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ORIGINAL RESEARCH

Presenting a novel approach for estimation the compressive strength of high strength concrete using ANN & GEP

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Abstract:
In this article, the application of artificial neural networks in predicting the degree of concrete compressive strength of High Strength Concrete (HSC) was investigated. For this purpose, use was made of the pattern recognition neural network and the obtained data from the experimental tests for predicting the compressive strength degree of HSC. Five inputs from the HSC mix design were utilized for predicting the degree of compressive strength, by application of the scaled conjugate gradient backpropagation algorithm in neural network. The outputs were classified into 5 strength groups of M1, M2, M3, M4 and M5. The simulation results shows 97.9% accuracy in classifying the different predefined degrees of HSC using the confusion matrix diagram. Moreover, the cross-entropy error obtained from testing the neural network (NN) model and correlation coefficient (R^2) of GEP for predicting compressive strength of the HSC were evaluated at 0.042096 and 0.9795, respectively, indicating high accuracy of the model. Application of this model could greatly help the persons, companies and research centers in terms of preparation and making of HSC with desired compressive strength, that are in need of this type of concrete.
Keywords: High strength concrete, Neural network, Pattern recognition, Confusion matrix, Cross-entropy error.

Introduction

Concrete is the most important and widely used construction material [1-5]. As shown by reports, the considerable high cement demand increased by 12% in 2019, expected to be doubled by 2050 [6]. A mixture of water, cement, and fine and coarse aggregates make up the conventional concrete [7]. Considering the great advancements in concrete technology, today, making high strength concrete is not a difficult task and just the construction cost might increase with respect to the type and amount of used additives. However in practice, making concrete with a compressive strength higher than 60 to 70 MPa having proper workability is difficult and costly. Concrete strength (CS) can be regarded as a critical performance parameter highly effective in the concrete structure design [8]. Increase of the concrete strength reduces its ductility and causes brittle behavior in concrete. Considering the importance of strength characteristics, especially the compressive strength in concrete, and preventing short term damages and the high cost of maintenance, today high strength concrete due to its high strength characteristics is widely used in the civil projects with high importance.
In 1992, the ACI 363 committee defined the high strength concrete as a concrete with 41 MPa or higher strength. Then this committee in the year 2001 approved a new definition for HSC where the specific compressive strength is 55 MPa or higher. The new value of 55 MPa was selected for this reason that this shows a strength level which needs special care in producing and testing the concrete, also it requires special design considerations for the structure [9].
The high strength concrete was first utilized in Chicago in the year 1965 [10]. Among the advantages of this type of concrete one could refer to the high compressive strength, high tensile strength, higher modulus of elasticity, lower permeability, higher durability due to lower porosity and greater bond strength between concrete and rebars. Among the effective factors to reach such high strengths one could mention the use of high strength gravel and sand with proper shapes, increase in the amount of used cement, limited size of the maximum aggregates, use of sand with proper modulus of softness and proper sand to cement ratio for better homogeneity. Furthermore, using the very fine grained materials with sizes less than 0.1 microns such as silica fume one could prepare a more compact concrete with very low porosity [11].
High strength concrete is mainly used for construction of columns in high rise buildings, offshore structures, road pavements, special purpose concrete structures and pre-stressed concrete bridges. Use of this type of concrete in the columns of high rise buildings reduces the column dimensions and increases the number of stories. Also this type of concrete is used for construction of bridge piers, and roof of spectator stands in the stadiums [12].
Artificial neural networks and genetic algorithms have currently had wide applications in different fields, particularly by civil engineers, for the prediction of the desired results. One of the main areas of interest is predicting concrete mechanical characteristics due to the considerable time and energy spent to obtain the intended laboratory outcomes [13].
Table 1 presents the details on the application of artificial neural networks and genetic algorithms for the CS prediction, obtained from relevant literature.

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Table 1. Application of ANN and GA approaches for the prediction of concrete strength

Sr. No	Algorithm used	Year	References
1	ANN, GEP	2022	[14]
2	GEP	2021	[15]
3	ANN, GA	2021	[16]
4	ANN, bagging and boosting	2021	[17]
5	GEP	2021	[18]
6	SBRS, GEP, ANFIS	2021	[19]
7	GEP	2021	[20]
8	GEP, DT and Bagging	2021	[21]
9	GEP	2020	[22]
10	ANN, GA	2020	[23]
11	GEP	2020	[24]
12	GEP and RF	2020	[25]
13	RSM, GEP	2020	[26]
14	GEP	2019	[27]
15	GEP	2019	[28]
16	ANN	2019	[29]
17	ANN	2019	[30]
18	GA	2019	[31]
19	ANN, ANFIS	2019	[32]
20	ANFIS	2018	[33]
21	ANN	2018	[34]
22	ANN	2018	[35]
23	GEP	2018	[36]
24	ANN, GEP	2018	[37]
25	ANN	2018	[38]
26	ANN	2017	[39]
27	ANN, MRA	2017	[40]
28	ANN, MLR, ANFIS	2017	[41]
29	ANN	2017	[42]
30	ANN	2017	[43]

Notes: GEP: Gene expression programming, ANN: Artificial neural network, GA: Genetic algorithm, SBRS: Step-By-Step Regression, ANFIS: Adaptive neuro fuzzy inference system, DT: Decision tree, RF: Random Forest, RSM: Response surface methodology, MRA: Multivariable regression analysis, MLR: Multiple linear regression.

The five compressive strength grades of high strength concrete during experimentation adopted target compressive strength ranges as presented in Table 2.

In neural networks for classification problem solving, pattern recognition model can be created with utilization of scaled conjugate gradient back propagation algorithm [44]. In this study, pattern recognition neural network model created to classify output as compressive strength grade of high strength concrete from inputs.

1. Materials and methods

2-1- Experimentation and neural network model for high strength concrete mixtures

The optimal mix design for concrete is obtained by selecting the available materials which make the concrete executable and ensure reaching the expected strength and other characteristics required for a hardened concrete by the designer. Some basic principles that should be considered for the high strength concretes are as follows:

2-1-1 Materials for high strength concrete mixtures

Correct In making the high strength concrete, it is recommended to use a sand with higher modulus of softness (about 3), as in this type of concrete often high amounts of fine grained cement and pozzolans are used and fine grained aggregates would not improve the mix workability. On the other hand, a coarser sand requires less water to reach a similar workability. The other reason is the effect of coarse sand during mixing operation which causes large shear stresses and prevents coagulation of cement paste [45].

The hydration rate increases in cements with higher softness and the desired strength reaches sooner. Therefore use of Portland cement type I is recommended. But too much softness requires much water, therefore there is no need for a cement with high softness (cement type II), unless where there is need for early strength of concrete. The compressive strength of aggregates in high strength concrete is very important and the aggregates strength should be minimum equal to the cement paste strength. A rounded shaped sand improves workability and reduces the amount of cement paste. But, crushed sand improves the bond strength between the aggregates and cement paste [9].

2-2- Proportioning and preparation of high strength concrete mixtures

If the amount of used cement for making high strength concrete is too much, it causes intense shrinkage of concrete [46] and reduces its ductility. On the other hand the obtained concrete in this way would be uneconomical. Therefore a cement with 390-560 kg/m^3 density is appropriate. Where this amount of cement is not enough to achieve the required strength one could use mineral additives or reduce the water to cement ratio. To reach a higher strength there is need for a smaller maximum size of aggregates. For a compressive strength of 70 MPa, the maximum size of 20-28mm is appropriate. For producing a concrete with 100 MPa strength, the maximum size of aggregates in the range of 10-14mm is desirable [45].

Table 2. Grades and target compressive strength range of high strength concrete mixtures

Compressive strength grade	Target compressive strength range (MPa)
M1	55-59.9
M2	60-64.9
M3	65-69.9
M4	70-74.9
M5	75-80

2-3- Pattern recognition neural network model for high strength concrete mixtures

In this multi-layer pattern recognition model, nine inputs including the Water-Cementitious Material Ratio (w/cm), Silica fume, Slag cement, High-reactivity metakaolin, Fly ash, Water, Cement, Fine aggregates and Coarse aggregates are assumed for classifying the degree of concrete compressive strength. They include 5 sets of the target groups named as M1, M2, M3, M4 and M5, shown schematically in Fig.1. In this model, 10 hidden layers were utilized. Also 70% of the data is assumed for training, 15% for validation and 15% for testing.

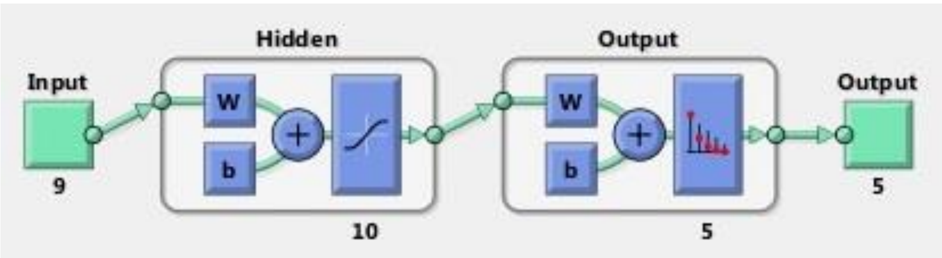

Fig. 1. Architecture of neural network for pattern classification

The data are given in Table 3.

Table 3. Range of different variables used in this study [9]

Variable	Range
w/cm (d_0)	0.25-0.35
Silica fume (d_1)	19-32 (kg/m^3)
Slag cement (d_2)	26-38 (kg/m^3)
High-reactivity metakaolin (d_3)	38-54 (kg/m^3)
Fly ash (d_4)	96-128 (lit)
Water (d_5)	192-214 (kg/m^3)
Cement (d_6)	399-533 (kg/m^3)
Fine aggregate (d_7)	954-974 (kg/m^3)
Coarse aggregate (d_8)	1663-1705 (kg/m^3)

2-4- Pattern recognition neural network model for high strength concrete mixtures

Gene expression programing (GEP) is a methodology for developing computer programs and mathematical modeling based on evolutionary computations inspired by natural evolutions [47]. In this method, a set of data is used to build a tree-like mathematical model [48]. Invented by Ferreira in 1999, this methodology was officially introduced in 2001 [49]. The basis of the algorithm used in GEP is to combine the dominant inheritance (i.e., genetic algorithm, GA) with genetic programing (GP) to cope with its own drawbacks. To this end, the GEP represents chromosomes in terms of expression trees (ETs) [47]. An ET resembles a protein in a natural cell, which determined the phenotype [50]. Ferreira further developed a simple yet efficient language, called Karva, for expressing the genes and generating ETs. Using this language, one can achieve a mathematical equation (program) composed of random terminal and operators extracted from each chromosome [48].

The five basic steps of designing a GEP algorithm are [47]:

• Definition of the fit function
• Defining terminals and functions
• Determine the structure of chromosomes (number of generations, length, and number of genes)
• Determining the linking function
• Determine the characteristics of the operators and, finally, algorithm implementation.

In this article, GeneXproTools 5.0 was utilized to investigate accuracy of some experimental data and present a model for estimating compressive strength of HSC. Four fundamental arithmetic operators (-, +, ×, /) and several primary mathematical functions (Exp, 3Rt, Max2, Avg2, Atan, Tanh) were and root mean square error (RMSE) was used as fitness function.

Fitness functions were used to maximize fitness and minimize estimation error measured as correlation coefficient (R^2) and RMSE, as per Equations (1) and (2), respectively [51]. These criteria could evaluate the efficiency and power of the model for producing significant forecasts.

$$R^2 = \frac{\sum_{i=1}^{n}(x_i - \bar{x})(x_i - \bar{y})}{\sqrt{\sum_{i=1}^{n}(x_i - \bar{x})^2 \sum_{i=1}^{n}(x_i - \bar{y})^2}} \tag{1}$$

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

Where: x=observed value, y=calculated value, $\bar{x}$=Average of observed values, $\bar{y}$=Average of calculated values, i=data point number, and n=total number of data points. Importantly, generalizability of GEP is largely determined by the choice of parameters [52].

Table 4 shows the GEP configuration that was used for compressive strength high strength concrete simulation.

Table 4. Configuration settings for GEP algorithm

Parameter	Description
Fitness Function	RMSE
Number of chromosomes	30

General	Genes	4
	Head size	10
	Tail size	11
	Gene size	32
	Linking function	Addition
	Function set	+,-,/,×, Tanh, Atan, Avg2, Max2, 3Rt, Exp
Genetic Operators	Mutation rate	0.00138
	IS Transposition rate	0.00546
	RIS Transposition rate	0.00546
	Inversion rate	0.00546
	One-point recombination rate	0.00277
	Two-point recombination rate	0.00277
	Gene recombination rate	0.00277
	Gene transposition	0.00277
Numerical Constants	Constants per gene	10
	Data type	Floating-Point
	Lower bound	-10
	Upper bound	+10

3- Result and discussion

The cross-entropy error is shown in Fig.2, which depicts the error between the obtained results from the validation test and the expected results. The cross-entropy error obtained from the neural network model in predicting the degree of HSC compressive strength was equal to 0.042096 at epoch 14. This shows high accuracy of the model.

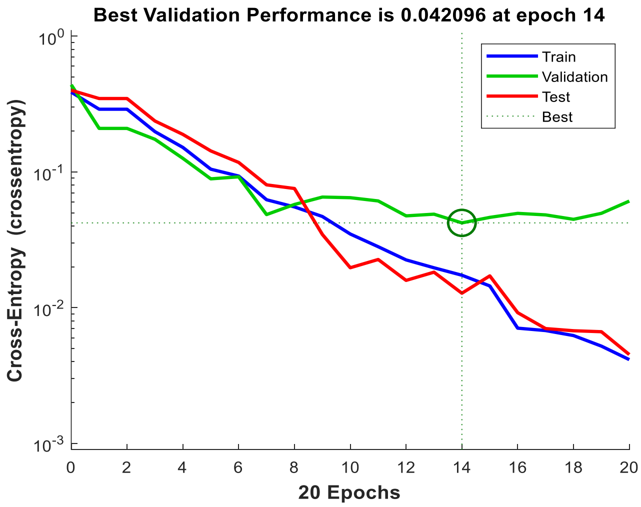

Fig. 2. Cross-entropy error for neural network with 10 neurons in hidden layer

The error histogram shown in Fig.3, depicts the artificial neural network performance. The training data are shown by the blue color, the validation data are shown by the green color and the test data are shown by the red color. According to Fig.3, for the compressive strength of HSC, all the error values are in the range of -0.5468 - 0.7197 which indicates a very negligible error.

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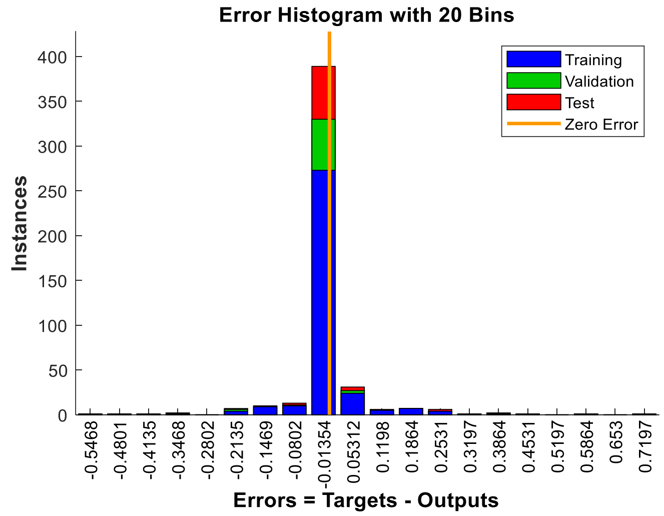


Fig. 3. Error histogram with 20 Bins

Fig.4 shows the confusion matrix. This matrix indicates the accuracy of classified data in the predefined groups in the training, validation and testing processes. The overall classification accuracy is equal to 97.9% which indicates correct classification percentage.

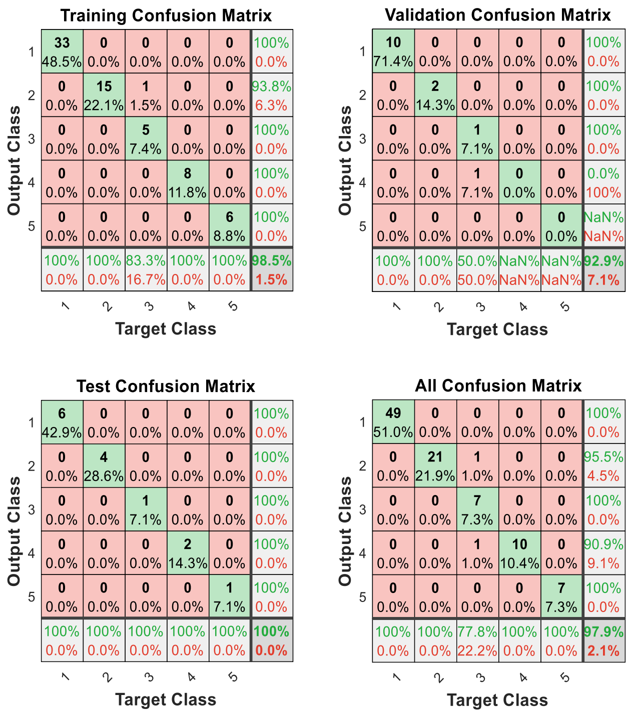
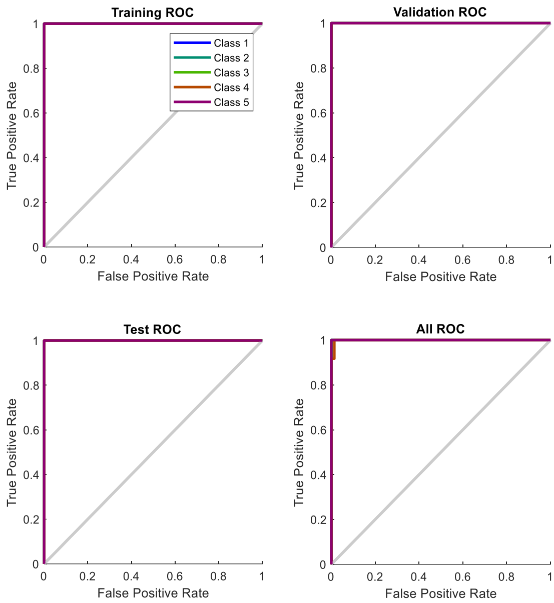


Fig. 4. Confusion matrix for 10 neurons in hidden layer respectively

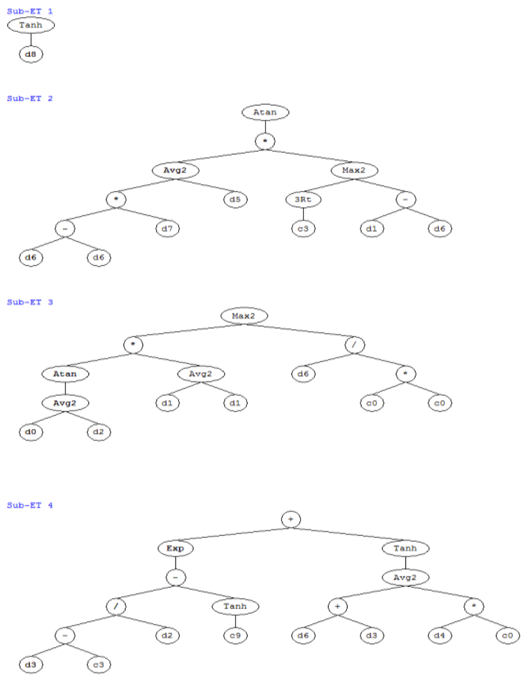
Effects of varying thresholds of normal values on the specificity of the test, receiver operating characteristics or ROC curve are shown separately for the training, validation, testing and all data in Fig.5. The X axis represents characteristic and the Y axis represents model sensitivity which exhibits model performance. The more the area under ROC curve approaches unity, or in other words the ROC curve is flat at the upper portion, then the model has a better performance. It means if the ROC curve reaches unity it would have 100% characteristic and 100% sensitivity.

According to the abovementioned issues, the performance of ROC curve in this research, due to having almost flat curves for classes of 1, 2, 3, 4 and 5, exhibits desirable results.



⊡ Fig. 5. ROC cure for neural network with 10 neurons in hidden layer

The final ET extracted using the GEP is demonstrated in Figure 6. It consists of four sub-ETs connected to one another through addition operator (+). Indeed, the figure shows the extracted associations between input data and outputs using the GEP algorithm. Using Figure 6, one can obtain a GEP-based equation, which is a complex mix of arithmetic operators, constants, and variables, for predicting compressive strength of HSC, CS_{HSC} (Equation 3).



⊡ Fig. 6. Expression tree (ET) from the GEP model

$$CS_{HSC} \square \left\{ \mathrm{Tanh}\, d_8 \right\} \square A\tan\left[\frac{((d_6 \square d_6) \square d_7) \square d_5}{2} \square \max\left\{ \sqrt[3]{c_3(GeneII)}; (d_1 \square d_6) \right\} \right] \square \max\left[\frac{A\tan(d_0 \square d_2)}{2} \square \frac{(d_1 \square d_1)}{2} ; \frac{d_6}{(c_0(GeneIII)) \square c_0(GeneIII))} \right] \square Exp\left[\left(\frac{(d_3 \square c_3(GeneIV))}{d_2}\right) \square \mathrm{Tanh}(c_9) \square \mathrm{Tanh}\left(\frac{(d_6 \square d_3) \square (d_4 \square c_0(GeneIV))}{2}\right) \right] \quad (3)$$

The values of constant parameters in Figure 6 and Equation (3) are given in Table 5.

Table 5. Magnitudes of constant parameters in Fig. 6 and Eq. (3)

Parameter	Value
C_0 (Gene III)	2.6999
C_0 (Gene IV)	0.1596
C_3 (Gene II)	-2.0322
C_3 (Gene IV)	-3.4305
C_9	2.0234

Figure 7 presents an analysis on the performance and validity of the GEP model by comparing the predicted values to corresponding experimental data. According to this table, prediction of compressive strength of HSC could be performed at an R^2 value of 0.9795, indicating very good correlation of predictions to experimental data.

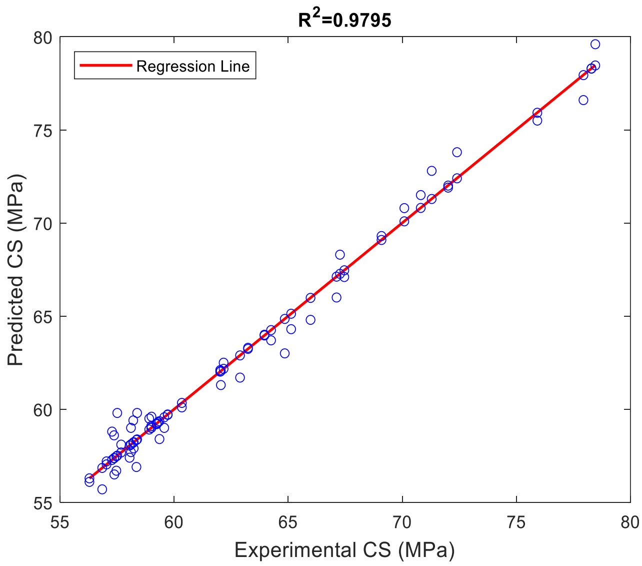


Fig. 7. Actual versus predicted CS_{HSC} using the GEP model

The conclusion

Although numerous studies have elaborated on the high-strength concrete so far, one can develop the existing models even further so that not only ease their application but also reduce their computational error. Accordingly, it is necessary to search for and utilize novel methods and software tools for presenting the model, as is investigated in the present research. Being among the newest evolutionary algorithms and providing adequate accuracy and high flexibility, the gene expression programming (GEP) has found more applications than similar techniques. Taking no assumption regarding the structure of the relationship between the dependent and independent variables, this technique utilizes the information contained in the data to establish a proper association between the variables and predict the output graph. On this basis, the core novelty of this research includes the use of artificial neural networks (ANNs) and a GEP-based software for identifying and presenting a new model for predicting compressive strength of high-strength concrete. Indeed, despite the comprehensiveness of this software, many researchers are yet to regard its powerful methodology, and only few practitioners in the field of concrete studies have actually acknowledged it recently. Elaborating on the presentation of a prediction model for compressive strength of high-strength concrete, this research can greatly contribute to the calculation and determination of compressive strength of high-strength concrete.

Selection of a proper mix design for making a concrete with the compressive strength desired by designer is of great importance. In this research, the experimental mix designs of HSC were successfully modelled using the pattern recognition neural network and by considering the scaled conjugate gradient propagation algorithm in the neural network. The input variables of HSC mix design for predicting the degree of target compressive strength were selected carefully based on the experimental results. The degrees of HSC compressive strength consisting of five classes were used during the training, validation and testing stages of the neural network. The degree of compressive strength resulted from the neural network model was assessed by cross-entropy error method yielding a value equal to 0.042096 which is desirable and indicates proper training and validation of the neural network. Moreover, correlation coefficient (R^2) of the results of GEP in predicting compressive strength of HSC was 0.9795, reflecting the high accuracy of the model Analysis of the model simulation confirmed this assumption that by extracting the collected mix design parameters and regarding the experimental results and also using the artificial neural network one could classify the compressive strength degree for high strength concrete with a high accuracy equal to 97.9%. Moreover, the equation developed by this model can be conveniently used, with no limitation on input parameters, by other individuals, companies, and/or research centers who are seeking to use this type of concrete.

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