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Predicting 28-Day Compressive Strength of Self-Compacting Concrete (SCC) Using Gene Expression Programming (GEP)

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Abstract: Self-compacting concrete (SCC) is an innovative building material that can flow and compact itself without the use of external vibrations. It is an effective material to enhance the use of industrial waste products such as fly ash and silica fume in concrete to reduce the carbon emissions from construction industry. Despite the many advantages of SCC over conventional concrete, there are very few methods that can effectively forecast compressive strength of SCC. It is due to the non-linear behavior of SCC in relation to its mixture components. Thus, an innovative machine learning technique called gene expression programming (GEP) is employed to estimate the strength of SCC. For this purpose, a database consisting of 231 datapoints is constructed using extensive literature search. The algorithm resulted in an empirical equation that relates compressive strength with seven most influential parameters: cement, fly ash, silica fume, coarse and fine aggregate, water, and superplasticizer. The dataset is split into two sets called the training and validation datasets having 70 and 30% of the data, respectively. The training and validation data will be used to train and validate the algorithm, respectively. The algorithm's accuracy is checked by calculating the four commonly used error metrices: mean absolute error, root mean square error, coefficient of correlation (R), and performance index (ρ) for both datasets. The statistical evaluation revealed that the errors are within the ranges specified in the literature. The accuracy of the algorithm is also verified by plotting scatter and series plots of training and validation datasets. Thus, the developed equation by GEP algorithm can be effectively used to forecast the 28-day compressive strength of SCC having fly ash and silica fume as mineral admixtures.

Keywords: self-compacting concrete (SCC), gene expression programming (GEP), machine learning (ML), artificial intelligence (AI), fly ash, silica fume

1. Introduction

Conventional concrete uses Portland cement as the main binding agent, which is the main source of carbon emissions from the construction industry (Onat & Kucukvar, 2020). The annual production of concrete is 25 billion tons, and it contributes significantly to the global CO_2 emissions. The concrete industry has changed rapidly in the past few years. One of the main advancements is the use of industrial waste products in place of cement. Many industrial wastes such as fly ash, limestone powder, silica fume, and slag have been used in concrete in place of cement. Thus, to foster the use of waste materials in concrete and reduce the associated carbon emissions, a special concrete called self-compacting concrete (SCC) has been introduced (Brouwers & Radix, 2005).

SCC is a special variant of concrete having enhanced flowing properties and it can compact itself without the use of external force. Due to these properties, it can be effectively used in places having delicate rebar structures or where conventional compaction methods are not applicable. Additionally, the use of SCC containing waste materials as mineral admixtures such as fly ash and silica fume results in good surface finish, higher strength, and improved working conditions (Asteris et al., 2016; Grdic et al., 2008). Several studies reported the use of secondary cementitious materials in SCC and their effect on the properties of SCC (Boukendakdji et al., 2009; Fathi et al., 2013; Gesoğlu et al., 2009; Gesoğlu & Özbay, 2007; Mohamed, 2018; Raman & Krishnan, 2017).

The mixture composition of SCC is the key to achieve the desired flowing and self-compacting properties. It includes use of higher quantities of fines such as sand and other mineral admixtures such as fly ash and silica fume. A superplasticizer is usually added along these fines to help achieve the desired flowability. Generally, SCC mixes have high water-to-cement ratio and low coarse aggregate as compared to the normal concrete (Valcuende et al., 2012). Although SCC has been readily used in the construction and it has the potential to revolutionize the construction industry, there are very few works attributed to accurate prediction of 28-day compressive strength of SCC. It is largely due to the non-linear behavior SCC has in relation to its mixture components (Asteris & Kolovos, 2019). Any variation in the cement, sand, mineral, or chemical additives can result in variation in strength of SCC

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(Boukendakdji et al., 2012). Another reason maybe the lack of expertise and familiarity required to accurately estimate the compressive strength of SCC. Thus, to foster the use of SCC in the construction industry, it is very important to have a method that can accurately forecast the 28-day compressive strength of SCC.

2. Literature Review

It is necessary to have an estimate of concrete strength prior to construction to make sure the safety and performance of the structure. Recently, the prediction of different properties of concrete using machine learning (ML) algorithms has emerged as an effective tool to reduce the construction waste and foster the use of waste materials in construction industry (Farooq et al., 2021; Sonebi, 2004). ML algorithms offer the advantage of identifying the hidden mechanisms in the data. It is due to their ability to learn patterns and associations from the data. Thus, ML algorithms can extract useful insights from the data and use them to make accurate predictions (Nunez et al., 2020). In the past, different ML algorithms such as artificial neural networks (ANNs), decision trees, support vector machine, and random forest (RF) have been utilized in the domain of civil engineering to predict different mechanical properties of concrete composites, soil compaction factors, slope failure, etc. (Alavi et al., 2010; Chen et al., 2022; Chu et al., 2021; Cui et al., 2021; Demir, 2015; Dias & Pooliyadda, 2001; Jalal et al., 2023; Khan et al., 2022; Marani et al., 2020; Qi & Tang, 2018; Saridemir, 2010; Singh et al., 2023; Wang et al., 2021).

Regarding the estimation of SCC properties using ML algorithms, Mai et al. (2023) employed different boosting algorithms like light gradient boosting machine (LGBM), extreme gradient boosting (XGB), and decision tree to forecast strength of SCC on a dataset of more than 350 samples using 17 input variables. The accuracy of the algorithms was assessed by using R^2 and mean absolute error (MAE). The results revealed that XGB is the most accurate algorithm with $R^2 = 0.992$ and average error equal to 1.438. Similarly, Siddique et al. (2011) leveraged neural networks to predict strength of SCC containing bottom ash as partial replacement of cement. The results revealed that ANN has excellent predictive ability demonstrated by MAE 0.63 and maximum correlation coefficient equal to 0.96. Also, De-Prado-gil et al. (2022) utilized various ML techniques including k-nearest neighbor (KNN), extremely randomized trees, gradient boosting, category boosting, RF, LGBM, inverse Gaussian, and Poisson Gaussian to predict CS of SCC containing recycled aggregates. The accuracy of the algorithms was assessed by using R^2 and the authors concluded that RF is the most accurate algorithm with $R^2 = 0.69$ and MAE = 0.05. The results indicate the robustness of ML algorithms to accurately predict different properties of SCC. In 2017, Kaveh et al. (2018) used multiadaptive regression spline (MARS)-based predictive model to predict strength of SCC modified with fly ash along with L-box ratio and V-funnel time. The study utilized a dataset of 114 samples and revealed that MARS predictive model can estimate the concrete strength with 92% accuracy and V-funnel time with 86% accuracy. Moreover, Asteris et al. (2016) conducted a study to predict CS of SCC having a variety of admixtures including fly ash, slag silica fume, limestone powder, etc. using ANN. The study concluded that ANN has immense potential to accurately predict different concrete composites demonstrated by the correlation between experimental and predicted values equal to 0.98. The summary of the literature review related to predicting strength of SCC using ML techniques is presented in Table 1. It is evident from Table 1 that there are not many works regarding the prediction of SCC compressive strength using gene expression programming (GEP) containing fly ash and silica fume.

Table 1
Summary of literature view

Algorithm used	Dataset	Prediction	Admixtures	Reference
ANN	205	Compressive strength	Fly ash, slag, rice husk ash	(Asteris & Kolovos, 2019)
ANN	114	Compressive strength	Fly ash	(Belalia Douma et al., 2017)
ANN	80	Compressive strength	Fly ash	(Siddique, 2011)
RF	131	Compressive strength	Fly ash, slag, silica fume	(Guo et al., 2020)
GEP	90	Compressive strength	Fly ash, rice husk ash	(Tanyildizi & Çevik, 2010)

3. Research Significance

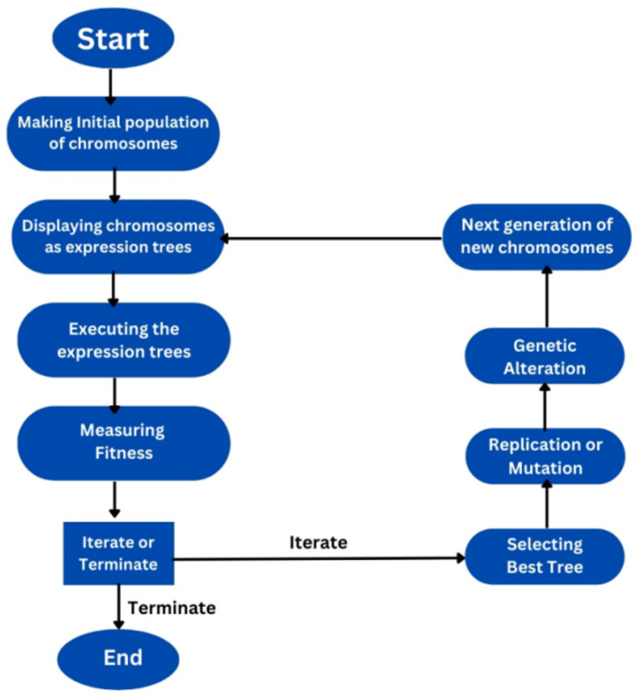
It is clear from literature review that the different ML techniques such as ANN, KNN, and RF can efficiently predict different properties of SCC. However, all the techniques used in previous studies are classified as black box techniques. It means that the user cannot visualize what is going on at the back of the prediction process. GEP offers the advantage of displaying the result in the form of an empirical equation relating the output and input parameters. Thus, the GEP technique is more transparent than other black box techniques. Also, in the literature, there are very few works focusing on predicting strength of SCC containing fly ash and silica fume using GEP. Thus, the significance of this study is to use a comprehensive dataset of experimental values of SCC strength having fly ash and silica fume as mineral admixtures obtained from published literature to develop a transparent and accurate prediction model using GEP.

4. Gene Expression Programming

GEP is a novel artificial intelligence technique that uses evolutionary algorithms. It is a subtype of genetic programming and is based on Darwin's principle of natural selection. The problem-solving technique of GEP is like genetic system in humans. The basic idea of GEP is to find solution of a problem by developing a mathematical expression called chromosome that contains multiple genes. GEP uses a set of functions to build these genes. These functions range from simple mathematical operations like addition, etc. to more complex ones like sin, cos, etc. The genes are created by combining these functions in different ways and then these genes are combined to create a computer program. The mathematical expression is encoded as string of fixed length and later it is represented as an expression tree (Koza, 1995).

The process of creating a computer program begins by defining the problem and the desired outcome. Then the GEP algorithm creates a population of random chromosomes and expresses them as expression trees. These expression trees are executed, and the value generated from the expression tree is compared with the actual value. If the initial termination criteria is satisfied, the algorithm stops, if the desired results are not achieved, these chromosomes go under the processes of mutation and recombination to create a new population of chromosomes. The best performing chromosomes are selected for the next generation, while others are discarded. This process of creating chromosomes is repeated for many generations until the required fitness is reached (Oltean & Grosan, 2003). After reaching the desired accuracy, the process is terminated, and the chromosomes are decoded to get a mathematical expression representing the solution of the problem. The main advantage of GEP is that it can discover underlying mechanisms and learn patterns and associations from data to reveal hidden relationships between variables, making it a suitable option to solve problems. The flowchart of GEP algorithm is shown in Figure 1.

Figure 1
Flowchart of GEP algorithm



5. Data Acquisition

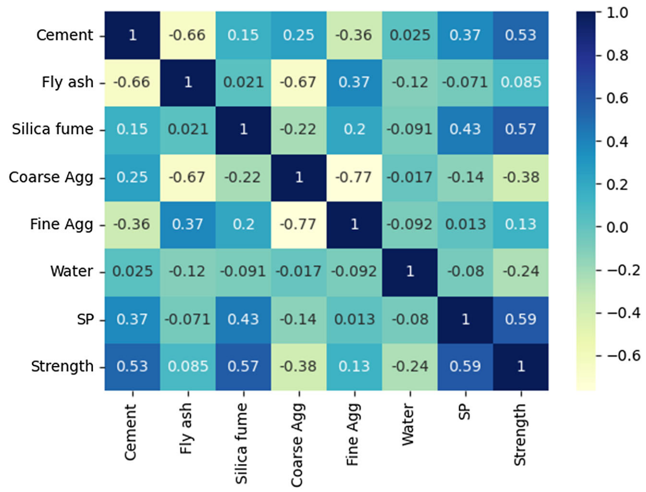
A database of experimental tests is important for the development of a GEP model. Thus, a database consisting of 231 data points is collected from internationally published literature (Bani Ardalan et al., 2017; Choudhary et al., 2020; Da Silva & De Brito, 2015; Felekoğlu et al., 2007; Guo et al., 2020; Leung et al., 2016; Ofuyatan et al., 2021; Ramanathan et al., 2013; Siddique, 2011; Wongkeo et al., 2014; Yang et al., 2021; Yazici, 2008; Zhao et al., 2015). A detailed evaluation was done to find the most influential parameters to predict the strength of SCC and the following seven parameters were selected: cement, fly ash, silica fume, coarse aggregate, fine aggregate, water, and superplasticizer.

The collected dataset is split into training dataset having 70% of the data used for training the algorithm and validation set having 30% of the data used for validation of the algorithm. This splitting is done to avoid overfitting of model to the training data (Gholampour et al., 2017). The range of the input and output variables used in the model development is given in Table 1. It is advised to use the developed models within the range given in Table 2. The frequency distribution histograms of variables used in the model are given in Figure 2.

Table 2
Range of variables used in model development

Parameters	Symbol	Minimum	Maximum	Standard deviation
Cement	d_0	311.98	135	542.10
Fly ash	d_1	145.45	0	390
Silica fume	d_2	17.90	0	67.5
Coarse aggregate	d_3	829.58	565	1091.4
Fine aggregate	d_4	851.36	630	1120
Water	d_5	180.79	150	202.10
Superplasticizer	d_6	1.33	0	8.70
Strength	f_c'	45.50	21.54	94.40

Figure 2
Frequency distribution of variables used in the model



This study uses seven input parameters to predict one output parameter. The relationships between these variables can be better understood by using a statistical technique called correlation matrix. It is frequently used to get information about the effect of fluctuation of variables and the relationship between input variables and the output. A positive correlation means that increase in one variable causes an increase in the other variable and a negative correlation implies that increase in one variable causes a decrease in the other variable. The correlation matrix of the variables used in model development is shown in Figure 3.

6. Performance Assessment

The accuracy and effectiveness of developed model will be assessed by using the following four commonly used error metrices:

$$\text{Mean absolute error (MAE)} = \frac{\Sigma\,|x - y|}{n}$$

Figure 3
Correlation matrix of the variables

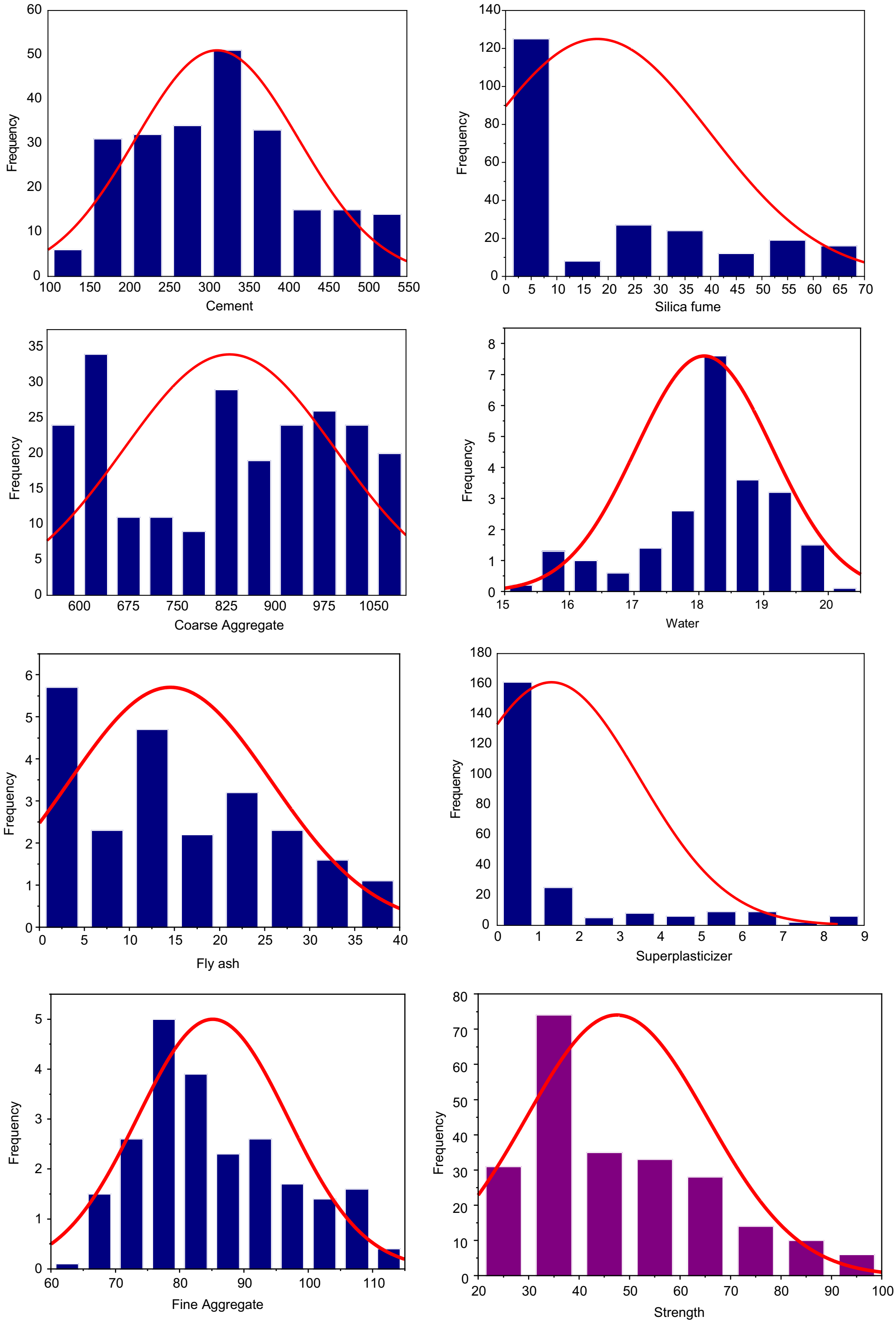
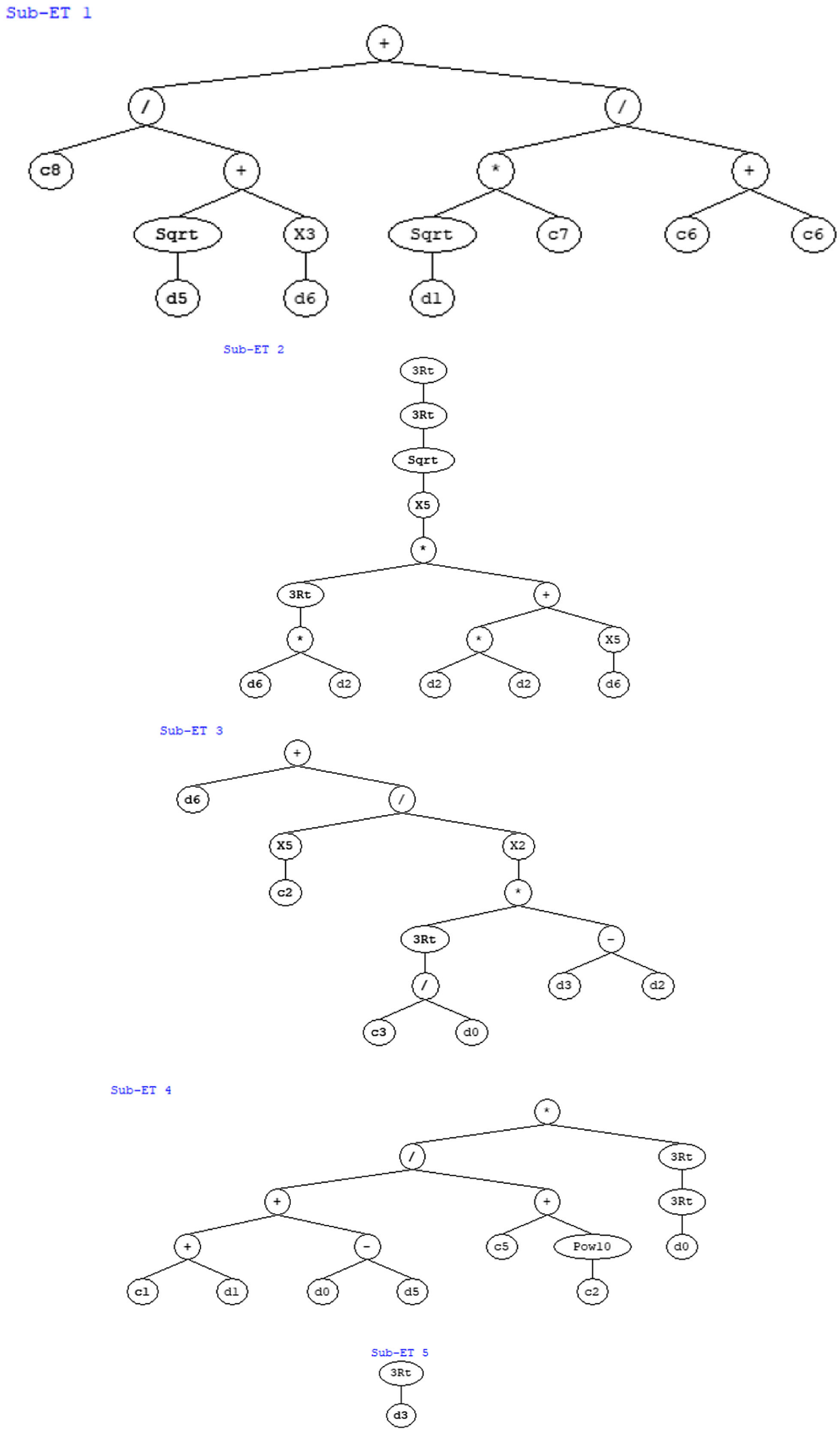


Figure 4
Expression tree representation of GEP model



$$\text{Root mean squared error (RMSE)} = \sqrt{\frac{\sum (x - y)^2}{n}}$$

$$\text{Coeff. of correlation (R)} = \frac{(n\sum xy - (\sum x)(\sum y))}{\sqrt{(n\sum x^2 - (\sum x)^2)(n\sum y^2 - (\sum y)^2)}}$$

$$\text{Performance index } (\rho) = \frac{\text{RRMSE}}{1+R}$$

For a model to be reliable, it should have R value greater than 0.8 and minimum value of other error metrices such as MAE and RMSE (Alavi et al., 2010). MAE measures the average deviation between actual and predicted values, whereas RMSE indicates the presence of large errors. The errors are squared before taking mean in RMSE, so it gives more weight to larger errors. Its value is always greater than MAE. A model with high RMSE implies that the percentage of predictions with larger errors is greater and should be minimized (Iftikhar et al., 2022). The performance index offers the advantage of considering the values of relative root mean square error (RRMSE) and R simultaneously. Its values range from zero to infinity and the model will be reliable if its value is less than 0.2 (Gandomi & Roke, 2015).

7. Model Development

The GEP algorithm is implemented using a software called GeneXpro Tools. For the development of an accurate model, various GEP tuning parameters need to be specified. These parameters are selected using literature recommendations and a trial-and-error method (Mousavi et al., 2010). The final parameters used in algorithm development are shown in Table 3.

Table 3
Parameters of GEP model

Parameter	Settings
No. of chromosomes	100
No. of genes	10
Head size	5
Linking function	Addition
Constants per gene	10
Data category	Floating
Lower and upper limits	−10 to 10
Functions	+, −, ×, sqrt, 10^x

The running duration of program is specified by population size of chromosomes. The number of chromosomes is set at 100 after many trials considering the accuracy and length of the resulting equation. The complexity of each expression tree and the resulting subexpression is specified by number of genes and head size. The number of genes is set to 10 after many trials. The linking function used for GEP model development is addition along other mathematical operations.

8. Results

The most important factor in the creation of a GEP model is to select the most influential parameters that affect the output. For this purpose, a thorough evaluation was carried out and several initial runs were performed to select the most influential parameters. The resulting equation by GEP algorithm is a function of the input parameters given below.

$$f_c' = (d_0,\ d_1,\ d_2,\ d_3, d_5, d_6,)$$

Figure 4 displays the expression tree given by GEP algorithm, and it is decoded to get the mathematical expression for the estimation of compressive strength. The equation thus derived is given below. The description of the variables used in GEP empirical equation is given in Table 2.

$$f_c' = A + B + C + D + E \tag{1}$$

Figure 5
Scatter plot of training data

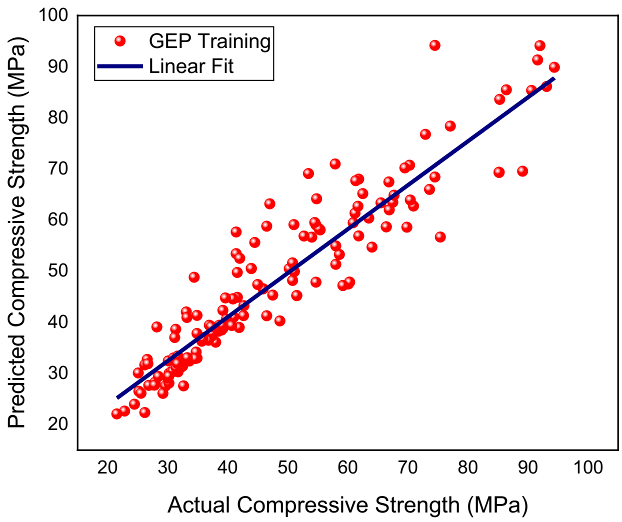


Figure 6
Scatter plot of validation data

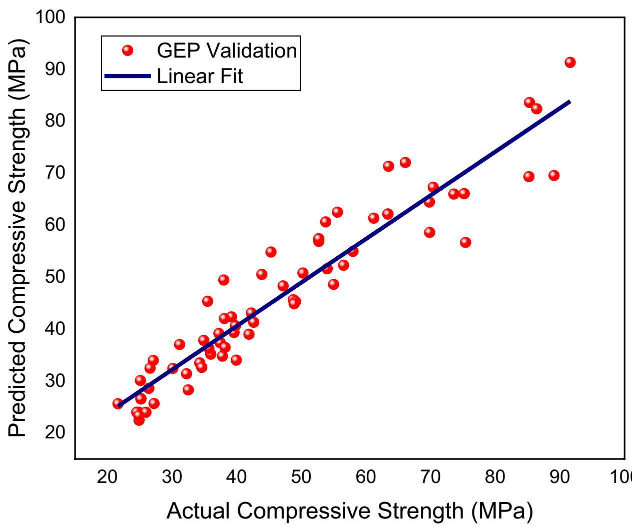
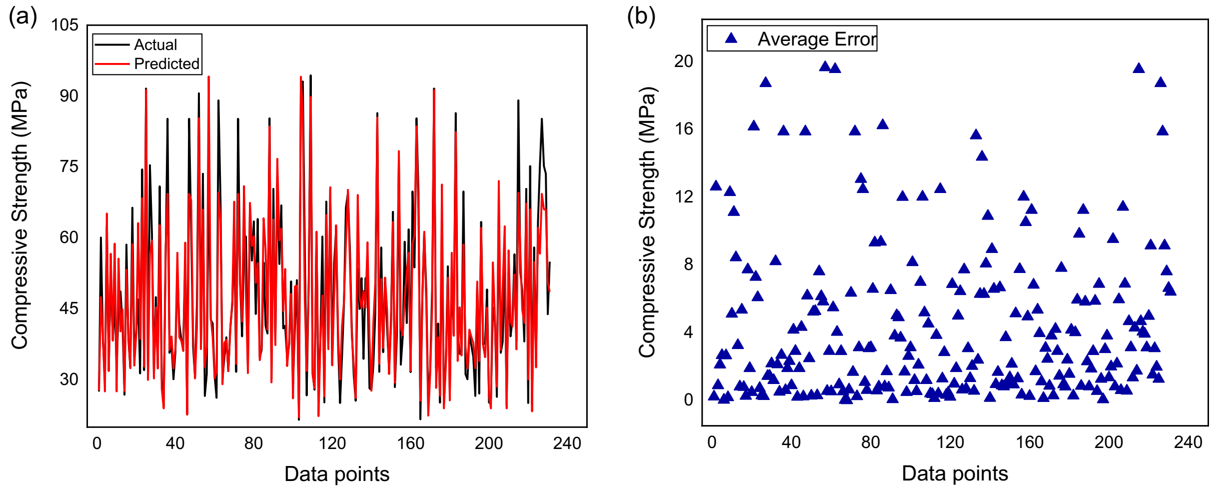


Figure 7
(a) Series plot of actual and predicted values and (b) average error distribution



where

$$A = \left(\frac{128.52}{\sqrt{d_5} + (d_6)^3} - 0.608\sqrt{d_1}\right)$$

$$B = \sqrt[3]{\sqrt[3]{\sqrt{\left(\sqrt[3]{d_2 d_6} \times ({d_2}^2 + {d_6}^5)\right)^5}}}$$

$$C = \left(d_6 + \left(\frac{(9.01)^5}{\left(\sqrt[3]{\frac{0.477}{d_o}} \times (d_3 - d_2)\right)^2}\right)\right)$$

$$D = \left(\left(\frac{(-82.52 + d_1) + (d_o - d_5)}{16.542}\right) \times \sqrt[3]{\sqrt[3]{d_o}}\right)$$

$$E = \sqrt[3]{d_3}$$

The accuracy of the developed model can be visualized by plotting the scatter plots between actual and predicted values for training and validation datasets. Figures 5 and 6 represent the scatter plot of training and validation data, respectively.

The error metrices are calculated for both datasets and are shown in Table 4. The R value of both datasets is greater than 0.8 and the performance index is less than 0.2, which shows the model is accurate and reliable. Also, the error values of validation are less than training data, which shows the problem of overfitting has been effectively removed. The difference between actual and predicted values can also be visualized by means of a series plot as shown in Figure 7.

Table 4
Error metrices of training and validation data

Metric	Training	Validation
MAE	4.36	4.30
RMSE	6.39	5.91
R	0.93	0.94
ρ	0.069	0.065

9. Conclusions

This study aimed at fostering the use of fly ash and silica fume in concrete by introducing a novel technique for estimation of 28-day compressive strength of SCC using GEP. The database consisting of 231 datapoints is constructed for this purpose and the algorithm resulted in an empirical equation relating strength to seven most influential parameters. The dataset was split into two sets called training and validation datasets. The accuracy of the developed equation is verified by calculating four commonly used error metrices for both training and validation datasets with the R value of training and validation data equal to 0.93 and 0.94, respectively. The other error metrices were also in the range specified in the literature. Thus, the developed equation can be effectively used to predict the 28-day compressive strength of SCC containing fly ash and silica fume as mineral admixtures.

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Ethical Statement

This study does not contain any studies with human oranimal subjects performed by any of the authors.

Conflicts of Interest

The authors declare that they have no conflicts of interest to this work.

Data Availability Statement

The data that supports the findings of this study is openly available with waleedbininqiad@gmail.com, and would be shared upon request via email.

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