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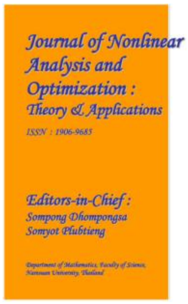

PREDICTION OF COMPRESSIVE STRENGTH OF HIGH STRENGTH CONCRETE USING ARTIFICIAL INTELLIGENCE AND MACHINE LEARNING TECHNIQUES

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ABSTRACT:
The direction of supervised machine learning and its algorithm is being followed in the prediction of the mechanical properties of concrete. In this study, an ensemble random forest (RF) and gene expression programming (GEP) technique are used to estimate the compressive strength of high strength concrete. The variables include the quantity of superplasticizer, water, and the ratio of coarse to fine aggregate. Model performance is further evaluated via the use of statistical techniques such as RSE, MAE, and RRMSE. The RF ensemble model works better than other models because it uses a weak base learner decision tree and gives a strong estimate of coefficient R2 = 0.96 with fewer errors. The GEP method demonstrates a satisfactory response between actual and anticipated values with an empirical connection. The RF and GEP models additionally undergo an external statistical review in order to verify the variables using data points. Artificial neural networks (ANNs) and decision trees (DT) are also used on a specific data sample, and comparisons with the aforementioned models are made. An essential parameter is produced by applying Python permutation properties to the variables. The machine learning algorithm establishes a substantial relationship between the objectives and predictions with fewer statistical observations, demonstrating the accuracy of the overall model.
Keywords: concrete strength; forecasting; genetic programming

Introduction

Due to its higher performance, high strength concrete (HSC) is becoming increasingly popular. Due to its very high strength and endurance, HSC has been recognised as excellent [1-4]. Because of its stronger strength than traditional concrete, which has been seen, its application in the current building sector has significantly expanded [5]. The penetration of its usage within the building business is due to a new technique that produces homogeneous and thick concrete as well as strengthens the strength characteristics [5,6]. It has frequently been utilised in columns, bridges, and steel tubes filled with concrete. The American Concrete Institute (ACI) claims that "HSC is the one that possesses a specific requirement for its working which cannot be achieved by conventional concrete" [7]. Various approaches for the mix design of HSC were put forth by numerous researchers. To get the desired strength, each mix design technique needs a certain set of experimental trials. It is an undeniable fact that experimental work takes a lot of time and costs a lot of money. The validity of the experimental work carried out over the world is also questioned due to inexperienced workers and machine mistake.

Machine learning ideas have been effectively applied in a variety of sectors in recent years for the predictions of various attributes. To get around lengthy experimental methods, the civil engineering construction sector has also embraced these strategies. The multivariate adaptive regression spline (MARS) [15,16], the genetic engineering programming (GEP) [17–20], the support vector machine (SVM) [21,22], the artificial neural networks (ANN) [23–25], the decision tree (DT), the adaptive boost algorithm (ABA), and the adaptive neuro-fuzzy interference (ANFIS) are a few examples of these methods. Using gene expression programming, Javed et al. [18] forecast the axial behaviour of a concrete-filled steel tube (CFST) with 227 data points. The author successfully establishes a solid association between experimental axial capacity and prediction [18].

By doing an experimental and literature-based investigation, Javed et al. are able to estimate the compressive strength of sugar cane bagasse ash concrete. The remaining data were collected from published literature, and experimental work was performed to validate the model. The GEP algorithm was utilised by the author to produce a satisfactory model between the goal values. In order to forecast the compressive strength of concrete-filled steel columns with recycled aggregate (RACFSTC), Nour et al. employed the GEP method. In the modelling portion of the RACFSTC column, the author employed 97 data points and found a strong association. By utilising a random forest technique based on beetle antennae search, Junfei et al. were able to estimate the compressive strength of self-compacting concrete. The author's persistently high correlation (R2= 0.97) with the experimental findings. In order to forecast the compressive strength of high-performance concrete, Qinghua et al. used a random forest technique. Similar to this, Sun et al. employed 138 data samples from published literature and an evolving random forest algorithm to forecast the compressive strength of rubberized concrete. This cutting-edge strategy performed better with an R2= 0.96 high coefficient connection. For estimating the mechanical strength characteristics of high-performance concrete and recycled aggregate concrete, ANN and other models have been utilised. Pala et al. investigated how silica and fly ash affected concrete's compressive strength. To examine the effects of various w/c ratios, percentages of silica, and fly ash on the performance of concrete, a thorough experiment was conducted. Additionally, ANN was used to illustrate the impact on the concrete strength parameters. A machine learning system based on GEP was utilised by Azim et al. to forecast the compressive arch action of a reinforced concrete structure. The author discovered that GEP works well for making predictions.

This study used ensemble random forest (RF) and gene expression programming (GEP) to assess the compressive strength performance of a high strength concrete (HSC). The data points gathered for the model were from papers that have been published, and they are given in Table S1. The compressive strength of HSC is predicted using GENEX protool software and Python-based Anaconda Spyder programming. Cement, water, the ratio of coarse to fine aggregates, superplasticizer, and compressive strength are the model's inputs and outputs, respectively. To display the connection between the input and output parameters, hex contour graphs are created. Permutation feature importance (PFI) and sensitivity analysis (SA) are used to determine the relative weights of each variable in relation to the desired output parameters. Additionally, statistical measurements are also included in the model evaluation process.

2. Research Methodology

2.1. Random Forest Regression

Breiman's 2001 proposal of random forest regression is seen as an advancement over classification regression. The quickness and adaptability with which the connection between input and output functions may be created are among RF's key characteristics. Additionally, RF manages enormous datasets more effectively than other machine learning methods. RF has been utilised in a variety of industries, including banking to forecast client behaviour, the pharmaceutical and medical industries, e-commerce, and the direction of stock market values. The major steps of the RF technique are as follows:

1. Collection of trained regression trees using training set.
2. Calculating average of the individual regression tree output.

3. Cross-validation of the predicted data using validation set.

The original training set is replaced with a fresh training set made up of bootstrap samples. Some of the sample points are removed and replaced with existing sample points during the execution of this phase. Out-of-bag samples are a different set of samples that are gathered from the deleted sample sites. 2/3 of the sample points are then used to estimate the regression function. In this instance, the model is validated using samples that were taken directly from the bag. Up till the requisite precision is attained, the process is repeated several times. The distinguishing feature of RFR is its built-in mechanism for removing the points for out-of-bag samples and using them for validation purposes. At the conclusion, each expression tree's total error is computed, demonstrating its effectiveness.

3. Experimental Database Representation

3.1. Dataset Used in Modeling Aspect

The number of parameters utilised and the data sample are used to evaluate the model. The published literature yielded a total of 357 datasets (see Table S1). To create a numerically based empirical relation for HSC, these points were taught, validated, and tested through modelling. To reduce the overfitting of data in machine learning methods, this is done. To determine the adamant correlation coefficient, the data were split into 70/15/15 groups. Behnood et al. use information from published literature to forecast the mechanical characteristics of concrete. For the training (70%), validation (15%), and testing (15%) sets, the samples were allocated at random. Similar to how the data was distributed previously, Getahun et al. predicted the mechanical characteristics of concrete.

3.2. Programming-Based Presentation of Datasets

Python version 3.7 programming on the anaconda platform has been used to show how different input factors affect the mechanical strength of HSC. The number of factors employed in experimental work affects the compressive strength of concrete. In order to predict the compressive strength of HSC, the following variables were used: cement content (Type 1), water, superplasticizer (polycarboxylate), and fine and coarse aggregate (20 mm). Python was used in Jupiter notebook to visualise the effects of various input parameters, as illustrated in Figure 1.

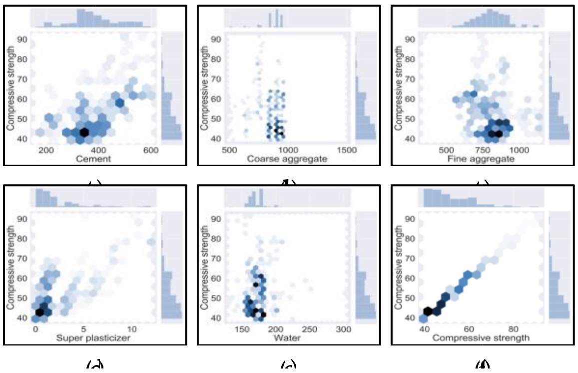


Figure 1. Hex contour graph of input parameters; (a) Cement; (b) Coarse aggregate; (c) Fine aggregate; (d) Super plasticizer; (e) Water; (f) Compressive strength.

Python is an efficient machine learning approach that enables users to have a deep understanding of the parameters that alter the functioning of the model. Python uses the seaborn command to plot the correlation among the desired parameters. Figure 1 represents the quantities that have a pronounced influence on the mechanical properties of HSC. The darkish region shows the optimal/maximum concentration of variables as depicted in Figure 1.

Table 1. Statistical description of all data points used in model (Kg/m3).

Parameters	**Cement**	**Fine/Coarse Aggregate**	**Water**	**Superplasticizer**
Mean	384.34	0.96	173.56	2.34
Standard Error	4.92	0.01	0.82	0.14
Median	360	0.92	170	1.25
Mode	360	1.01	170	1
Standard Deviation	93.00	0.26	15.56	2.69
Sample Variance	8650.50	0.06	242.19	7.24
Kurtosis	0.36	6.45	15.59	2.88
Skewness	0.14	2.12	2.45	1.79
Range	440	1.86	170.08	12
Minimum	160	0.23	132	0
Maximum	600	2.1	302.08	12
Sum	137,212.84	344.07	61,963.8	837.61
Count	357	357	357	357

Table 2. Statistical description of training data points used in the model (Kg/m^3).

Parameters	**Cement**	**Fine/Coarse Aggregate**	**Water**	**Superplasticizer**
Mean	383.29	0.97	173.72	2.42
Standard Error	6.06	0.01	1.08	0.17
Median	360	0.92	170	1.37
Mode	320	1.01	170	1
Standard Deviation	95.95	0.27	17.17	2.74
Sample Variance	9206.57	0.07	295.07	7.54
Kurtosis	0.60	5.82	14.42	2.96
Skewness	0.19	2.08	2.48	1.82
Range	420	1.86	170.08	12
Minimum	180	0.23	132	0
Maximum	600	2.1	302.08	12
Sum	95,823.1	242.79	43,431.75	606.43
Count	250	250	250	250

Table 3. Statistical description of testing data points used in the model (Kg/m^3).

Parameters	**Cement**	**Fine/Coarse aggregate**	**Water**	**Superplasticizer**
Mean	387.04	0.92	172.18	1.98
Standard Error	12.46	0.02	1.34	0.33
Median	400	0.90	170	1
Mode	360	0.75	170	1
Standard Deviation	95.76	0.18	10.35	2.55
Sample Variance	9170.56	0.03	107.25	6.55
Kurtosis	0.22	6.82	0.18	4.75
Skewness	0.17	1.66	0.33	2.19
Range	440	1.22	45.2	12
Minimum	160	0.58	154.8	0
Maximum	600	1.80	200	12
Sum	22,835.54	54.38	10,159.18	117.09
Count	54	54	54	54

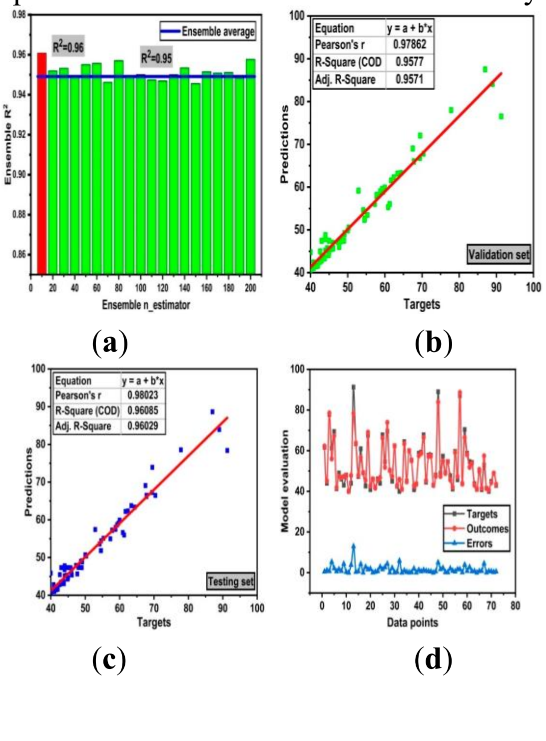
Parameters	Cement	Fine/Coarse Aggregate	Water	Superplasticizer
Mean	390.52	0.90	173.07	2.10
Standard Error	12.58	0.02	1.21	0.34
Median	378	0.90	175	1
Mode	360	1.04	180	0.5
Standard Deviation	89.86	0.15	8.67	2.47
Sample Variance	8076.29	0.02	75.21	6.11
Kurtosis	1.08	0.52	-0.18	2.17
Skewness	0.17	0.61	-0.62	1.65
Range	440	0.73	38.32	10.5
Minimum	160	0.66	154	0
Maximum	600	1.39	192.32	10.5
Sum	19,916.87	46.34	8826.8	107.57
Count	55	55	55	55

Like other genetic algorithm models, the GEP-based model is greatly impacted by the input parameters (variables) that it is built on. The generalising fitness of these models was significantly influenced by these factors. The model time is a crucial factor to consider when evaluating the model's efficacy. To guarantee that the generalised model always evolved in proper time, care must be taken while choosing the sets that regulate the model time. To get the highest correlation, these parameters are chosen using the hit-and-trial approach. In modelling, the Root Mean Squared Error (RMSE) was used. Additionally, tree-like architectural components are used to indicate how well the GEP-based model performs.

5. Results and Discussion

5.1. Random Forest Model Analysis

As shown in Figure 2, Random Forest is an ensemble modelling approach that utilises a weak learner to provide the greatest performance. These supervised learning algorithms provide unwavering accuracy in terms of correlation. For maximum coefficient determination, the model is split into twenty submodels, as shown in Figure 2a. It is obvious that the sub-model offers a strong link and is equal to 10 outbursts. It results from the employment of a decision tree, a weak learner, in the ensembling method. Additionally, as shown in Figures 2b,c, the model provides a strong correlation (R2 = 0.96) between experimental and predicted values as well as positive validation findings. Additionally, as seen in Figure 2d, the model's performance exhibits reduced inaccuracy.



(a) (b)

(c) (d)

Figure 2. Model evaluation (**a**) Ensemble model with 20 submodels; (**b**) validation based on RF; (**c**) testing based on RF; (**d**) error distribution of the testing set.

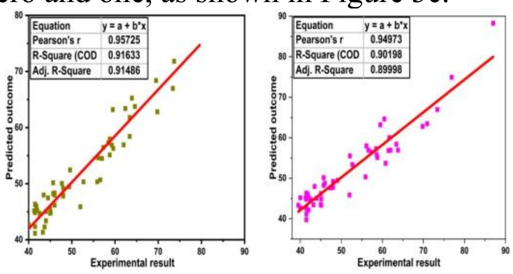
Random forest is used to apply statistical analytical checks on the model performance. This indirect approach demonstrates model performance. The RMSE, MAE, RSE, and RRMSE are employed in these statistical studies to check the model's mistakes, as indicated in Table 5. The RF model exhibits reduced error in the prediction area since it is an ensemble one model.

Table 5. Random forest (RF) statistical analysis.

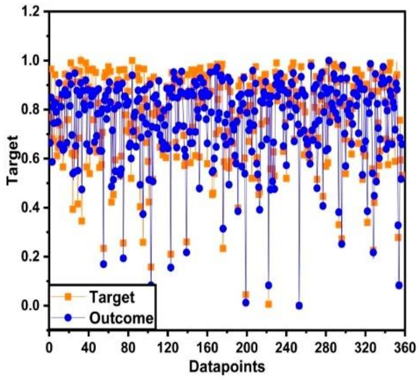
Model	**RMSE**		**MAE**	**R2**	
Fc	Validation	Testing	Validation Testing	Validation	Testing
	1.22	1.42	0.475 0.495	0.967	0.041
	RRMSE		**RSE**	**P(row)**	
	Validation	Testing	Validation Testing	Validation	Testing
	0.0186	0.021	0.072 0.053	0.024	0.025

5.2. GEP Model Evaluation

Figure 3 illustrates model assessment and how it represents the difference between observed and anticipated values. An efficient method to evaluate the strength parameters of HSC is to use a machine learning algorithm based on GEP. Regression analysis is typically used in machine learning to evaluate models. Regression analysis demonstrates that any model with a value near to one is unquestionably accurate, as shown in Figure 3b. It demonstrates that the testing and validation sets' regression line is very nearly 1. Regression analysis of the validation and test sets is shown in Figures 3a and 3b with the coefficient of determination R2. This result exceeds 0.8 and represents the model's accuracy as 0.91 and 0.90 for the testing (see Figure 3a) and validation (see Figure 4b) sets, respectively. To demonstrate the accuracy of the data, the collected data from published literature were additionally normalised within the range of zero and one, as shown in Figure 3c.



(**a**) (**b**)



(**c**)

Figure 3. Model evaluation (**a**) Validation results of data based on GEP; (**b**) testing results of data; (**c**) normalized range of data.

The model's performance is assessed statistically using the MAE, RRMSE, RSE, and RMSE, as done similarly in a random forest model, as shown in Table 6. The model performs better when the coefficient is larger and the error is lower. Most mistakes have an R2 value larger than 0.8 and are located below 5 MPa. As a result, it shows how accurate the finished model is. The model's performance is additionally assessed by additional analysis, which includes calculating the standard deviation (SD) and covariance (COV). The results show that the SD and COV values are 0.16 and 0.059, respectively.

Table 6. Statistical calculations of the proposed model.

Model	RMSE		MAE		RSE	
	Validation	Testing	Validation	Testing	Validation	Testing
	1.42	1.62	0.575	0.595	0.092	0.023
Fc	RRMSE		R		P(row)	
	Validation	Testing	Validation	Testing	Validation	Testing
	0.0286	0.031	0.957	0.031	0.014	0.015

By measuring the discrepancy between the testing set's actual objectives and anticipated values, as seen in Figure 5, the accuracy and performance of the machine learning-based model are assessed. As can be seen, the model accurately predicted a result that was close to or equal to the experimental values. Additionally, according to the error distribution of the testing set, the greatest error is 7.47 MPa, with 86% of the data sample falling below 5 MPa and 13.88% falling between 5 MPa and 8 MPa. As a result, the GEP-based model provides both the empirical equation indicated in Equation (9), as well as excellent accuracy in terms of correlation. By applying this equation, users will be able to determine the compressive strength of concrete.

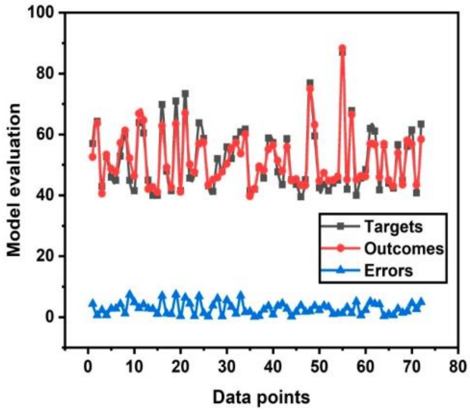


Figure 4. Distribution of data with error range.

6. Statistical Analysis Checks on RF and GEP Model

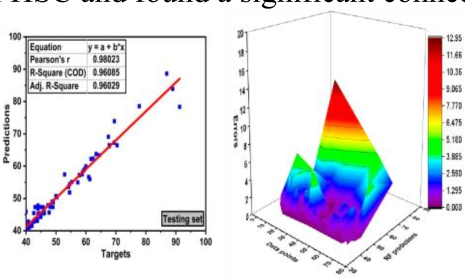
Any model's accuracy is reliant on data points. The accuracy of the overall model will increase as the points rise. Based on the ratio of input data samples to its parameters, Frank et al. provide an optimum solution. For the model to function well, this ratio has to be three or higher. In this investigation, 357 data samples with the four previously indicated variables and a ratio of 89.25 are used. This ratio value is noticeably greater, demonstrating the model's accuracy. Similar methods were employed by Farjad et al. to validate the model and provide conclusive outcomes with a ratio higher than 3. Researchers propose many methods for the external statistical validation of a model. The slope of the regression line's (k' or k) slope was used by Golbraikh et al. to validate their model. This line compares experimental and anticipated data to see how accurate the model is. Any value higher than 0.8 or close to 1 will result in the model performing obstinately. The results of all these external audits are summarised in Table 8.

Table 8. Statistical analysis of RF and GEP models from external validation.

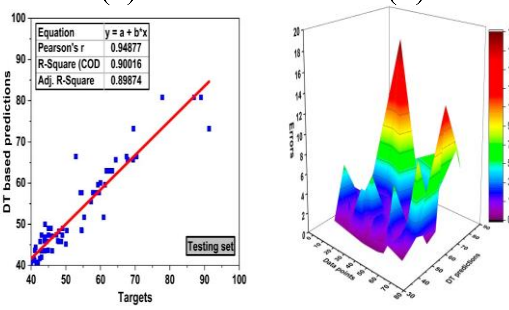
S.No	Equation	Condition	RF Model	GEP Model
1	$k = \frac{\sum_{i=1}^{n}(e_i \times m_i)}{e_i^2}$	$0.85 < k < 1.15$	0.99	0.98
2	$k^0 = \frac{\sum_{i=1}^{n}(e_i \times m_i)}{m_i^2}$	$0.85 < k < 1.15$	1.00	1.00
3	$R_0^2 - \frac{\sum_{i=1}^{n}(m_i - e_i^0)^2}{\sum_{i=1}^{n}(m_i - m_i^0)^2}, e_i^0 = k \times m_i$	$R_0^2 \quad 1$	0.99	0.97
4	$R_0^{\prime 2} - \frac{\sum_{i=1}^{n}(e_i - m_i^0)^2}{\sum_{i=1}^{n}(e_i - e_i^0)^2}, m_i^0 = k^0 \times e_j$	$R_0^2 \quad 1$	0.99	0.99

7. Comparison of Models with ANN and Decision Tree

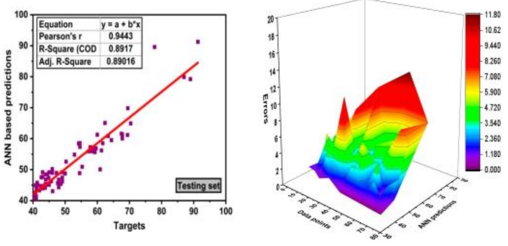
Figure 5 compares the ensemble RF and GEP technique with the ANN and DT supervised machine learning algorithms. These methods are separate algorithms, much as GEP. To produce an adamantly high connection, RF is an ensemble model that combines a base learner as an individual learner and models it with bagging approach. Remember that all models are built using Python (Anaconda). Figure 5 displays the model comparison. When the model's R^2value is 0.96 and its error distribution is displayed in Figures 5a and 5b, the RF explosion in the model's performance can be noticed. Individual models ANN, DT, and GEP, with R^2 values of 0.89, 0.90, and 0.90, respectively, demonstrate good responsiveness. The error distribution of a decision tree with a maximum error under 10 MPa is shown in Figure 5d. However, the maximum error is listed as 18.19 MPa. As illustrated in Figures 5f,h, ANN and GEP models also exhibit a similar pattern, with maximum error values of 11.80 MPa and 7.48 MPa, respectively. Additionally, researchers predicted the mechanical characteristics of high strength concrete using several algorithm-based machine learning approaches. Ahmed et al. predicted the mechanical characteristics of HSC (slump and compressive strength) using an ANN method. The author used ANN to analyse the model, and the results showed a significant connection between slump and compressive of around 0.99. Using RF and M5P methods, Singh et al. predicted the mechanical characteristics of HSC and found a significant connection.



(**a**) (**b**)

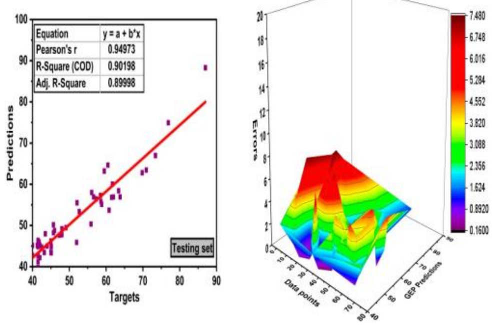


(**c**) (**d**)



(**e**) (**f**)

Figure 5. *Cont.*

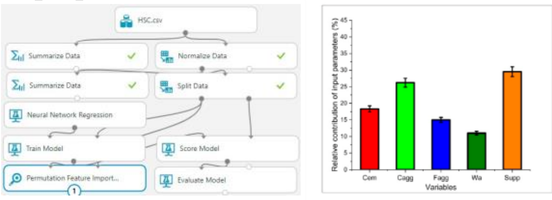


(**g**) (**h**)

Figure 5. Model evaluation with errors (**a**) RF regression analysis; (**b**) error distribution based on the RF model; (**c**) decision tree (DT) regression analysis; (**d**) error distribution based on DT; (**e**) artificial neural network (ANN) regression analysis; (**f**) error distribution based on ANN; (**g**) GEP regression analysis; (**h**) error distribution based on GEP.

8. Permutation Feature Analysis (PFA)

The most important factors influencing the compressive strength of HSC are identified using permutation feature analysis (PFA). PFA is carried through using a Python programming extension. The PFA findings are displayed in Figure 6. The findings indicate that all the factors taken into account in this study have a significant impact on the compressive strength characteristic of HSC. Superplastizer, however, has a greater impact than the other factors.



(**a**) (**b**)

Figure 6. Permutation analysis of input variables (**a**) model base (**b**) contribution of input variables.

9. CONCLUSIONS

The greatest results come from applying supervised machine learning to forecast the mechanical properties of concrete. Rather than establishing an experimental setup, this will let the user predict the required attributes. The following traits are inferred using the machine learning technique.

1. An ensemble method called random forest routinely performs better than predicted and observed values. It is the outcome of integrating a weak learner as the base learner in the decision tree, which establishes the coefficient. R2 is equal to 0.96.
2. Unlike an ensemble approach, GEP is a stand-alone model. It offers a strong link with the empirical relationship. One may manually compute a forecast for the mechanical characteristics of high strength concrete using this connection.
3. The RF and GEP models are contrasted using ANN and DT. R2 = 0.96 indicates a persistent link, but RF explodes. The GEP model's R2 is 0.90. Results for the ANN and DT models are 0.90 and

0.89, respectively. Furthermore, RF generates less errors than other standalone algorithms. That's due of the bagging mechanism used by RF.
4. One important HSC parameter is permutation characteristics. Consequently, all of the variables have been taken into account while identifying the critical variables in experimental study.

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