JOURNAL OF MECHANICS OF CONTINUA AND MATHEMATICAL SCIENCES
www.journalimcms.org

ISSN (Online) : 2454 -7190 Vol.-19, No.-3, March (2024) pp 1-21 ISSN (Print) 0973-8975

PREDICTION OF CONCRETE MIXTURE DESIGN AND COMPRESSIVE STRENGTH THROUGH DATA ANALYSIS AND MACHINE LEARNING

Mohammad Hematibahar[1], Makhmud Kharun[2]

[1,2] Department of Reinforced Concrete & Masonry Structures, Moscow State University of Civil Engineering, Moscow, Russia.

[1] eng.m.hematibahar1994@gmail.com, [2] miharun@yandex.ru

Corresponding Author: **Makhmud Kharun**

https://doi.org/10.26782/jmcms.2024.03.00001

(Received: January 13, 2024; Revised: February 26, 2024; Accepted: March 08, 2024)

Abstract

Concrete is the most used building material in civil engineering. The mechanical properties of concrete depend on the percentage of materials used in the mix design. There are different types of mixture methods, and the purpose of this study is to investigate the mechanical properties of concrete using the mixture method through data analysis. In this case, more than 45 mixture designs are collected to find the estimated mixture design. The estimated mixture design was found by correlation matrix and the correlation between materials of concrete. Moreover, to find the reliability of the compressive strength of concrete through data mining, two models have been established. In this term, Linear Regression (LR), Ridge Regression (RR), Support Vector Machine Regression (SVR), and Polynomial Regression (PR) have been applied to predict compressive strength. In this study, the stress-strain curve of the compressive strength of concrete was also investigated. To find the accuracy of machine learning models, Correlation Coefficient (R^2), Mean Absolute Errors (MAE), and Root Mean Squared Errors (RMSE) are established. However, the machine learning prediction model of RR and PR shows the best results of prediction with R^2 0.93, MAE 3.7, and RMSE 5.3 for RR. The PR R^2 was more than 0.91, moreover, the stress-strain of compressive strengths has been predicted with high accuracy through Logistic Algorithm Function. The experimental results were acceptable. In the compressive strength experimental results R^2 was 0.91 MAE was 1.07, and RMSE was 2.71 from prediction mixture designs. Finally, the prediction and experimental results have indicated that the current study was reliable.

Keywords: Data Mining, Concrete Compressive Strength, Prediction Method, Reliability, Artificial Intelligence, Machine Learning

I. Introduction

Concrete is the most widely used construction in engineering. The mechanical properties of concrete depend on the composition of the mixture. Many studies conducted indicate the new type of concrete with the new mixing method. The use of data analysis and computer programming was a neglected idea in this field. The link between computer programming and concrete mixture design can help to find the most optimal concrete mixture design. In this regard, Data mining, Artificial intelligence (AI), and Machine Learning (ML) have a different application in engineering, and technology [II, III, XIV, XX, XLIV]. Data mining is applied in many types of manufacturing to new learning and solving intricate problems. Large companies most often use data mining in financial processes. Not only, financial companies are using data mining, but also engineers and developers are utilized data mining. For example, the concrete prediction compressive strength is a suitable cause for data mining [XIV].

Data mining, ML, and AI are being used by manufacturers and other engineers to find new and better ways to reduce production time and materials [V, VII, XXIX]. Currently, many researchers prefer to apply data mining, ML, and AI to predict the mechanical properties of concrete. While, they used some limited variable properties of concrete materials to find the compressive strength [XV, VI, XVI, XXVIII, XXXV, XLIII]. For example, Shahmansouri et al. [XXXVIII] presented a new method to forecast the compressive strength of natural zeolitic concrete. The curing period of concrete was the main factor of their study. More than 56 mixture designs were used in their study. The Root Mean Square Errors (MSE) were evaluated to determine the accuracy of the prediction results. Their compressive strength prediction results illustrate that the MSE was 1.6. The prediction results show high accuracy. However, ML is not able to find mixture design and the quality of concrete. While, Artificial Neural Network (ANN) is able to predict the mechanical properties such as compressive strength of concrete [XVII, VI, VII]. For example, Chopra et al. [XIII] predicted the compressive strength of concrete using the ANN method. They applied the ANNs method based on a curing period between 28-days, and 91-days. The Leveberg-Marquardt (LM) training function is applied through ANN to predict the compressive strength results. According to their results, the accurate compressive strength prediction and coefficient of determination (R^2) were more than 0.8, but other parameters such as concrete quality and percentage of mixture design were ignored. The programming is not able to understand the quality of the mixture of materials, and the programmer has to add a new way to indicate the quality. Another neglect of the programming method was the lack of collecting data, the programming method is not able to collect all data about the concrete. Another example, Topcu and Saridemir [XLI] established the ANN and Fuzzy Logic (FL) method to predict the compressive strength of concrete. In the current study, the predicted method was based on fly ash as a variable material. Their results show that R^2 was more than 0.9. R^2 was accurate as fly ash was the main variable. Chiadighikaobi et al. [XII] analyzed the effect of the old method of structural design using soft computing and compared them with the modern method of structural design. According to the results, the R^2 was more than 0.44. In another example, Kashyzadeh et al. [XXVII] used a new method to predict the compressive strength via shape and size of different types of dry aggregates. They understood that the shape and size of aggregates are effected on the compressive strength. They found that the compressive strength for aggregates on the cold wind process is increased more than 8%. In fact, they used two principle parameters: first the shape of the aggregates, which is related to the quality of the materials, and then the environmental impact of the material. Kashyzadeh et al. [XXVII] presented new types of data mining algorithm, however their study neglected the influence of other parameters such as curing period, cement quality, etc. In another example of environmental factor, Kashizadeh et al. [XXVII] studied more than 108 cube of concrete with different types of aggregates, and curing temperature to predict the compressive strength of concrete. They understood that 15ºC is the best temperature of water in the curing period. In another example, Nguyen et al. [XXXIV] collected more than 330 mixture designs to predict the compressive strength the best method of compressive strength prediction. The variable materials were fly ash and geo-polymer. The lack of focus on the other types of material was a great gap in their prediction method. Kumar et al. [XXX] used ML methods, Gaussian Progress Regression (GPR), Support Vector Machine Regression (SVR), and Ensemble Learning (EL), to lightweight-concrete mechanical properties such as compressive strength prediction. Their results are shown that R^2 was more than 0.98 for GPR prediction method. In fact, they used many type of programming method to find accurate prediction compressive strength results, while, they result had not enough variables. Sami Ullah et al. [XXXVII] applied SVR and Random Forest (RF) methods to find the forecasting results of lightweight foam concrete (LFC) compressive strength. Their results show that RF method was able to predict with high accuracy. However, they did not indicate the quality of LFC parameter to find reliable results. J. Alghamdi [XXV] developed a new method to find the optimal mix design of concrete through machine learning. He used decision trees method to predict the concrete mixture designs. Hematibahar et al. [XXIII] established Logistic function to find the accurate compressive strength results. Their method was unrelated to materials of concrete. They used a new method to predict the mechanical properties of concrete, but they were unable to find the optimal mixture percentage of materials for the concrete mixture through prediction. In another example, Hasanzadeh et al. [XIX] predict the mechanical properties of basalt fiber high-performance concrete using ML and find the relationship between the mechanical properties and different concrete samples. According to the results, the ML technique is possible to predict concrete properties with high accuracy. According to their results, the compressive, tensile, flexural strengths are predicted with R^2 more than 0.9. The R^2 results are shown that, their results were reliable. Kaewunruen et al [XXVI] studied the railway prestressed concrete sleepers through machine learning. They used namely deep learning, Bayesian Neural Network and random forest. Finally, they found that the results were validation. In fact, the R^2 was more than 0.99 in their study. Nafees et al [XXXIII] predicted the plastic concrete through machine learning using bagging and decision tree adaptive reinforcement models, multilayer perceptron neural network, and support vector machines and compared with a modified random forest learning model to predict the compressive strength and tensile strength of concrete. Their results illustrated that R^2 was more than 0.93 and 0.86 for compressive strength and tensile strength respectively. Chiadighikaobi et al. [XI] studied on the self-healing concrete prediction by adding Trichoderma eesei Fungus to healing concrete and using machine learning to forecast concrete mechanical behavior. According to the R^2 results was more than 0.98 which shows that the compressive strength with additional fungus was effective. The previous studies concentrated on using some variables to find the compressive strength prediction. While, the compressive strength of concrete is related to many variables such as materials, quality of materials, and environmental conditions. A thorough study on the reliability of concrete prediction results through mixed design estimation with data mining has been ignored. This study investigated the accuracy of data mining and machine learning methods. In this study, the compressive strength of experimental results, and prediction results are compared together. The mixture design of concrete was found according to the correlation matrix of data mining. This study has focused on one of the neglected concrete machine learning areas. This subject has been concentrated on designing concrete via computer programming and machine learning. However, other studies, have analyzed different parameters of materials on the concrete mechanical properties. In this case, Linear Regression (LR), Support Vector Machine Regression (SVR), and Ridge Regression (RR) have been applied to forecast the compressive strength as the novelty of the current study. The current study has been focused on finding the mixture design of concrete through data mining and applying the experimental method to find the reliability of the data mining. The Polynomial Regression (PR), and stress-strain curve of compressive strength have been predicted to find the reliability of the current method as well.

Finally, the results show, however, that the prediction of compressive strength is accurate through machine learning, this technique, and data were also able to predict mixture designs and compressive strength with high accuracy.

II. Materials and Methods

Methodology

The focus of the present study was on data science and machine learning to find the concrete mix design and percentage of concrete materials, the reliability of concrete compressive strength, and data mining using experimental and predictive methods. Through data mining, concrete mixture designs have been predicted. For this purpose, more than 45 mixture designs have been collected to calculate the correlation between materials of concrete, and the impact factor of each concrete property. The mixture designs were found according to the correlation matrix of the collected data via data mining Fig. 1 shows the Machine learning and Artificial Intelligence methods definitions. In this term first, the data scientist is the process of collecting data and finding the correlation between the properties of a collection. To predict the values of each collected data, a method such as Machine Learning, and Artificial Intelligence are applied. According to the literature review, the most of authors established a data science technique to find the compressive strength of concrete. While, the current study, uses data science to predict the mixture design with forecasting compressive strength for the first time. The current article has investigated the accuracy of the data mining to find the mixture designs and compressive strength of concrete. In this term, first, the collected data have been prepared, and the correlation matrix was plotted. The data set had different types of material such as cement, fly ash, superplasticizer, silica fume, and coarse and fine aggregates with different sizes. Next, the mixture design of concrete has been estimated according to the data mining process. Finally, an experimental test has been applied to find the reliability of the data mining method. Moreover, to find the prediction compressive strength, two methods of prediction have been established. For the first time, the current study has used Linear Regression (LR), Polynomial Regression (PR), and Ridge Regression (RR) to predict the results.

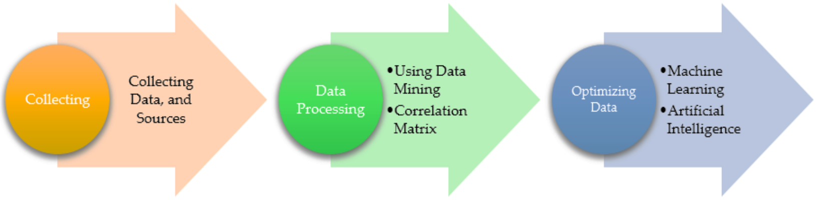


Fig. 1. Algorithm of Data Science.

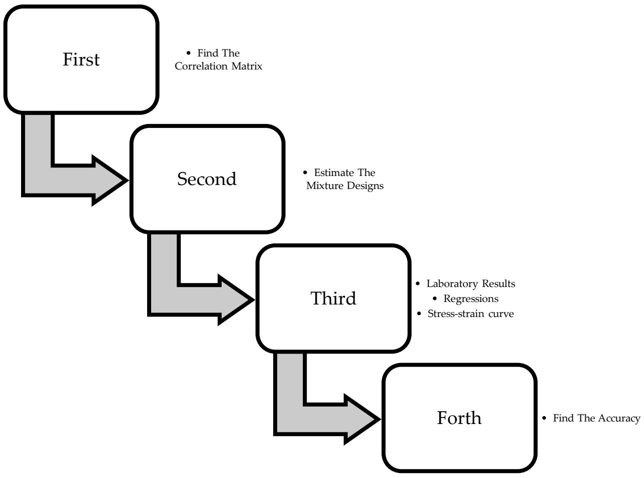


Fig. 2. Algorithm of current study.

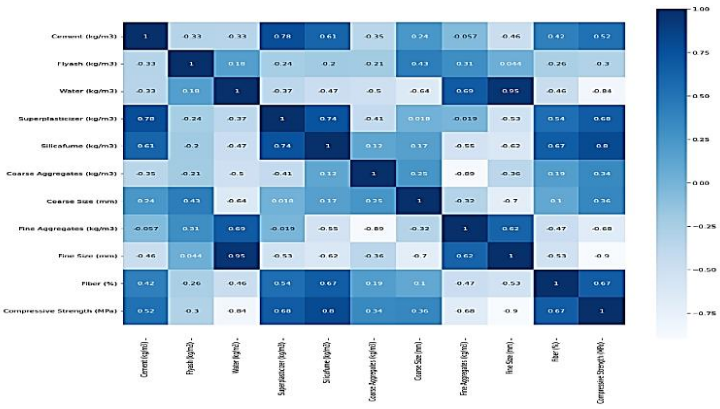


Fig. 3. Heat map correlation matrix

Data Mining Correlation

In this study, cement, water, fly ash, superplasticizer, fine, and coarse aggregates, size of fine, and coarse aggregates, silica fume, and different types of fiber have been collected. Fig. 3 shows the correlation matrix between compressive strength and materials of concrete. According to the correlation matrix, the most positive effective materials on compressive strength were silica fume, fiber, superplasticizer, and cement with, 8%, 67%, 68%, and 52% respectively.

According to the information, the silica fume was the most effective material, and cement's effectiveness was 52%. It should be noted that material engineers must use silica fume to improve the concrete compressive strength, C-S-H composition and crystallization, and the developer of the program has not neglected the materials for data collection [XXI].

To the weakness of compressive strength, the water with more than 84 % negative effect was the maximum. The optimal percentage of water should be calculated for each type of concrete. Since the fine aggregates hurt the concrete compressive strength. Fig. 3 shows, that the negative effect of increasing fine aggregate weight was more than 68%, and the small size of fine aggregates had more than 90% negative impact on the compressive strength of concrete. While the increasing weight of coarse aggregates had a positive impact on compressive strength with more than 34%.

Mixture Design Method

In this study, the mixture designs were derived from data mining of collecting data. The data mining information has been illustrated in Fig. 4-6. The mixture designs were found according to the compressive strength, and cement weight. For example, Fig. 4 shows, the compressive strength of a concrete sample can be between 80 MPa, and90 MPa where the cement was between 440 Kg/m3, and 460 Kg/m3, and fine aggregates were 585 Kg/m3. In other means, the compressive strength of different samples of concrete has been estimated through data mining graphs.

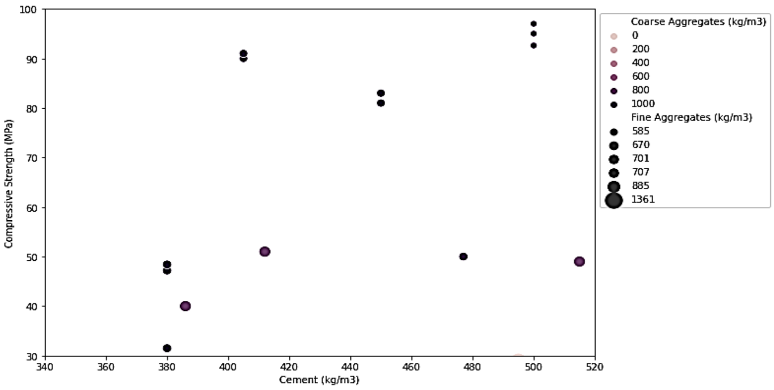


Fig. 4. Correlation between, compressive strength, cement, coarse, and fine aggregates.

In another example, Fig. 5 shows the correlation between, compressive strength, cement, water, and coarse aggregates. The best water weight was between 180 Kg/m3, 180 Kg/m3, and 187.5 Kg/m3. Moreover, 800 Kg/m3 of coarse aggregates have been the best results of compressive strength with more than 50 MPa.

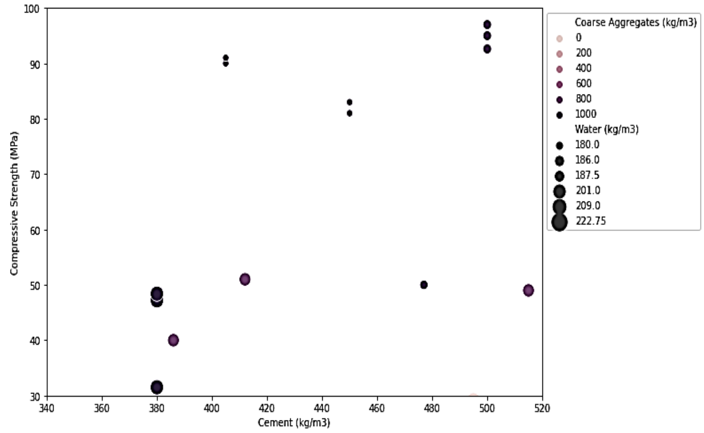


Fig. 5. Correlation between, compressive strength, cement, water, and coarse aggregates.

To find the best size of aggregates, Fig. 6 shows the correlation between, compressive strength, cement, fine aggregate size, and coarse aggregate size. The proper size of fine aggregates was 1.3 mm for compressive strength of more than 90 MPa, and 6.5 mm for coarse aggregates had the best compressive strength results.

Finally, the mixture designs have been estimated through data mining. Table 1 shows the mixture design and prediction of compressive strength. The material percentages have been applied to find the accuracy of data mining results.

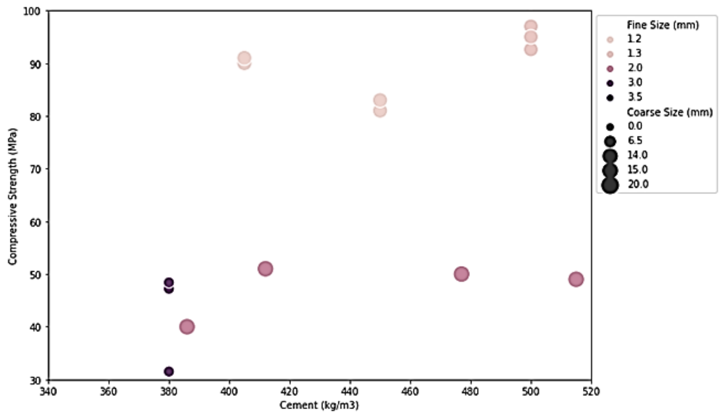


Fig. 6. Correlation between, compressive strength, cement, fine aggregates size, and coarse aggregates size.

Table 1: Estimated mixture design through data mining

Specimens	Cement (Kg/m^3)	Water (Kg/m^3)	Coarse Aggregates (Kg/m^3)	Fine Aggregates (Kg/m^3)	superplasticizer (Kg/m^3)	Micro Silica (Kg/m^3)	Basalt Fiber %	Prediction Compressive Strength (Kg/m^3)
A	450	180	450	400	12.5	125	1.2	80-90
B	450	180	500	450	12.5	152	1.2	80-90
C	450	180	650	500	12.5	125	1.2	80-90
D	500	190	450	600	12.5	125	1.2	90-100
E	500	190	500	700	12.5	125	1.2	90-100
F	500	165	450	600	12.5	125	1.2	90-100
G	500	165	500	700	12.5	125	1.2	90-100

Material, and Experimental Methods

To prepare the concrete, ordinary Portland cement (OPC), manufactured by Sabzevar factory, Sabzevar, Iran, coarse aggregates (size between 14 mm, and 6.5 mm), fine aggregates (size between 2 mm, and 1.2 mm), and water established, Micro silica, and Superplasticizer, and basalt fiber. Seven mixture designs are evaluated by the data mining method. First group (A, B, C, and D) mixtures have 0.4, and 0.38 water/cement ratios. While, the (E, F, and G) mixtures are used at 0.38, and 0.33 water/cement ratios. To prepare concrete, a concrete pan mixer (constant speed of 48 rpm) mixed all materials. First, coarse, and fine aggregates are mixed through a 133-liter mixer for about 2 minutes, next cement is added to the mixture, and water is also mixed. In this way, the concrete was set in the mold. The 100x100x100 mm^3 cube has been used for the compression testing. The concrete samples were put under water at 15 ^{o} F temperature for 28 days as a curing period. Due to the compression test, GOST (GOST 10180-2012 Concretes. Methods for the strength of Russia), and ASTM C293 / C293 (American Society for Testing and Materials) have been applied [IX, X, XVII].

Programming Method

The programming method is divided into two parts: soft programming and machine learning. Both methods have been programmed through the Python Plugin Anaconda. Fig. 7 shows the algorithm of the current study.

Fig. 7. Soft learning and Machine learning plan in the current study.

Fig.7 shows that Polynomial Regression is available through soft learning, and Linear Regression and Rigid Regression are available through machine learning.

Soft Programming Method

Hematibahar et al [XXIII] has been investigated the predicting the compressive stress-strain of concrete. Due to finding the stress-strain of the concrete, current study used the Logistic Algorithm to find the compressive stress-strain of the compressive strain of concrete. The current algorithm is able to find the compressive stress-strain of the concrete with accuracy:

$$L_u(\varepsilon_m) = u\varepsilon_m(\varepsilon_t - \varepsilon_m) \qquad (1)$$

Where L_u is the Logistic Function, ε_m is the strain of the concrete on the compressive strength, the ε_t maximum strain of the concrete. u is defined as the Real Parameter of Logistic Function:

$$u = \frac{f_c'}{\varepsilon_m(\varepsilon_t - \varepsilon_m)} \qquad (2)$$

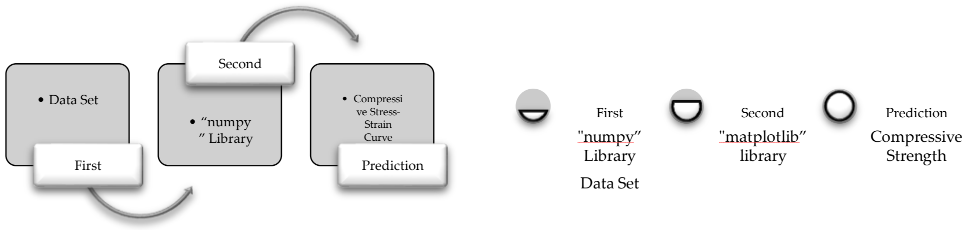
where f'_c is the compressive strength and u is the Real Parameter of the Logistic Function. Due to predicting the compressive stress-strain curve, the “numpy” library has been established. First, the Equations (1-2) have been defined in the Python. Second, according to Equation (2) the compressive strength of concrete has been defined for Python. Finally, the results show the compressive stress-strain curve (Fig. 8 (a)).

The Polynomial Regression has been predicted by soft programming. First, data has been defined by “numpy” library in Python, and second “matplotlib” library has been used to collaborate the experimental results through Polynomial commands. Finally, the validation results have been calculated by different methods (Fig. 8 (b)).

The a_n, is the coefficient of a polynomial function that has different values at various conditions. As well as, the a_0, is the Y-intercept of the Polynomial function or constant value. The Polynomial function Equation (3) is defined as [XXXVI]:

$$y_x = a_n x^n + a_{n-1}x^{n-1} + a_{n-2}x^{n-2} + \cdots + a_1 x^1 + a_0 \qquad (3)$$

where a known as the Polynomial function coefficient, x is the variable, and $y_{(x)}$ is the dependent variable to x in Equation (3).



(a) (b)

Fig. 8. Algorithm of soft learning programming: (a) Compressive stress-strain prediction; (b) Compressive strength prediction

Machine Learning Methods

To predict the compressive strength, two machine learning methods have been established. Linear Regression (LR), and Ridge Regression (RR) are used to find the prediction mechanical properties such as compressive strength. To prepare a program, the python software has been used in this study due to coding machine learning. The Linear Regression (LR) Equations are defined [XIX]:

$$y = ax + b \tag{4}$$

where x and y are variables, and a and b are the slope and intercept Ridge regression (RR) Ridge regression, known as Tikhonov regularization, was applied as the main statistical method for calibration. This regression method is applied to reduce the variability of the estimates by intentionally introducing bias into the coefficient estimate with a penalty appraiser. [XXXII] (Equation (5)):

$$\sum_{i=1}^{n}(y_i - X_i^T K - K_0)^2 + M\sum_{j=1}^{P} K_j^2 \tag{5}$$

where X_i is the vector of independent variables in the observation i, n is the number of observations; p is the number of independent variables; j denotes the sequence of the number of parameters; and K_j denotes the "jth " regression coefficient within the total number of p; X_i^T denotes transposed X_i; y_i is the dependent variable value in the observation i; K is the vector of regression coefficients; K_0 is the intercept coefficient. Support Vector Machine (SVM) known as the SL technique, was developed in the 1990s. SVM is a complex machine learning algorithm which was used by researchers to solve challenging engineering issues, such as predicting. When SVM is used in regression applications, it is called SVR [XIX] Due to the prediction of the results, LR and RR have been programmed through machine learning. In this term firs, the data has been defined in Python. The "Pandas" library has been used for finding the correlation matrix, "corr ()" command has been defined to find the correlation matrix.

The “skylearn” library has been applied to predict the results through machine learning. In this case, the data split train testing method has been utilized. Split train testing is a model validation technique that simulates the possibility of how a model performs on new data train model and training set known as “x_train, y_train”, and test model and test set is known as “x_test, y_test”. Next, the commands of Linear, Support Vector Machine Regression, and Rigid Regression have been programmed by importing from “sklearn.linear_model”. (Fig. 9).

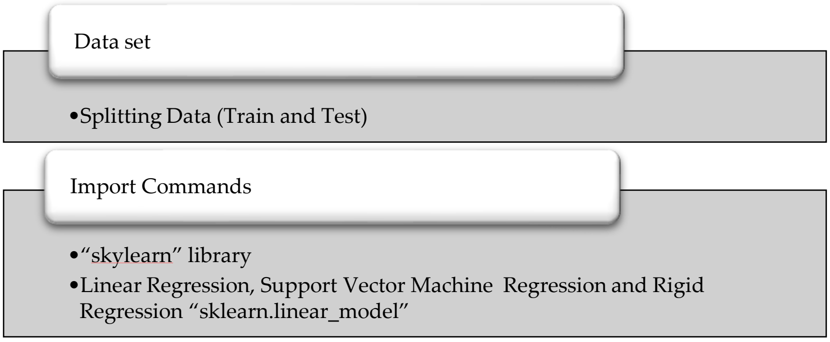


Fig. 9. Machine learning algorithm of current study.

Validation

The current study applied four different types of validation types to find the best prediction methods. To find the most accurate method the Correlation Coefficient (R^2), Mean Absolute Errors (MAE) and Root Mean Squared Errors (RMSE) Wilcoxon signed-rank test have been applied. Equation (6) illustrates the R^2 formula:

$$R^2 = 1 - \frac{\sum^n (y-\hat{y})^2}{\sum^n (y-\bar{y})^2} \tag{6}$$

where y, $\hat{y}$, and $\bar{y}$ are the actual, predicted, and mean of the actual value, respectively. The MAE method equation is equal to the sum of the numerical differences of the community set values divided by whole numbers (Equation (6)). The MAE equation is defined as (Equation (7)):

$$MAE = \frac{1}{n} \sum^n |y - \hat{y}| \tag{7}$$

RMSE calculates the average deviation of each actual data point and the predicted results. (Equation (8)):

$$RMSE = \sqrt{\frac{1}{n} \sum^n (y - \hat{y})^2} \tag{8}$$

Wilcoxon signed-rank test is presented to find the distribution between experimental results and prediction results. The Wilcoxon signed-rank test under 0.05 shows the true distribution numbers [I]

$$W = \sum_{i=1}^{N} [sgn(x_{2,i} - x_{1,i})\, R_i \tag{9}$$

Where W is testing statistics N_r is the sample size, sgn is the sign function $x_{2,i}, x_{1,i}$ corresponding to ranked pairs from two distributions, and R_i is rank i.

III. Results

Mechanical Properties, and Failure Mechanism

The experimental results show, that the close compressive strength results in prediction. The results show that data science can predict concrete mixture design. The R2 has been calculated as more than 0.91, RSME as more than 2.71, and MAE, as more than 1.07. Wilcoxon signed-rank test was more than 0.015. The Wilcoxon signed rank test shows that the distribution between the experimental and predicted results was small, this condition indicates that the results are accurate. According to the results, the A specimen has less than 0.01 MPa errors, and the E specimen has more than 12.8 MPa errors (Table 2). According to the results, A was the optimal mixture design with 0.1 error. However, the D specimens had maximum compressive strength, while the A specimens had the best results according to Table 2. The water/cement ratio was more than 0.4, the fine and coarse aggregates were more than 400 and 450 kg/m3 respectively for A specimen.

Table 2: Experimental, estimated, and errors of compressive strength results.

Specimens	A	B	C	D	E	F	G
Experimental Compressive Strength (MPa)	85.1	86	87.9	97.3	95.5	95.2	95.5
Predicted Compressive Strength (Mid-point) (MPa)	85	85	85	95	95	95	95
Errors (MPa)	0.1	1	2.9	2.3	0.5	0.2	0.5

According to the results, Data mining can find the mixture design with high accuracy. Fig. 10 illustrates that the maximum error was for C and D with 2.9 (MPa) and 2.3 (MPa) specimens. And fewer errors were for A and F with 0.1 (MPa) and 0.2 (MPa)

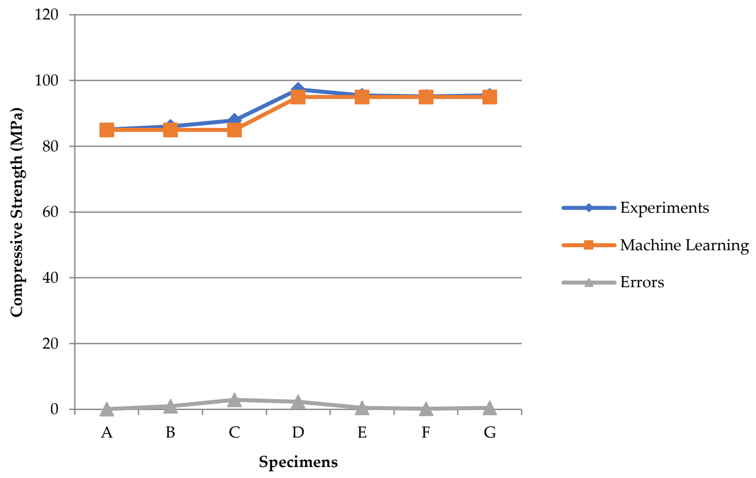


Fig. 10. The Experimental, Machine Learning, and Errors figure

The failure mechanism is another neglected problem to find the compressive strength. The compressive strength is related to the failure model and failure mechanism. [XIX].

Machine Learning Prediction

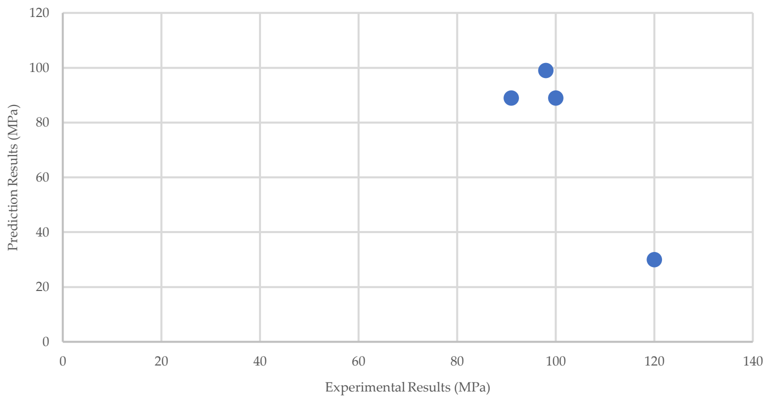


Fig. 11. Ridge Regression compressive strength results.

Two models have been predicted through machine learning techniques. The results show that the RR method was more reliable. In this method, R^2 was 0.93, RSME, 5.36, and MAE 3.74. The LR method R^2 results were more than 0.90, RSME, and MSE results were more than 9.49, and 8.20 respectively. The LR results were not accurate, and reliable. In this case, the R^2 was 0.76, and RSME, and MAE results were 39.04, and 23.14 respectively (Fig. 11 and Fig. 12).

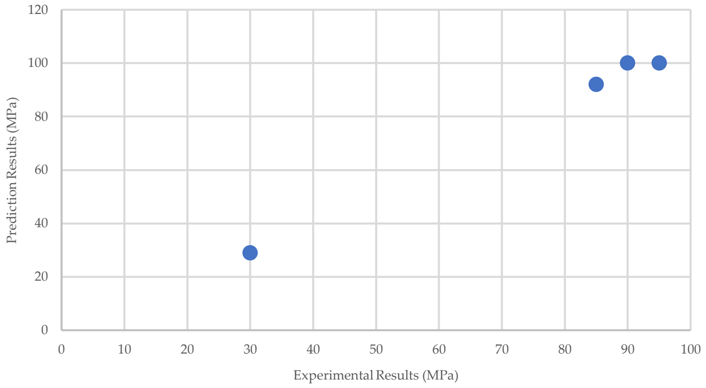


Fig. 12. Linear Regression compressive strength results.

Polynomial Regression Results

The polynomial regression results have been illustrated in Fig. 13. The results of R^2 show that the polynomial regression had similar accuracy to the RR method. PR coefficient of determining results was more than 0.93 and the RR was more than 0.91. The difference between RR, and PR is that PR is independent from the parameters and variable. However, both of the regressions had a high amount of accuracy [XIX].

However, the Wilcoxon signed-rank test results of RR were 0.13, the R^2 shows that the RR was regression. Moreover, the Polynomial Regression results were better than RR and LR in the Wilcoxon signed-rank test, MAE, and RSME with 0.02, 1.74, and 2.78 respectively. The results of the Wilcoxon signed rank test show that the experimental results and the prediction results had a close distribution (Table 3).

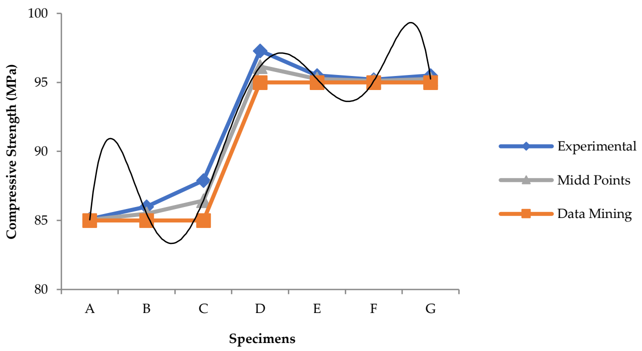


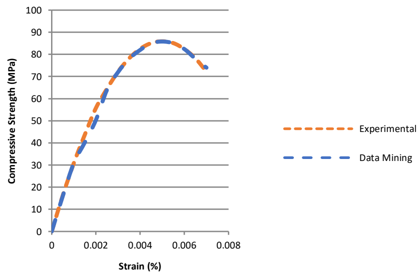
Fig. 13. Polynomial regression of the current study.

Table 3: Validation of the different methods

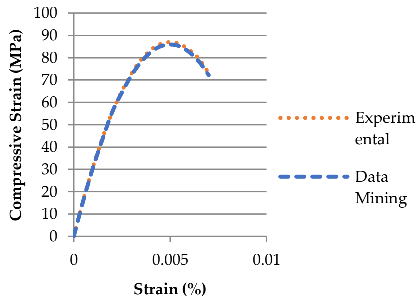
	MAE	RMSE	R^2	Wilcoxon signed-rank test
Linear Regression	39.04	23.14	0.76	0.25
Rigid Regression	3.74	5.36	0.93	0.13
Polynomial Regression	1.74	2.78	0.91	0.02
SVR	2.02	8.9	0.6	0.8

Soft Programming Stress-Strain Curve

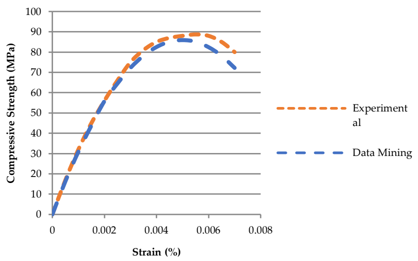
Stress-strain curve results are illustrated in Fig. 14. The Logistic Algorithm was able to predict the stress-strain curve of experimental and data mining results with high accuracy. The Logistic algorithm has been predicting the compressive stress-strain curve of 7 samples with high accuracy according to the previous study [XXII].



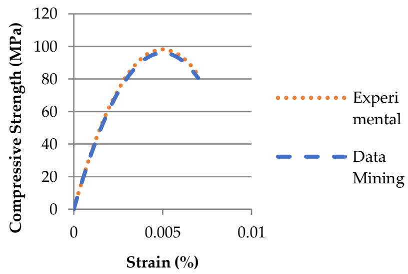
(a)



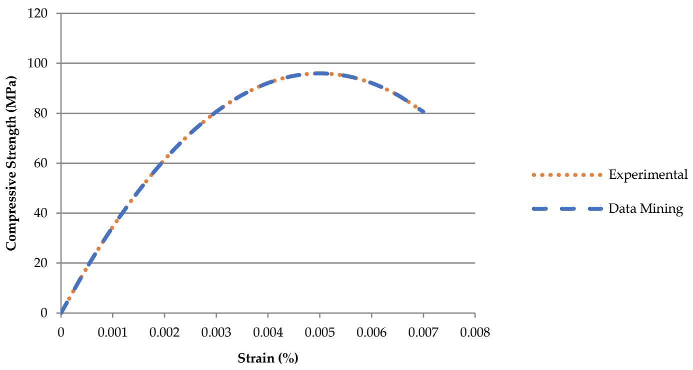
(b)



(c)



(d)



(g)

Fig. 14. The stress-strain curve of compressive strength(a), A sample, (b); B sample; (c); C sample, (e); E sample, (f), F sample, (g); G sample.

The Fig. 14 stress-strain curve helps to find the absorbent energy of the cube of the specimen under compression test.

IV Discussion

The current paper studies both experimental and prediction results of the compressive strength of concrete. However, the Ridge Regression predicted the compressive strength of concrete with more than 0.97 (R^2) accuracy, and experimental compressive strengths show different results. The novelty of the current study was applying Linear Regression, Rigid Regression, and Polynomial Regression to forecast the compressive strength and compare with experimental results for the first time.

In terms of prediction method, the current study predicts a compressive study with more than 0.97 R^2 Results. The current study used the Ridge Regression (RR) machine learning method to predict the compressive strength. This method shows that the RR method is accurate and reliable. In this term, Hasanzadeh et al. [XIX] predicted the mechanical properties of concrete through polynomial regression. They used Polynomial Regression and the SVR method to predict the compressive, tensile, and flexural strength. Their results show that the R^2 was more than 0.99. In another example, Sami Ullah et al. [XXXVII] predicted geo-polymer concrete compressive strength via machine learning. They collected more than 300 mix properties for the data mining process. Finally, they predicted compressive strength with more than 0.90 for $R^{2.}$ In another example, Liu [XXXI] used the XG Boost method to predict the compressive strength of a concert. Their results show that the XGBoost accuracy (R^2) was more than 0.99. Hematibahar et al. used a logistic map algorithm to predict the compressive strength of concrete. Their results show that R^2 was equal to 0.96. Topcu and Saridemir [XLI] studied the Artificial Neural Network to forecast the compressive strength of concrete with different percentages of fly ash. Their results show that R^2 was more than 0.9. In another example, Son, and Yang [XL] examined the uniaxial compressive strength of concrete through machine learning. Their results have proved that Gradient boosting R^2 results were more than 0.91 to predict the compressive strength of concrete. Kaewunruen et al [XXVI] result for predicting prestressed concrete sleepers illustrated that R^2 values were more than 0.95, and 0.99 for Bayesian ridge, and Random forest prediction methods via machine learning technique.

Shen et al [XXXIX] predicted the ultra-high-strength concrete (UHSC) through machine learning via XGBoost, AdaBoost, and Bagging methods. Cement content, fly ash, silica fume and silicate content, sand and water content, superplasticizer content, steel fiber, steel fiber aspect ratio, and curing time have been considered as the dataset in their study. According to the results, the R^2 was 0.9, while, the Polynolynal Regression and Linear Regression have more than 0.91 and 0.93 R^2 in the current study. Hsieh [XXIV] used (k-NN) with cross-validation to predict the compressive strength of concrete and rock. He used an instance-based learning (IBL) algorithm to forecast. Finally, he found that R^2 was 0.931 for 7-NN prediction. Vakharia and Gujar [XLII] found that forecasting compressive strength and Portland cement composition using ten k cross-validation has more than 0.95 R^2 accuracy. They used four machine learning models Isotonic regression, Artificial neural network, Support vector machine, and Random forest. However, they did not examine the prediction method with real experiments. According to the experimental results, the R^2 was more than 0.91 for experimental results and more than 0.93 for prediction via Rigid Regression.

The experimental results illustrated different results instead of prediction methods. Most studies demonstrated that the compressive strength is able to predict with more than 0.9 R^2 results.

V. Conclusion

In this paper, the reliability of data mining experimental, and predicted results has been investigated. Different mixtures have been examined via data mining methods, and machine learning predicts compressive strength. The mixture designs and estimated compressive strength are calculated through data mining. The results show that the predicted compressive strengths were more than the experimental results. The experimental results were shown that R^2 =0.91. The machine learning method shows that RR had the best regressing with more than 0.93 for R^2 while Wilcoxon signed-rank test was not suitable. Moreover, the LR results were more than 0.76 for R^2. The Wilcoxon signed-rank test shows that the PR had the most stable distribution with 0.02 and R^2 with more than 0.91. The results show that the SVR method was not able to predict compressive strength. Overall, the current method can predict the mixture design through the machine learning method. Moreover, the current study can progress to find the reliability of other ANNs and machine learning methods with experimental results. Civil engineers can find and predict compressive strength with high accuracy through the current method. Overall, the current study was the following. The prediction of the design mixture is reliable. The results show that R^2 was more than 0.91. Data mining can find the mixture design with high accuracy. The logistic Algorithm was able to predict the compressive stress-strain curve with high accuracy.

The compressive strength via machine learning was accurate. The Ridge Regression (RR) R^2 was more than 0.97. It should be noted that compressive strength can be predicted through machine learning.

Conflict of Interest:

There was no relevant conflict of interest regarding this article.

References

I. A. Sultan A, A. Mashrei M, A. Washer G. Utilization of Wilcoxon-Mann-Whitney Statistics in Assessing the Reliability of Nondestructive Evaluation Technologies. Structures, 27, (2020), 780–7.

II. Adnan Ikram RM, A. Ewees A, Singh Parmar K, Yaseen Z, Shahid S, Kisi O. The viability of extended marine predators algorithm-based artificial neural networks for streamflow prediction, 131, (2022a), 109739.

III. Adnan Ikram RM, Dai HL, Mirshekari Chargari M, Al-Bahrani M, Mamlooki M. Prediction of the FRP reinforced concrete beam shear capacity by using ELM-CRFOA, ; 205, (2022b),112230.

IV. Adnan Ikram RM, Goliatt L, Kisi O, Trajkovic S, Shahid S. Covariance Matrix Adaptation Evolution Strategy for Improving Machine Learning Approaches in Streamflow Prediction. Mathematics, 10, 2022c, 2971.

V. Agrawal R. Sustainable design guidelines for additive manufacturing applications. Rapid Prototyping Journal, 28(7), (2022), 1221–40.

VI. Akande KO, Owolabi TO, Twaha S, Olatunji SO. Performance Comparison of SVM and ANN in Predicting Compressive Strength of Concrete. IOSR J Comput Eng,16(5), (2014), 88–94.

VII. Akter S, Ali RME, Karim S, Khatun M, Alam MF. Geomorphological, Geological and Engineering Geological Aspects for Sustainable Urban Planning of Mymensingh City, Bangladesh. Open J Geol, 8:73 (2018) 7–52.

VIII. AlAlaween W, Abueed O, Gharaibeh B, Alalawin A, Mahfouf M, Alsoussi A, et al. The development of a radial based integrated network for the modelling of 3D fused deposition. Rapid Prototyping Journal, (2022) ahead-of-print(ahead-of-print).

IX. ASTM C293 / C293M - 16 Standard Test Method for Flexural Strength of Concrete (Using Simple Beam with Center-Point Loading). Vol. 2016. ASTM International. Epub ahead of print; Available from: https://doi.org/10.1520/C0293_C0293M-16

X. ASTM C1202-19 Standard Test Method for Electrical Indication of Concrete's Ability to Resist Chloride. ASTM International. Epub ahead of print; 2009. Available from: https://doi.org/10.1520/C1202-19

XI. Chiadighikaobi PC, Hematibahar M, Kharun M, A. Stashevskaya N, Camara K. Predicting mechanical properties of self-healing concrete with Trichoderma Reesei Fungus using machine learning. Cogent Engineering. 11(1), (2024) :2307193.

XII. Chiadighikaobi PC, Kharun M, Hematibahar M. Historical structure design method through data analysis and soft programming. Cogent Engineering, 10, 1 , (2023) 2220499.

XIII. Chopra P, KumarSharma R, Kumar M. Prediction of Compressive Strength of Concrete Using Artificial Neural Network and Genetic Programming. Advances in Materials Science and Engineering, 7648467, (2016), 10.

XIV. Dębska B. Assessment of the Applicability of Selected Data Mining Techniques for the Classification of Mortars Containing Recycled Aggregate. Materials, 15, (2022),8111.

XV. Erdal HI. Two-level and hybrid ensembles of decision trees for high performance concrete compressive strength prediction. Eng Appl Artif Intell, 26, (2013), 1689–97.

XVI. Farooq F F, Czarnecki S, Niewiadomski P, Aslam F, Alabduljabbar H, Ostrowski KA, et al. A comparative study for the prediction of the compressive strength of self-compacting concrete modified with fly ash. Materials, 14, (2021), 4934.

XVII. Fl¨ory S, Pottmann H. Ruled surfaces for rationalization and design in architecture. LIFE information On Responsive Information and Variations in Architecture, (2010) 103–9.

XVIII. GOST10180. Betony. Metody opredeleniya prochnosti po kontrolnym obraztsam [Concretes. Methods for determination of strength by control samples]. Vol. 36. 2013.

XIX. Hasanzadeh A, Vatin NI, Hematibahar M, Kharun M, Shooshpasha I. Prediction of the Mechanical Properties of Basalt Fiber Reinforced High-Performance Concrete Using Machine Learning Techniques. Materials.15, (2022), 20, 7165.

XX. Hazarika BB, Gupta D, Natarajan N. Wavelet kernel least square twin support vector regression for wind speed prediction, 29 (2022), 86320–36.

XXI. Hematibahar M, Esparham A, Vatin NI, Kharun M, Gebre TH. Effect of Gelatin Powder, Almond Shell, and Recycled Aggregates on Chemical and Mechanical Properties of Conventional Concrete. STRUCTURAL MECHANICS OF ENGINEERING CONSTRUCTIONS AND BUILDINGS. (2023); 19.

XXII. Hematibahar M, Ivanovich Vatin N, A. Alaraza H, Khalilavi A, Kharun M. The Prediction of Compressive Strength and Compressive Stress-Strain of Basalt Fiber Reinforced High-Performance Concrete Using Classical Programming and Logistic Map Algorithm. Materials.;15 , (2022a) 19,:6975.

XXIII. Hematibahar M, Vatin NI, Alaraza HAA, Khalilavi A, Kharun M. The Prediction of Compressive Strength and Compressive Stress–Strain of Basalt Fiber Reinforced High-Performance Concrete Using Classical Programming and Logistic Map Algorithm. Materials.;19, (2022b) 15:6975.

XXIV. Hsieh SC. Prediction of Compressive Strength of Concrete and Rock Using an Elementary Instance-Based Learning Algorithm. Advances in Civil Engineering, (2021),10.

XXV. J. Alghamdi S. Classifying High Strength Concrete Mix Design Methods Using Decision Trees. Materials, 15, (2022) 1950.

XXVI. Kaewunruen S, Sresakoolchai J, Huang J, Zhu Y, Ngamkhanong C, M. Remennikov A. Machine Learning Based Design of Railway Prestressed Concrete Sleepers. Appl Sci.12, (2022), 10311.

XXVII. Kashyzadeh KR, Amiri N, Ghorban S, Souri K. Prediction of Concrete Compressive Strength Using a Back-Propagation Neural Network Optimized by a Genetic Algorithm and Response Surface Analysis Considering the Appearance of Aggregates and Curing Conditions. Buildings.;12 , (2022) ,438.

XXVIII. Khan MA, Memon SA, Farooq F, Javed MF, Aslam F, Alyousef R. Compressive strength of fly-ash-based geopolymer concrete by gene expression programming and random forest. Adv Civ Eng, 2021, 6618407.

XXIX. Khorasani M, Loy J, Ghasemi A, Sharabian E, Leary M, Mirafzal H, et al. A review of Industry 4.0 and additive manufacturing synergy. Rapid Prototyping Journal, 28, 8 (2022) , 1462–75.

XXX. Kumar A, Harish CA, Raj Kapoor N, Mazin AM, Kumar K, Majumdar A, et al. Compressive Strength Prediction of Lightweight Concrete: Machine Learning Models. Sustainability, 14, (2022), 2404.

XXXI. Liu Y. High-Performance Concrete Strength Prediction Based on Machine Learning. Hindawi.; (2022), 5802217,7.

XXXII. Mao F, Zhao X, Ma P, Chi S, Richards K, M. Hannah D, et al. Revision of biological indices for aquatic systems: A ridge-regression solution. Ecological Indicators, 106, (2019),105478.

XXXIII. Nafees A, Khan S, Javed MF, Alrowais R, Mohamed AM, Vatin NI. Forecasting the Mechanical Properties of Plastic Concrete Employing Experimental Data Using Machine Learning Algorithms: DT, MLPNN, SVM, and RF. Polymers,14, (2022),1538.

XXXIV. Nguyen KT, Nguyen QD, Le TA, Shin J, Lee K. Analyzing the compressive strength of green fly ash based geopolymer concrete using experiment and machine learning approaches. Constr Build Mater, 247, (2020), 118581.

XXXV. Peng X, Zhuang Z, Yang Q. Predictive Modeling of Compressive Strength for Concrete at Super Early Age. Materials, 15, (2022), 4914.

XXXVI. Riener C, Schabert R. Linear slices of hyperbolic polynomials and positivity of symmetric polynomial functions. arXiv preprint.

XXXVII. Sami Ullah H, Khushnood RA, Farooq F, Ahmad J, Vatin NI, Zakaria Ewais DY. Prediction of Compressive Strength of Sustainable Foam Concrete Using Individual and Ensemble Machine Learning Approaches. Materials, 15, (2022)3166.

XXXVIII. Shahmansouri AA, Yazdani M, Hosseini M, Akbarzadeh Bengar H, Farrokh Ghatte H. The prediction analysis of compressive strength and electrical resistivity of environmentally friendly concrete incorporating natural zeolite using artificial neural network. Construction and Building Materials, 317, (2022), 125876.

XXXIX. Shen Z, Farouk Deifalla A, Kaminski P, Dyczko A. Compressive Strength Evaluation of Ultra-High-Strength Concrete by Machine Learning. Materials, 15, (2022) 3523.

XL. Son J, Yang S. A New Approach to Machine Learning Model Development for Prediction of Concrete Fatigue Life under Uniaxial Compression. Appl Sci,12 (2022),9766.

XLI. Topçu İB, Sarıdemir M. Prediction of properties of waste AAC aggregate concrete using artificial neural network. Computational Materials Science, 41, 1, (2007) 117–25.

XLII. Vakharia V, Gujar R. Prediction of compressive strength and portland cement composition using cross-validation and feature ranking techniques. Construction and Building Materials,225 , (2019), 292–301.

XLIII. Yang D, Yan C, Liu S, Jia Z, Wang C. Prediction of Concrete Compressive Strength in Saline Soil Environments. Materials, 15, (2022), 4663.

XLIV. Zheng X, Peng X, Zhao J, Wang X. Trajectory Prediction of Marine Moving Target Using Deep Neural Networks with Trajectory Data. Appl Sci, 12, (2022), 11905.