may varies greatly depending on factors such as the kind of cement, aggregate, mineral and chemical admixtures, and other similar factors. So, the need for proper mix design arises to tackle the chances of concrete failure (Akbar et al., 2020). The optimization of mix design should be employed for the concrete based on various laboratory tests.

The experimental strength requires more labor and time, and may have some errors associated with the test. Therefore, it would be beneficial to have a model that is both robust and predictive and that could estimate compressive strength as a function of the proportions of the mixture (Sobhani et al., 2010). This would result in an optimized mix design and reduce the empirical and labor-intensive nature of "trial batching" approaches, which are the current basis of industrial practice. It is difficult to develop physical models that can predict strength because chemical data, particularly which are required to estimate reaction kinetics, are considerably less readily available. Although the mechanical properties of the component materials and cement hydrates are better understood, this is not the case for chemical data (i.e., without empirical calibration) (Chithra et al., 2016; Dantas et al., 2013; Kaveh & Khavaninzadeh, 2023). To overcome this complexity, artificial intelligence (AI) is the best option for the prediction of strength, deformation, modulus of rupture, etc. (Chaabene et al., 2020). Thus, it is crucial to use statistical and machine learning (ML) approaches to forecast the growth of compressive strength as a function of the concrete's mixing proportions (Asteris et al., 2021; Duan et al., 2013). In recent times, the majority of investigations have applied various conventional ML techniques such as k-nearest neighbor (kNN), naïve Bayes' (NB), support vector mechanism (SVM), random forest (RF), decision tree (DT) and extremely randomized trees (ERT) to evaluate the strength of concrete at the desired curing ages (Liu, 2022; Mohtasham Moein et al., 2023; Thai, 2022). However, neural networks (NN) can provide a better prediction than conventional ML algorithms. Several studies focused on numerous linear and non-linear regression equations in the last decade owing to the significance of the study issue (Lin & Wu, 2021; Paruthi et al., 2022; Shahmansouri et al., 2021). Using AI for modeling has been a hotbed of academic activity. ANN learning has been demonstrated to be robust to errors in the training data, and it has been successfully used to learn real-valued, discrete-valued, and vector-valued functions. Thus, this technique has been implemented to determine the compressive strength of concrete containing industrial waste (Abhilash & Tharani, 2021; Alhazmi et al., 2021; Fakhri et al., 2017; Gupta & Sachdeva, 2021; Kioumarsi et al., 2023; Lam et al., 2022; Parhi & Patro, 2023; Verma et al., 2023). There are various ANN algorithms which can be used for ML modeling. Binary classification tasks are often dealt with using perceptron. Image and video processing tasks are done using convolutional layers to extract the spatial features. Recurrent neural networks (RNN) and long short-term memory (LSTM) are used to handle sequential dependencies. The gated recurrent unit (GRU) is another type of RNN that is more computationally efficient and has fewer parameters for the prediction purposes. Self-organizing maps (SOM) is used for clustering and dimensionality reduction tasks. SOMs map input data to a low-dimensional grid. Radial basis function network (RBFN) utilizes radial basis functions as activation functions and is particularly suitable for function approximation tasks. Bayesian regression is an algorithm that combines neural networks with Bayesian inference (Kaveh & Servati, 2001). It allows for probabilistic modeling and uncertainty estimation in predictions. The advantage of BR is its ability to provide not only point predictions but also uncertainty estimates, which can be valuable in decision-making and risk assessment (Garoosiha et al., 2019). Scaled conjugate gradient (SCG) is an optimization algorithm used in training neural networks (de-Prado-Gil et al., 2022). It combines the advantages of conjugate gradient methods with adaptive step-size control. The advantage of SCG is its fast convergence rate, efficient memory usage, and suitability for large-scale neural networks. SCG can be particularly useful when training deep neural networks or dealing with large datasets (Garoosiha et al., 2019). The Levenberg–Marquardt (LM) algorithm is another optimization technique used in training neural networks. It combines the advantages of the Gauss–Newton method and gradient descent. LM is known for its fast convergence and robustness. It is particularly efficient for problems with small training datasets and can be useful when dealing with noisy or ill-conditioned problems. Systems based on artificial neural networks (ANNs) are motivated to capture these phenomena because of the possibility of tremendous parallelism made possible by distributed representations. While artificial neural networks (ANNs) are an effective solution for prediction issues, there are still drawbacks to using them, as evidenced by past research (Getahun et al., 2018). Some recent studies show DNN models to be more effective and reliable than ANN. Recently, researchers have employed DNN for the strength prediction of foamed concrete (Nguyen et al., 2019), rubber concrete (Ly et al., 2021), high-performance concrete (Liu, 2022), eco-friendly concrete (Lv et al., 2022), and recycled concrete (Deng et al., 2018). Search also shows that these models can be used as surrogate models in reliability analysis (Shubham et al., 2022). The literature survey shows that most of these DNN models have been developed using less data. So, those models are not very effective in prediction when implemented over a large range. The present study aims to develop a DNN model for the prediction of compressive strength based on the dataset formed through the collection of data from different construction sites. It provides an edge to the DNN model because the dataset will have a wide range of variation among the parameters and the size of dataset being large.

The goal of this research is to create a prediction model that employs neural networks to precisely forecast the compressive strength of concrete, including the integration of industrial wastes. While earlier research has frequently utilized artificial neural network (ANN) techniques, they lack the capacity to give insights into the relative relevance of diverse elements impacting compressive strength. To solve this restriction, this research incorporates deep neural networks (DNN) into the model to improve its efficiency. In this investigation, a big dataset with over 1000 data points covering a broad variety of parameters was used. The goal is to promote sustainability in concrete manufacture by facilitating a deeper knowledge of the behavior of concrete mixes that include industrial wastes. The purpose of this paper is to evaluate the potential of DNN using a large quantity of experimental data to forecast the compressive strength of concrete including different kinds of industrial wastes. It is believed that using DNN in this work, a more accurate and robust prediction model may be constructed. The incorporation of a varied variety of experimental data will improve the model's dependability and give useful insights into the use of industrial wastes in concrete manufacturing. Finally, this study advances information and understanding of concrete mixture behavior, which may help researchers and industry experts make educated choices to enhance the sustainability and performance of concrete production processes.

Description of the dataset

A total of eight input parameters were considered which are cement (C), water (W), fly ash (F), ground granulated blast furnace slag (GGBS), super-plasticizer (S), coarse aggregate (CA), fine aggregate (FA), and concrete age (T). The compressive strength was employed as the output variable for the target data sets. A total of 1030 data have been used. The range and the abbreviations of the parameters are mentioned in Table 1.

The complete description of the dataset is mentioned in Table 2. The data collected through different construction sites provided an advantage of a wide range of implementation and availability of an ample amount of data so that DNN can be implemented. The heat map, which is a depiction of the correlation matrix, is shown in Fig. 1. A pair plot (as shown in Fig. 2) may be used to get a better understanding of the distribution of variables between a pair of variables, while a correlation matrix can reveal the value of the correlation coefficient that exists between the input variables.

Table 1 Input and output parameters for the NN model used in this study

Parameter	Notation	Minimum	Maximum
Cement	C	102	540
GGBS	G	0	359.4
Fly ash	F	0	200.1
Water	W	121.8	247
Super-plasticizer	S	0	32.2
Coarse aggregates	CA	801	1145
Fine aggregates	FA	594	992.4
Age of the concrete	T	1	365
Compressive strength	CS	2.33	82.60

Neural network prediction modeling

ANN architecture was conceptualized after the biological neurons found in the body, which served as a source of inspiration (Naderpour et al., 2018). ANN is based on a network of interconnected components referred to as artificial neurons. Each artificial neuron sends a signal to another artificial neuron through the connections between them. Every connection is given a weight, and that weight may be used to change the amount of signal intensity (Kaveh et al., 2008; Verma et al., 2023). The ANN architecture consists of an input layer, a hidden layer, and an output layer. The number of neurons in the input and output layer is equal to the number of input parameters and output parameters, respectively (Siddique et al., 2011). The most common ANN algorithms for predicting the value of target variable of heterogeneous, anisotropic, and non-uniform materials like concrete are supervised learning algorithms like Bayesian regularization (BR), scaled conjugated gradient (SCG), and Levenberg–Marquardt (LM) (Chhabra et al., 2023). 'nntool' command present in MATLAB has been used to access the mentioned algorithms. In general, the LM method was created to give numerical solutions to the issue of minimizing a non-linear function. The LM methodology is often a hybrid of the steepest descent technique and the Gauss–Newton algorithm (Deng et al., 2018). The SCG algorithm uses much less memory than the LM method for processing the data. The SCG is based on supervised learning using second-order gradients. While the BR technique takes longer processing time than the other algorithms studied in this research, it can provide excellent generalization for tough, tiny, or noisy datasets. This approach enables the ANN model to be built using just the training datasets, eliminating the need for separate training and validation datasets.

Table 2 Description of input and output parameters for the considered model

Parameters	C	G	F	W	S	CA	FA	T	CS
Count	1030	1030	1030	1030	1030	1030	1030	1030	1030
Mean	281.17	73.89	54.18	181.56	6.20	972.92	773.58	45.66	35.82
Standard deviation	104.51	86.27	63.99	21.35	5.97	77.75	80.18	63.17	16.71
Minimum	102.00	0.00	0.00	121.80	0.00	801.00	594.00	1.00	2.33
25%	192.38	0.00	0.00	164.90	0.00	932.00	730.95	7.00	23.71
50%	272.90	22.00	0.00	185.00	6.40	968.00	779.50	28.00	34.45
75%	350.00	142.95	118.30	192.00	10.20	1029.40	824.00	56.00	46.14
Maximum	540.00	359.40	200.10	247.00	32.20	1145.00	992.60	365.00	82.60

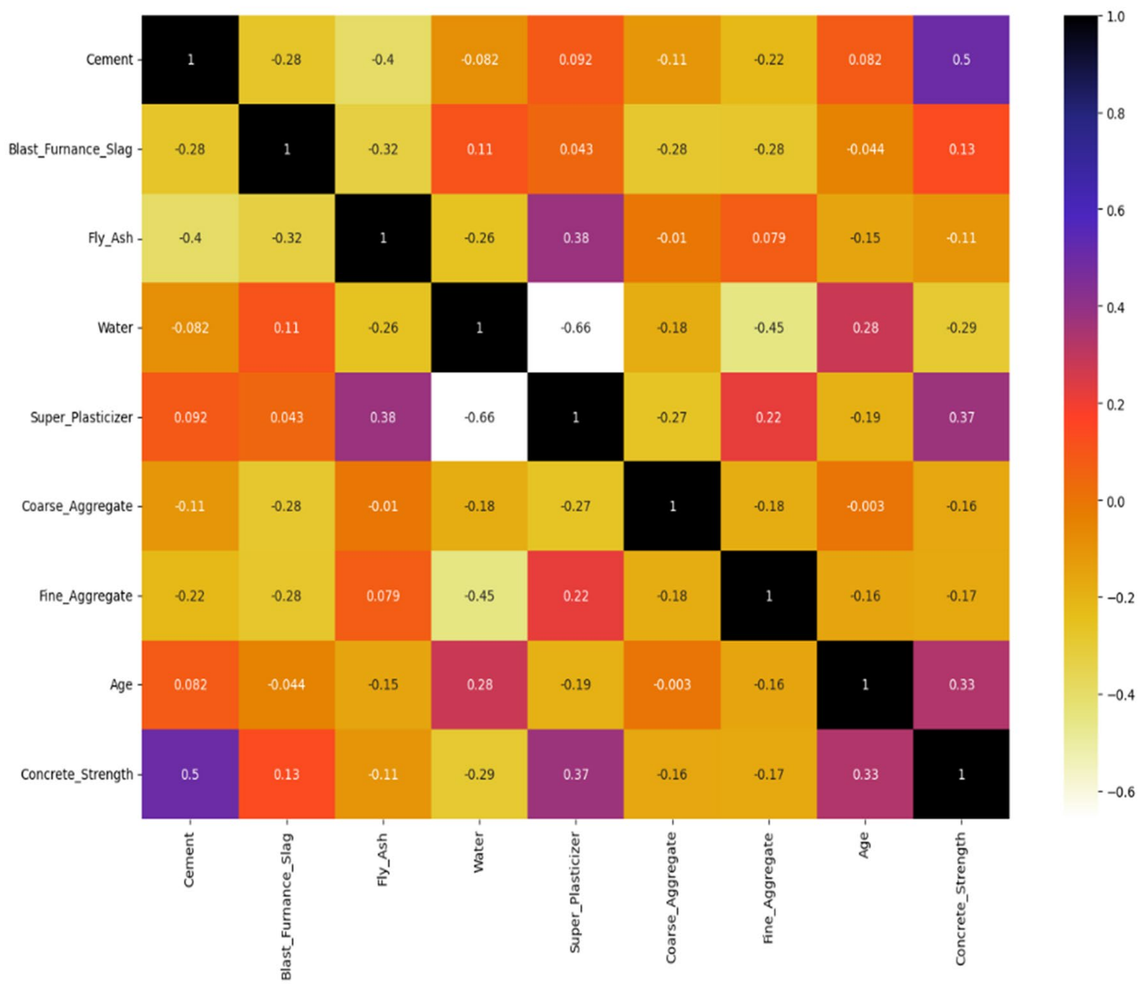

Fig. 1 Heat map showing the correlation between the parameters

DNN is an improvized ANN technique in which the number of hidden layers can be increased over more than two (Ly et al., 2021). They display actions that are characteristic of the human brain. Deep neural networks can find overall solutions when provided with adequate data. Nevertheless, a DNN employs several different optimization strategies to offset the impacts of the limitations related to prior multilayer neural networks (Munir et al., 2022). This is done to improve the accuracy of the DNN. One of the downsides of the present iteration of the multilayer neural network is an issue referred to as overfitting, which is also known as overtraining (Stel et al., 2022). This indicates that the accuracy of the predictions produced using the information utilized during training is high, but that the accuracy of the predictions made using fresh data that were not used in training is relatively low (Mai et al.,

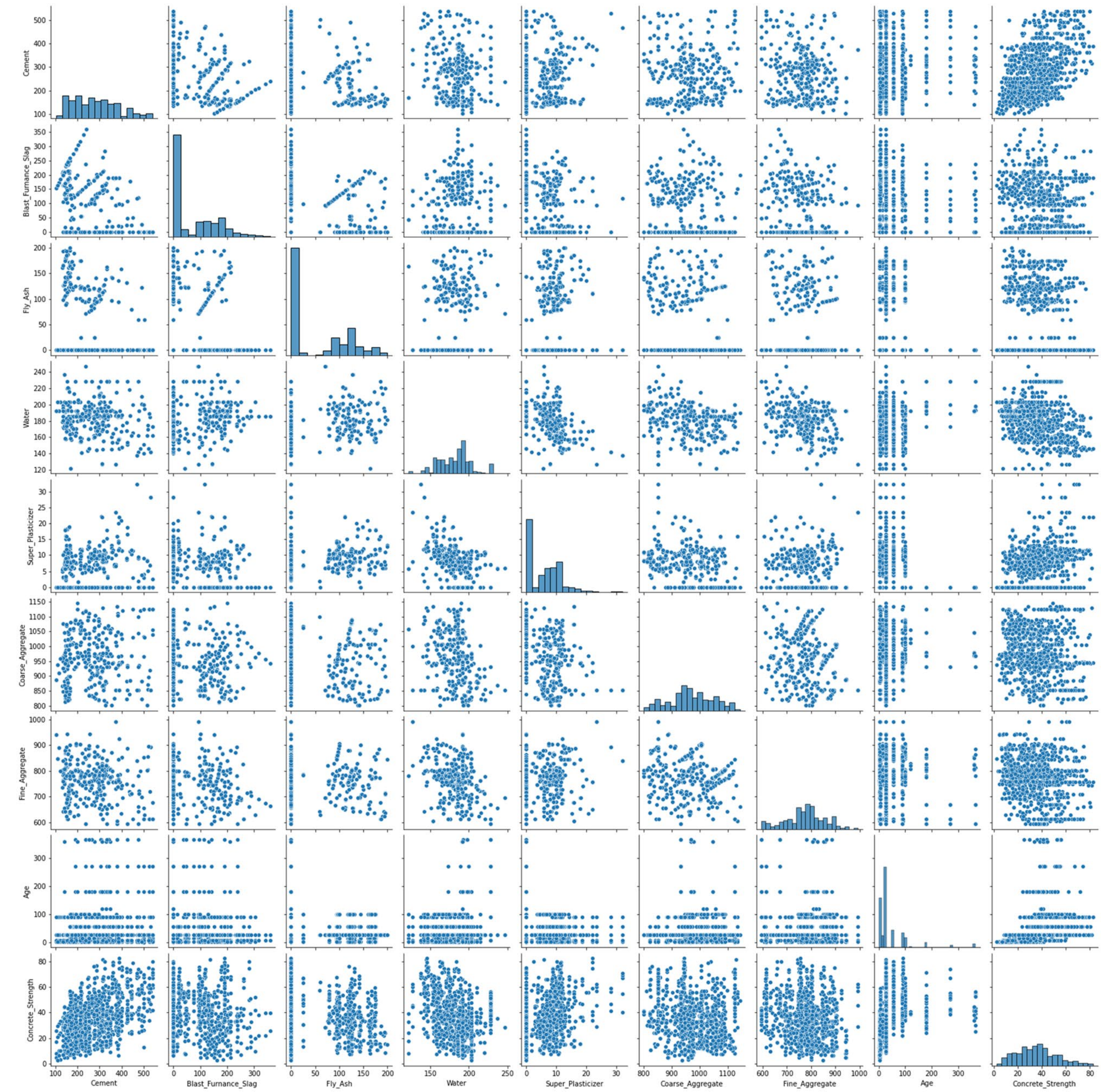

Fig. 2 Pair-scatter plot of the input variables

2023a). This is because only the essential input vectors are trained to an excessive degree.

Methodology

The suggested model has been constructed using three distinct inbuilt techniques including BR, SG, and LM was calculated to estimate the compressive strength of high-strength concrete. The proposed methodology is diagrammatically depicted in Fig. 3. The model is evaluated based on the error and coefficient of determination (R^2). The ANN architecture is modified to increase prediction efficiency. For the development of DNN, initially, a baseline linear regression model is used.

The data present in the used dataset were further used to develop the ANN model. The dataset was shuffled to obtain a better result. The shuffled dataset was then divided into three subsets 70% for training, 15% for testing, and the remaining 15% for validation using MATLAB.

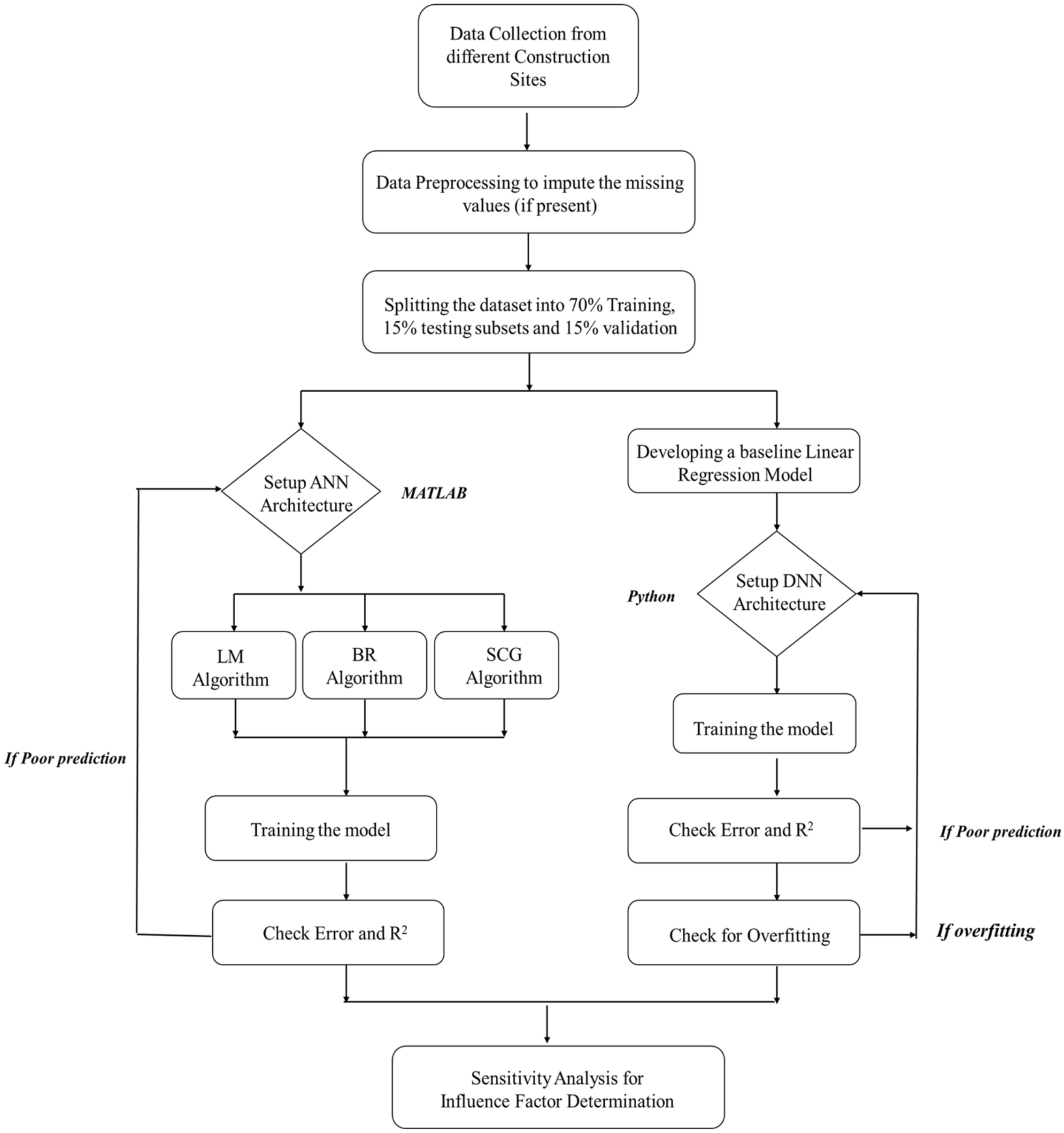

Fig. 3 Proposed methodology of the present study

The ANN model consists of an input layer, a hidden layer, and an output layer. In this study, the number of neurons in the input and output layer was constant, i.e., 8 and 1, respectively. The variation was done in the number of neurons present in the hidden layer as shown in Fig. 4. The obtained R^2 value in each case has been discussed in Table 3 for all the algorithms. Then after, the DNN model is developed by splitting the dataset into training and testing subsets. During the process, the initial model had an architecture of 8–12–10–8–6–1 which was updated to 8–64–64–64–1 to deal with the overfitting problem. The baseline and updated DNN architecture are shown in Fig. 5. In addition, a sensitivity analysis was performed to determine the effect of the most influential and contributing input attributes on the output prediction.

Result and discussion

A quantitative evaluation of a prediction model performance is the difference between the predicted and experimental values. The constructed ANN and DNN model hold good if the statistical parameters such as coefficient of determination (R^2), absolute average error (AAE), root mean square error (RMSE), and mean square error (MSE) values satisfy the

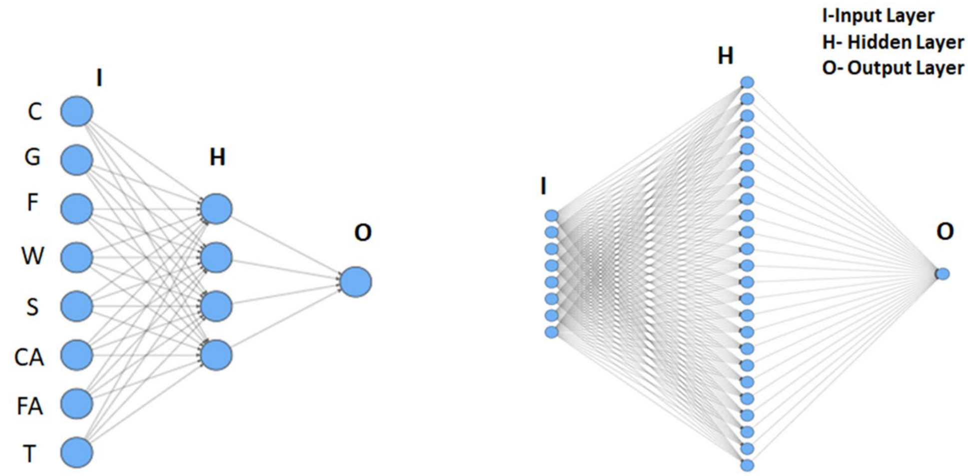

Fig. 4 Variation of the number of neurons in the hidden layer from 4 to 24

Table 3 Values of R^2 obtained in different cases for the LM, BR, and SCG algorithms

Algorithm	ANN architecture	R^2
LM	8–4–1	0.961
	8–8–1	0.979
	8–12–1	0.976
	8–16–1	0.968
	8–20–1	0.982
	8–24–1	0.984
	8–28–1	0.983
BR	8–4–1	0.971
	8–8–1	0.977
	8–12–1	0.981
	8–16–1	0.986
	8–20–1	0.988
	8–24–1	0.991
	8–28–1	0.990
SCG	8–4–1	0.932
	8–8–1	0.945
	8–12–1	0.941
	8–16–1	0.934
	8–20–1	0.919
	8–24–1	0.937
	8–28–1	0.934

proposed model criteria (Chhabra et al., 2023; Debbarma & Ransinchung, 2022). The proposed model is said more precious and high accuracy when the model gives the R^2 value close to 1. The above statistical parameters can be computed using Eqs. (1), (2), and (3).

$$AEE = \frac{1}{n}\sum_{i=1}^{n}(ai - pi) \quad (1)$$

$$R^2 = \sqrt{\frac{\sum_{i=1}^{n}(ai - pi)^2}{n}} \quad (2)$$

$$RMSE = \sqrt{\frac{1}{n} \times \sum_{j} ||a_i - p_i||^2} \quad (3)$$

where a_i = actual or experimental value, p_i = predicted or output value, and n = no. of concrete sample.

Performance of algorithms in artificial neural network model

Each curve represented the performance of the training dataset, the validation dataset, and the test dataset. The entire dataset was then randomly divided into 70% training set, 15% testing set and the remaining 15% as validation set. These performance curves' test data resulted from this procedure.

Figure 6 demonstrates that based on the regression and MSE values, it is feasible to conclude that the LM approach has a more precise prediction model than the SCG and BR methods, respectively. Figure 7 is a histogram displaying the MSE values derived from the supervised learning models developed in this study. During the training phase, it was determined that the LM-ANN successfully trains the data with an MSE of 1.7 MPa, followed by the BR-ANN and SCG-ANN with MSE values of 3.8 and 8.2 MPa, respectively. The validation of the LM performed much better than other methods, with an MSE of 2.9 and 5.1 MPa, respectively. On the other hand, LM-ANN errors were much greater than.BR and SCG. Figure 8 illustrates the performance of the model.

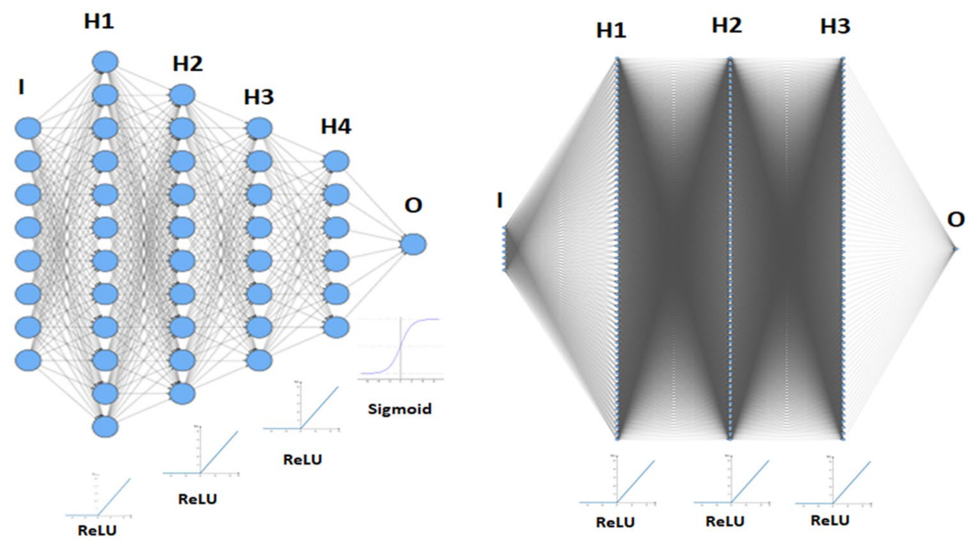

Fig. 5 Variation of the DNN architecture used in the present study

Performance of the deep neural network model

For developing a DNN model, the dataset was checked for the presence of any missing values so that it can be imputed. However, the dataset was not having any missing values. So, the input and output variables were marked. In the next step, the dataset was scaled to carry out the standardization and then shuffled randomly to remove the presence of linearity among the datasets. Then after, normalization was done based on which the first DNN model was developed. In this step, the 'RMSprop' optimizer was used which is like gradient decent optimizer. The vertical oscillations are controlled by the RMSprop optimizer. Hence, the rate of learning can be enhanced, and the algorithm will be able to take greater, more rapid horizontal steps. The data analysis shows that the concrete mix from lean concrete to high-grade concrete is present in the dataset. Figure 9 shows the distribution of compressive strength data in form of a density plot and box-plot, respectively.

The first step in the development of a baseline model is to select the type of prediction algorithm. It is clear from the pair plot that all the input variables show linear behavior. So, the multiple linear regression model was used as the base model (named Model 1). It was observed that this model did not give a good result for prediction. Moreover, based on the error plot, it can be inferred that the difference in the training and validation loss in terms of mean absolute error (MAE) and mean square error (MSE) is more. So, there was a need for improving the model for the validation data. The DNN architecture of the Model 1 was 8–12–10–8–6–1 with ReLU (rectified linear unit) as the activation function for the first three hidden layers while the Sigmoid activation function has been used for the last hidden layer. Then Model 2 with 8–64–64–64–1 architecture was used with ReLU as an activation function in each hidden layer. It was observed that the value of R^2 value increased from 0.38 to 0.96. However, the issue with the model was the presence of overfitting. Figure 10 shows the error histograms with the modification in the models. So, the next step was to remove the overfitting from the model. The training and validation loss in terms of MAE and MSE gave an idea about it (as shown in Fig. 11). For this purpose, the basic architecture of the DNN model was kept the same in Model 3. The activation function in the first two hidden layers was ReLU while in the last hidden layer was Sigmoid.

Figure 12 depicts the change in the regression plots of Model 1, Model 2 and Model 3. It is quite clear that the performance of the model was increased through the rigorous changes in the DNN architecture. The final model gives an R^2 value of 0.972 which is higher than the previous models developed in this study.

Comparison of considered algorithms

Based on the results obtained through different models, it is necessary to check the performance and to determine which model is performing the best (as shown in Fig. 13). For this purpose, R^2 and RMSE values are taken as the ranking parameters. It was observed that the DNN model outperforms the ANN model in terms of R^2 value. However, RMSE value is quite high but almost near to the value in case of ANN-BR. Table 4 shows the ranking of these algorithms based on their performance.

Feature importance

The relevance of feature importance technique is that it evaluates the utility of input data in forecasting the target variable for predictive model (Mai et al., 2023b). The feature

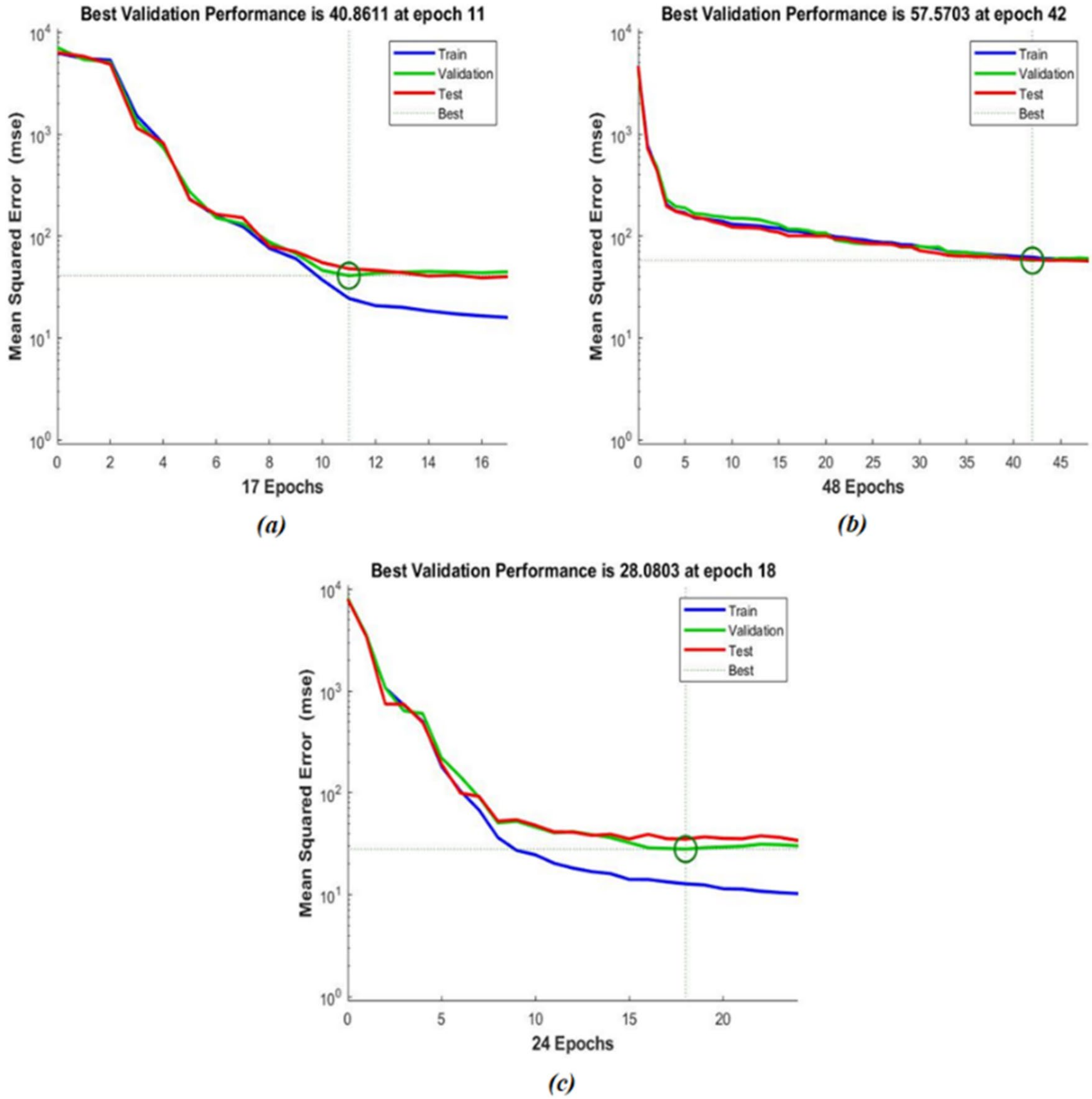

Fig. 6 Model performance of ANN using **a** LM algorithm, **b** BR algorithm, and **c** SCG algorithm

importance was determined using sensitivity analysis. This analysis is aimed to assess the relative influence of input variables on the output of the proposed ANN strength predicting model (Nguyen et al., 2023). On the other ways, the predictive model has increased the performance and efficiency by the impact of each input characteristics on concrete. In this research, the proportionate effect of each input characteristic on outputs was calculated using L. Milene's suggested technique and the number of weight corrections as shown in Eq. 4 (Milne, 1995).

$$IF = \frac{\sum_{j=1}^{Nhid} \frac{wji}{\sum_{i=1}^{Ninp} wji} xWoj}{\sum_{k=1}^{Ninp}\left(\sum_{j=1}^{Nhid} \frac{wjk}{\sum_{i=1}^{Ninp} wij} xwoj\right)} \tag{4}$$

where IF = influence factor for an input parameter to the output prediction, N_{inp} = number of inputs, N_{hid} = the number of hidden units, w = connection weight, I = input unit, and O = output unit.

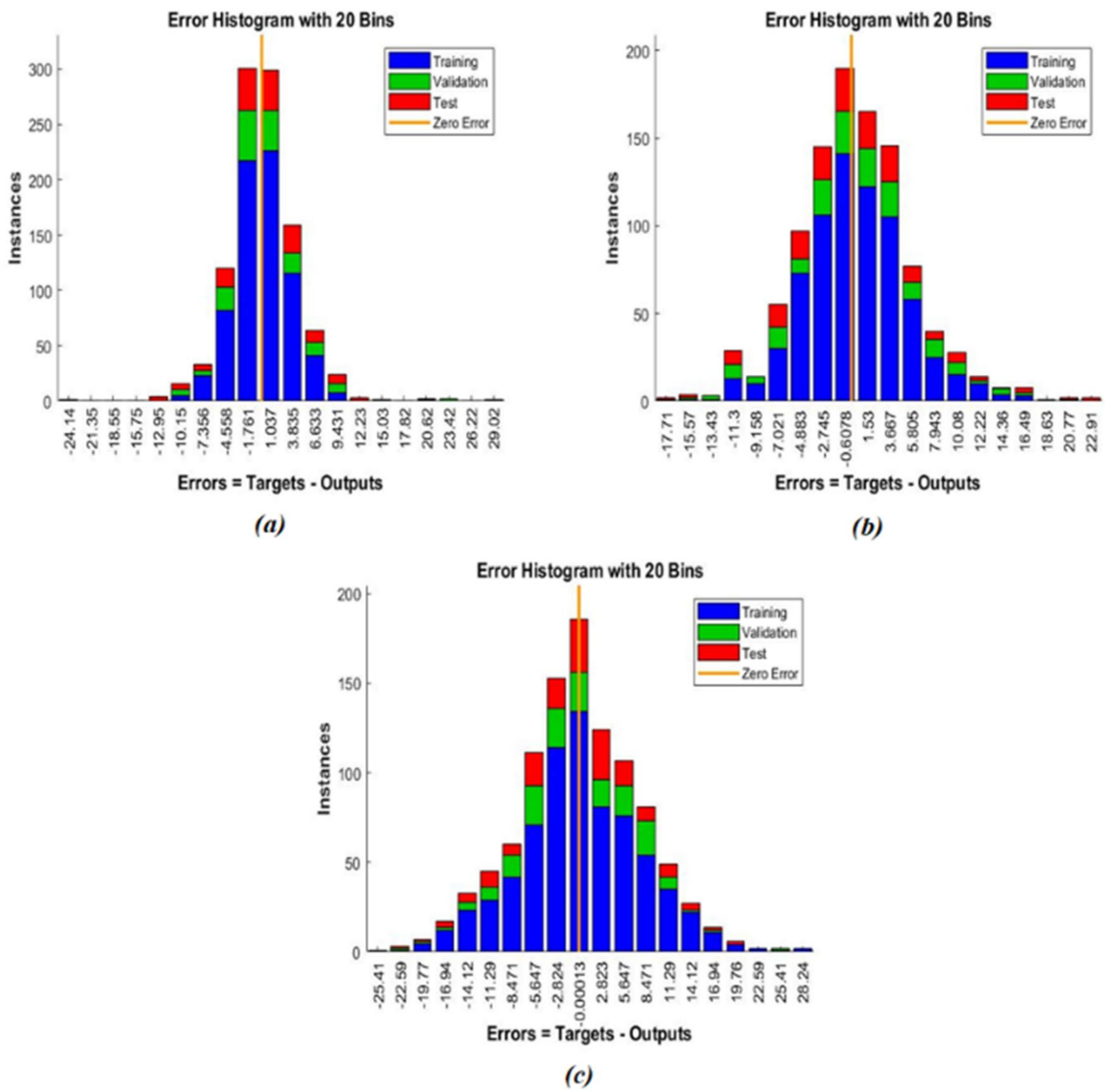

Fig. 7 Error histograms of considered algorithm (LM, BR, and SCG)

Sensitivity analysis depicts the normalized scores of influential parameters and their importance. It can be inferred from Fig. 14 that the cement content has the most influence (score = 12.85) on the compressive strength of concrete in this study. As the dataset is altered, it is essential to keep in mind that the feature influence score might potentially shift. In addition, it is interesting to note that none of the input characteristics has non-negligible significance levels. This is because all of these characteristics represent the basic input parameters in almost all engineering projects that are connected to concrete mix designs.

Taylor diagram

Taylor diagram is a graphical tool used to compare and visualize the similarity between two sets of data, typically model output and observations (Biswas et al., 2021). The diagram consists of a scatter plot and a set of statistics that provide information on the correlation, variance, and bias of the two datasets (Khursheed et al., 2021). The *x*-axis and *y*-axis of the scatter plot represent the standard deviation and correlation coefficient between the two datasets, respectively. The model output is plotted on the *x*-axis, while the observations are plotted on the *y*-axis. Each point on the scatter plot represents a particular location or time in the dataset (Kumar et al., 2023).

The statistics included on the diagram are the correlation coefficient, root mean square error (RMSE), and standard deviation ratio. The correlation coefficient indicates how well the two datasets are correlated, with a value of 1 indicating a perfect correlation. The RMSE indicates the difference in variance between the two datasets, with lower values

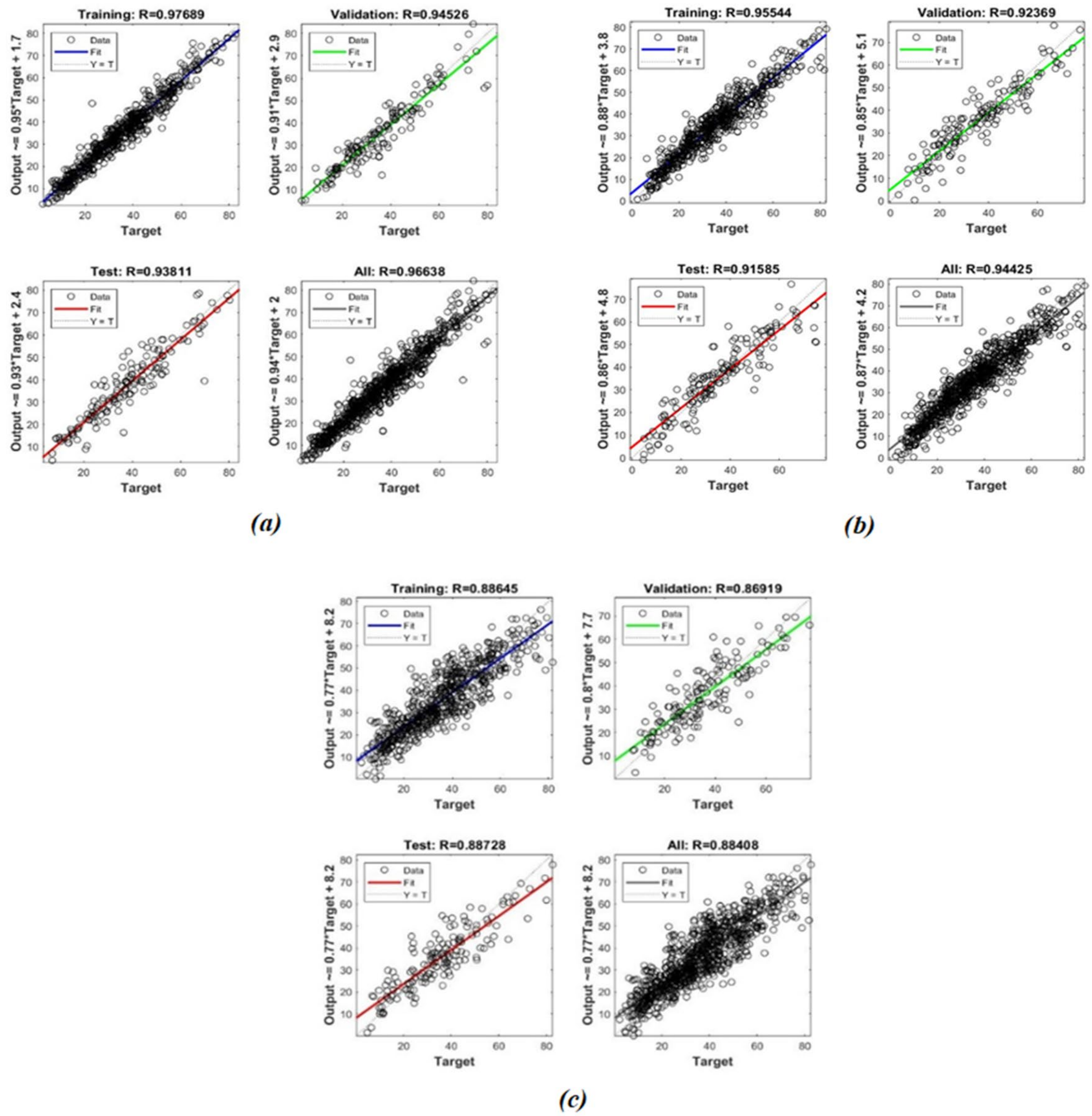

Fig. 8 Regression plots of ANN model **a** LM algorithm **b** BR algorithm and **c** SCG algorithm

indicating better agreement. The standard deviation ratio is the ratio of the standard deviation of the model output to the standard deviation of the observations, with values closer to 1 indicating better agreement. Taylor diagram is a useful tool for comparing the performance of different models or for evaluating the performance of a single model over time. It allows for a quick and intuitive assessment of the degree of agreement between the model output and observations and can help identify areas where the model may be over- or under-predicting.

The prediction models developed in the present study are DNN and ANN models based on LM, BR, and SCG algorithms. The relative rankings for each model based on R^2 and RMSE were discussed in the previous subsection. The performance of the models can be understood using Taylor diagram as shown in Fig. 15. This method includes all the prediction model performances on the same scale which has been depicted under a single diagram. The standard deviation of actual compressive strength (as calculated earlier) is 16.70. This is marked with a bold dotted line (referred to as ‘ref’ in the figure). All models (DNN, LM-ANN, and LM-BR in this case) lying inside this area are suitable for prediction. It can be observed from the figure that DNN and LM-ANN are found to be in close vicinity with low standard deviation. Moreover, the SCG-ANN model is found to have low performance in the prediction of compressive strength.

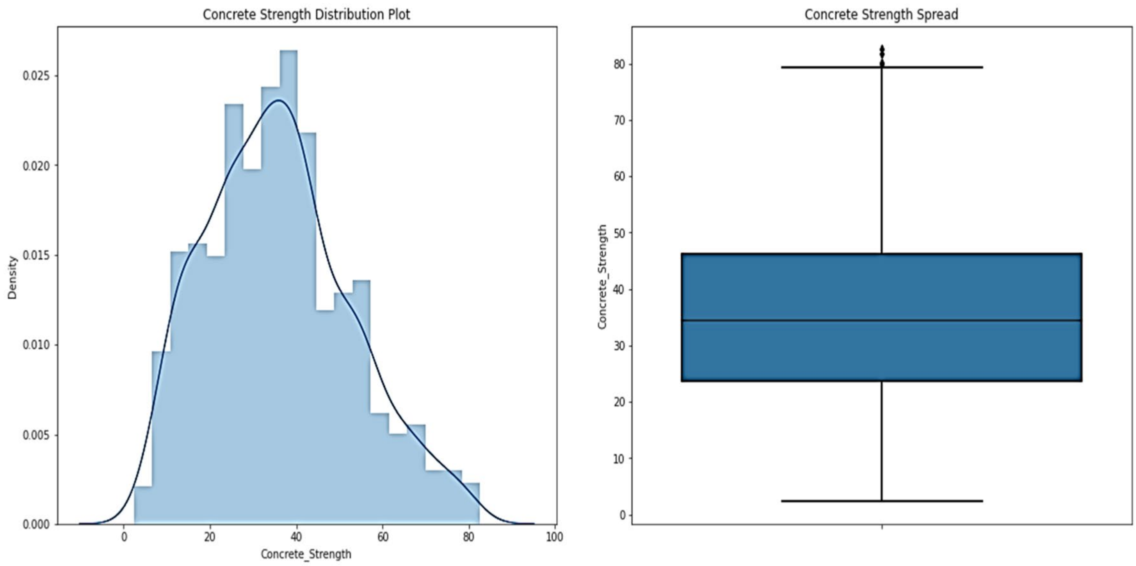

Fig. 9 Output data visualization for the present study

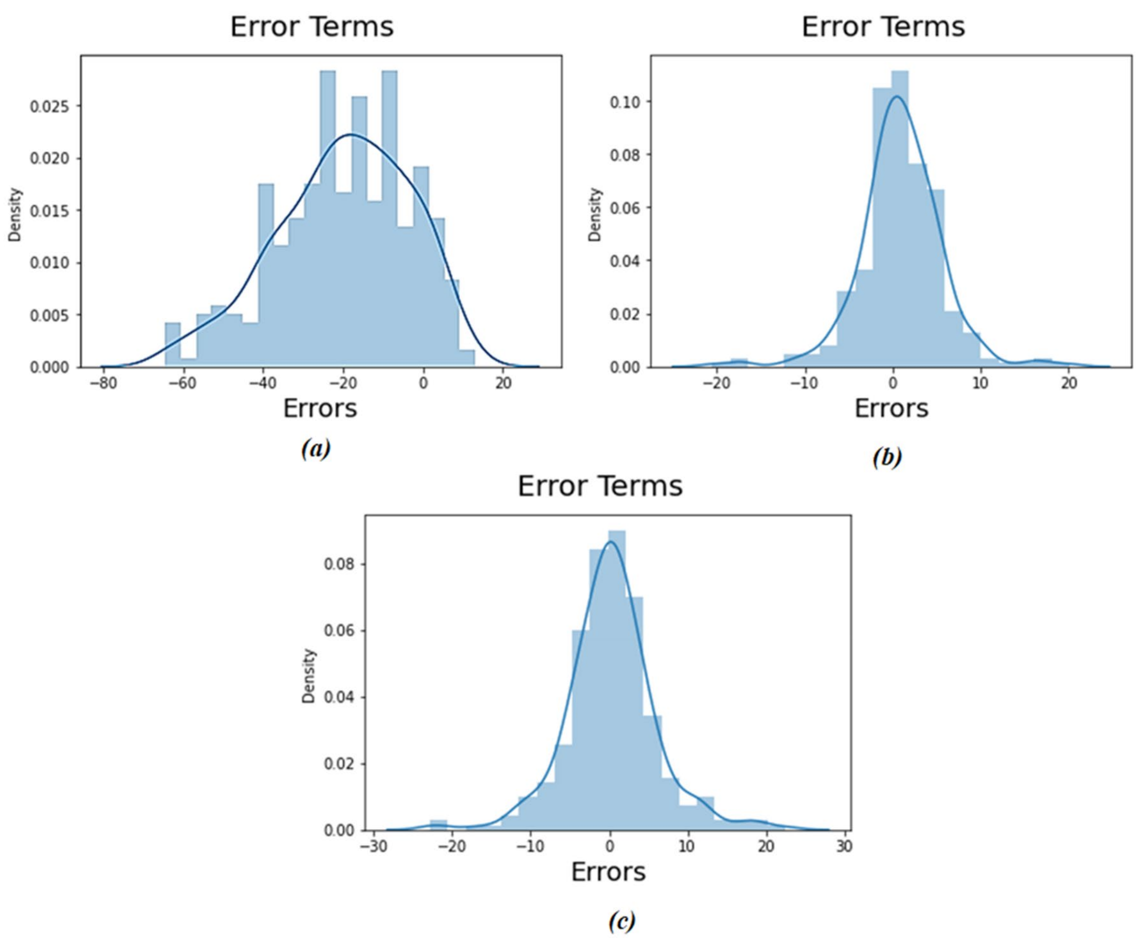

Fig. 10 Error histogram of the DNN models **a** Model 1 **b** Model 2 and **c** Model 3

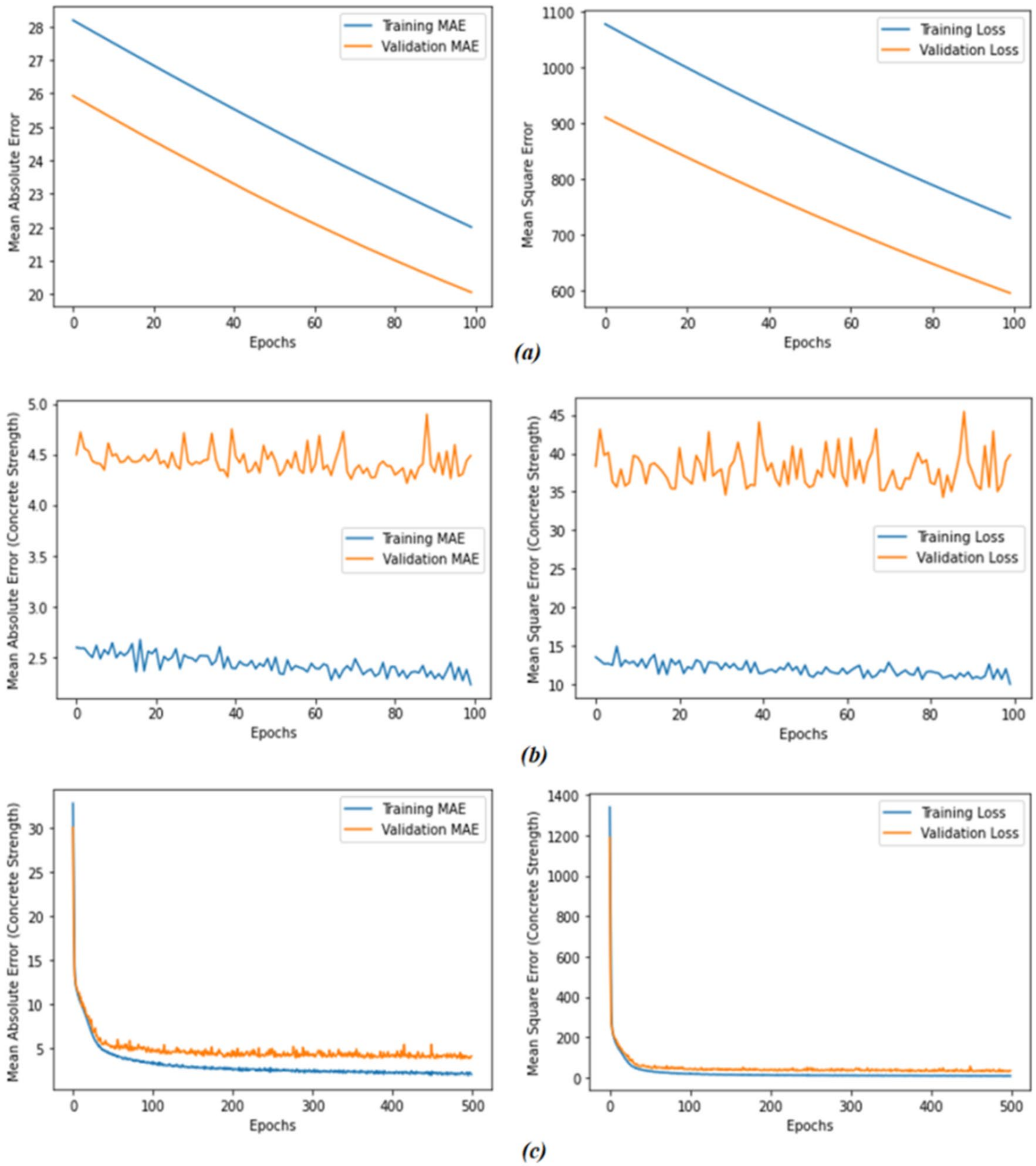

Fig. 11 Mean absolute error and mean square error wrt epochs in **a** Model 1 **b** Model 2 and **c** Model 3

Conclusion

In the present study, NN models were developed to predict the compressive strength of concrete containing industrial waste. It was observed through the literature that most of the studies are done using the ANN technique. The issue with these neural networks is the nature of the dataset. The dataset used for the present study contains a wide range of data. So, the novelty of this research is to develop an efficient DNN prediction model which can be implemented to predict the compressive strength in a vast range of values.

This study used feed-forward ANN with supervised learning to predict the compressive strength of high-strength concrete mixtures including industrial wastes. For supervised learning, the LM-ANN, BR-ANN, and SCG-ANN algorithms were taken into consideration. After experimenting with various configurations of deep neural networks in terms of hidden layers, activation functions, optimizers, and the total number of neurons, a model with three hidden layers, each consisting of 64 neurons, was found to be optimal. Below are the conclusions that may be derived from this study:

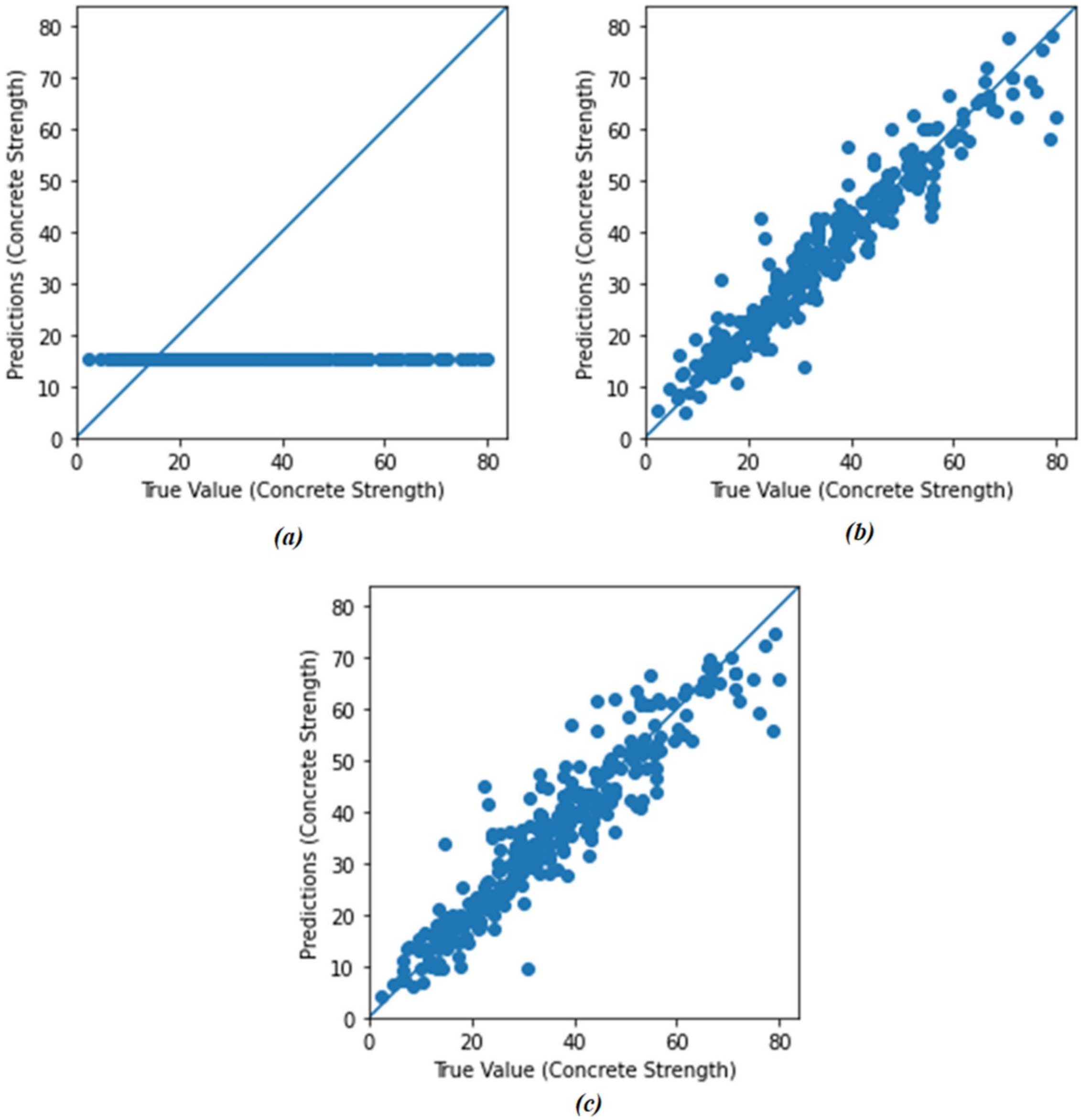

Fig. 12 Regression plots of the test data **a** Model 1 **b** Model 2 and **c** Model 3

- The ANN-based prediction model performed very well in predicting the values of compressive strength across all methods. However, it was discovered that the BR-ANN model had the highest coefficient of determination, exceeding 0.95. The neural design corresponding to 24 neurons in the hidden layer yielded the greatest results. In the testing phase, the R^2 values for the created networks of LM-ANN (8–24–1), BR-ANN (8–24–1), and SCG (8–24–1) are 0.938, 0.916, and 0.887, respectively.
- The DNN model yields a better prediction value than the ANN model. This has also been validated through Taylor's diagram. It was observed that the DNN model was found to be performing well having an R^2 value of 0.972 with the error being compared to the error obtained in the ANN model. The architecture was changed and different combinations of hidden layers, the number of neurons, and the associated activation functions were tried to achieve an optimized model.
- A sensitivity analysis revealed that the cement content is the most important element affecting the concrete strength. Other elements like water content, silica fumes, and the age of concrete also have a major impact on the strength. Among all the parameters, water content has a negative impact on the compressive strength of concrete.

Conclusively, all the models except ANN-SCG have R^2 values greater than 0.90. So, these models are categorized under excellent prediction models and thus, can be

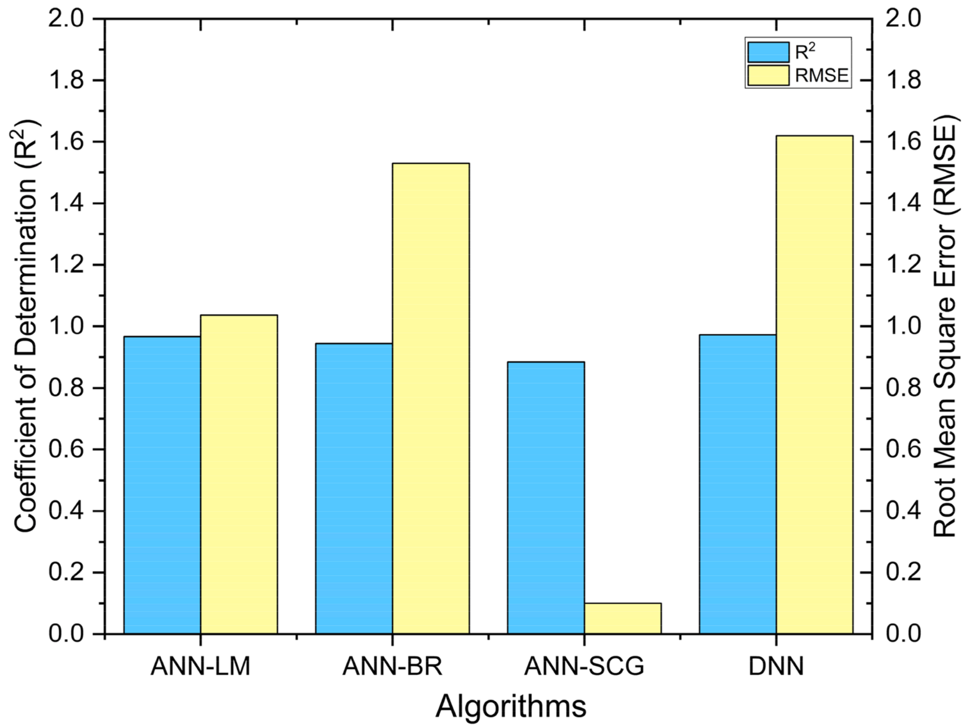

Fig. 13 Comparison of algorithms based on R^2 and RMSE values

Table 4 Performance of different algorithms used in this study

Algorithms	R^2	RMSE	Ranking based on R^2 value	Ranking based on RMSE value	Overall ranking
ANN-LM	0.966	1.037	2	2	2
ANN-BR	0.944	1.53	3	3	3
ANN-SCG	0.884	0.01	4	1	4
DNN	0.972	1.62	1	4	1

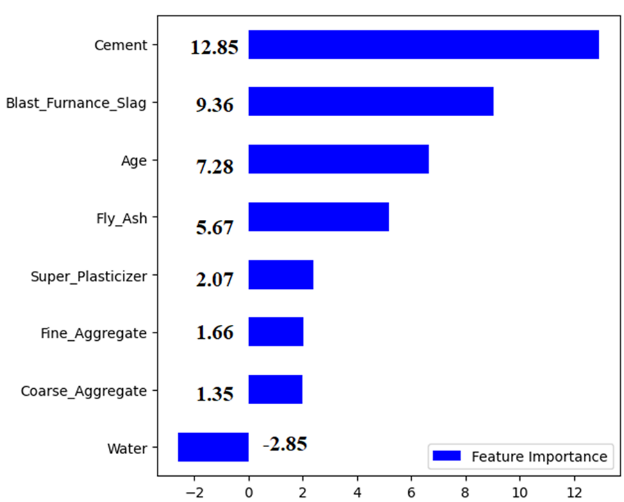

Fig.14 Influence of input parameters on concrete compressive strength

implemented in the field of civil engineering. The current study has some limitations that include the associated uncertainties which have not been accounted (which may include both epistemic and non-epistemic uncertainties) and the DNN-based prediction model yields higher RMSE as compared to the other considered algorithms. The future scope of the present study lies in the updating of the model to increase efficiency. Different optimization techniques like CATBoost, XGBoost, swarm particle optimization, LightGBM, etc., can be used along with DNN for this purpose.

Author contributions Consent to submit has been received explicitly from all co-authors. Authors whose names appear on the submission have contributed significantly to the work submitted.

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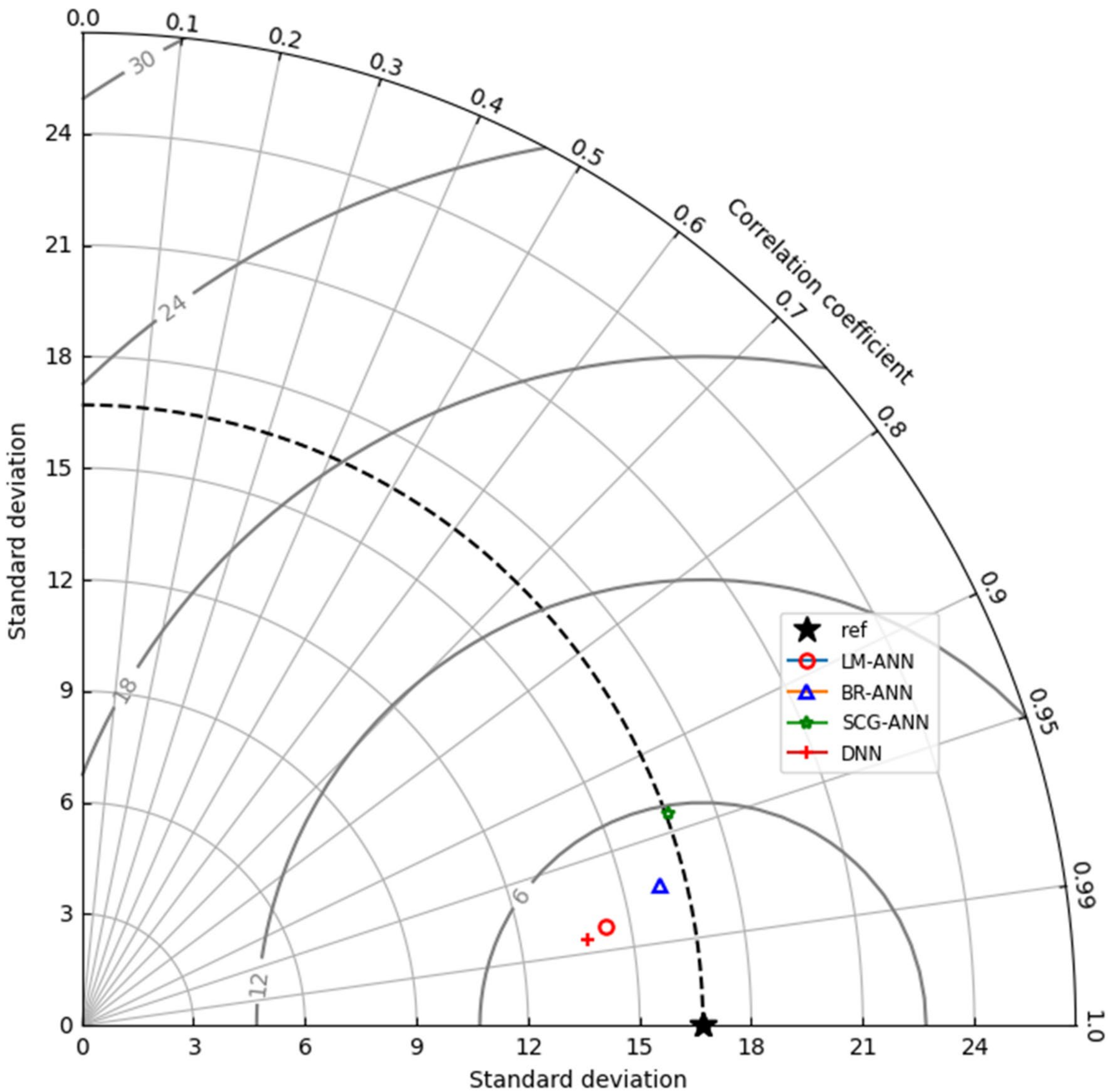

Fig.15 Taylor diagram for different NN models used in this study

Availability of data, material, and code Some or all data, models, or codes generated or used during the study are available from the corresponding author by request.

Dataset link https://github.com/ks1320/Concrete-Test-Reports/blob/main/Concrete_Strength_Assignment%20(1).csv.

Declarations

Conflict of interest No potential conflict of interest in the subject matter is discussed in this manuscript.

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