DOI: 10.15849/IJASCA.251130.01

Int. J. Advance Soft Compu. Appl, Vol. 17, No. 3, November 2025
Print ISSN: 2710-1274, Online ISSN: 2074-8523

Classification and Regression Tree Analysis of Compressive Strength in Fiber Reinforced Concrete (FRC)

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Abstract

Fibers have been utilized widely in concrete mixes as promising construction materials to enhance concrete mechanical properties (compressive and tensile strengths), improve toughness and durability, and address the excessive crack widths in reinforced concrete elements. Metallic (steel) fibers have been used in several structural applications as an alternative to reinforcement and to enhance the flexural performance of reinforced concrete elements. However, using steel fibers in concrete is associated with several shortfalls including their susceptibility to corrosion and high environmental impact. To address these issues, non-metallic fibers have been introduced to improve the durability of concrete under harsh conditions and reduce the carbon footprint. Available research on concrete compressive strength investigated the influence of different types of fibers, aspect ratios (l/d), volume fraction, and water/cement ratio experimentally. However, research on machine learning to analyze and predict the influence of these parameters on concrete compressive strength has not attracted the same level of coverage. Therefore, this paper employed 210 datasets obtained from experimental research conducted on the compressive strength of fiber concrete and developed a supervised machine learning (ML) based regression tree analysis. Results of the classification and regression tree revealed that the water-to-cement ratio is the most influential parameter that affects the compressive strength of concrete.

Keywords: *Fiber-reinforced concrete, compressive strength, machine learning, classification, regression tree.*

Received 4 May 2025; Accepted 2 July 2025

1 Introduction

Fiber-reinforced concrete (FRC) is defined as a composite material characterized by cement matrix and discrete fibers according to CEB-fib Code [1]. Generally, the matrix is represented by concrete or mortar, while fibers can be natural or man-made (steel, carbon, glass, and polypropylene, synthetic). Since the 1960s, a considerable amount of research has been carried out on various fibers as innovative construction materials. Several codes such as ACI 544 [2] acknowledge that the inclusion of fibers in concrete matrix enhances concrete's mechanical properties including compressive and tensile strengths, cracking capacity, flexural behavior and toughness.

Concrete compressive strength is the main mechanical characteristic that defines concrete since it behaves in a brittle manner under tension. Experimentally, the uniaxial compression relationship of concrete is typically derived using a standard 150×300 mm cylinder test. Alternatively, cubes with a 150 mm cross-section could be used, and the results should be modified accordingly since cube specimens give higher compressive strength comparatively. The typical stress-strain relationship under compression follows a linear behavior up to 40% of the mean compressive strength, and then the behavior follows a parabolic [3]. In the case of fiber-reinforced concrete, FRC follows compressive behavior patterns similar to plain concrete [4].

Several experimental studies examined the influence of fibers on the mechanical properties of concrete. A previous study carried out by Shi, et al. [5] investigated the impact of basalt-macro polypropylene hybrid on concrete considering three volume fractions (0.3%, 0.7% and 1%), and two different compressive strengths (30 MPa and 60 MPa). Results revealed that adding fibers improved the initial post-cracking strength and energy absorption as compared to plain concrete, moreover, using hybrid macro polypropylene and basalt fibers improved the compressive strengths by up to 10%. In terms of the influence of the type of fiber and content on concrete mechanical properties, several researchers [6-8] evaluated the impact of fiber's shape and content on the compressive strength of concrete in addition to the pull-out strength. Wu, et al. [7] investigated the influence of end-hooked, straight, corrugated, steel fibers with contents up to 3%, findings of this study revealed that fibers with hooked ends resulted in higher improvements in the compressive strength.

Generally, compressive and splitting tensile strengths tend to decrease in concrete mixes with high w/c ratio, this is attributed to the higher porosity, weaker bonding and more formation of micro-cracks associated with high w/c ratio. Inclusion of fibers in concrete mixes with a high water-to-cement ratio has shown to increase concrete density, reduce water absorption and voids, and consequently enhance the mechanical properties of concrete Alwesabi et al. [9]. Further, the influence of the size of fiber on concrete compressive strength was investigated experimentally in the previous studies [10-12], research evaluated the impact of different aspect ratios (length /diameter). Results of previous the study [11] revealed that fibers with high aspect ratios are associated with better compression resistance, whereas the study conducted by Yoo, et al. [10] reported that compressive strength was barely affected by the inclusion of a higher ratio.

Despite the extensive work conducted on predicting concrete mechanical properties, accurately predicting FRC properties remains challenging due to the complex interactions of concrete constituents. To overcome this issue, several researchers [13-15] performed and developed sensitivity analysis to evaluate the relationship between the input variable (mixing water, cement, superplasticizer content, silica fume content, and fine and coarse aggregate contents) and the compressive strength of concrete. Sensitivity analysis contributes towards the evaluation to what extent each input parameter influences the prediction of the output [16]. Available research indicated that different techniques can be utilized to perform sensitivity analysis depending on the type of model (artificial neural networks, classification trees, Sobol and stepwise multiple regression. For instance, the ANNs model can be analyses by using the partial derivatives approach, the conventional stepwise method, and the weights method [15]. Another study conducted by Dabiri, et al. [17] performed a sensitivity analysis based on the Pearson correlation coefficient. Authors employed the correlation coefficient to determine the frequency with which the input factors emerge and the dependency between two variables. Similarly, Mousavi et al. [18] employed the frequency approach to determine the input importance, results revealed that the water content, binder content and testing age were significant input parameters for compressive strength prediction of high performance concrete.

The critical review of the literature conducted on concrete compressive strength indicates that researchers developed different predictive models for the compressive strength of conventional (plain) concrete including linear regression, artificial neural networks, and support vector regression. However, research paid little attention to FRC mixtures. For a better understanding of the sensitivity of compressive strength in FRC to each influencing parameter including the type of fiber, volume fraction, aspect ratio (length /diameter), and water-cement ratio, a non-linear regression analysis using the machine learning method is utilized to develop regression and classification models that predict the relationship between the compressive strength of FRC and independent variables. Classification and Regression Tree (CART) analysis was performed to evaluate the influencing parameters and models were developed considering the experimental results of FRC compressive strengths obtained from 210 datasets available in the literature.

2 Related Work

Evaluating the influence of innovative materials such as fibers on concrete compressive strength requires the incorporation of the relation between compressive strength and various parameters including mixture compositions and material characteristics. This has attracted a paramount interest in predicting concrete mechanical properties due to the lack of empirical expressions in design codes and standards. Therefore, several researchers introduced different methods to predict concrete compressive strength to optimize the mix ratio with less time by employing machine learning [19-21]. Machine learning has gained popularity in several engineering practices as an emerging technique that can facilitate the development of several predictive algorithms [22]. Predictive models in civil engineering applications can explain how concrete performance can be predicted based on different parameters through optimized solutions that could balance its performance. Al-Shamiri, et al. [23] developed an extreme learning machine model to predict the compressive strength of concrete, and concrete mechanical properties were modelled as a function of different input variables including water, cement, coarse and fine aggregate, and superplasticizer. Results indicated a reliable prediction of the compressive strength of HSC. Findings of the study conducted by Davawala, et al. [24] on predicting compressive strength using various machine-learning techniques revealed that predicted results of compressive strength closely matched the actual values.

Further, Han, et al. [25] developed variable importance measures through random forest algorithm to select variables with high importance on concrete compressive strength, authors considers age and water-to-binder, coarse-to-fine aggregate ratio, fly ash-to-water ratio, and blast furnace slag-to-water ratio. Results of this investigation indicated that input parameters age and water-to-binder were more influential and significant on the model compared to the other parameters. Based on an ensemble classification and regression tree, Ren, et al. [26] employed a dataset of 328 concrete mixtures compressive strengths for conducting importance analysis. Results indicated that the most significant factor that influencing concrete compressive strength was the age of concrete, followed by stone powder content. Recently, Albostami, et al. [27] employed the sensitivity analysis to investigate the influence of different parameters i.e., recycled plastic aggregates content, cement content, and superplasticizer dosage on the compressive strength of self-consolidated concrete, results indicated that the effects of the considered parameters on predicting concrete mechanical properties were significant.

3 Data Description

This study examines the sensitivity of the compressive strength of the FRC to various parameters considering the experimental results obtained from literature. This research employed 210 datasets of FRC compressive strength collected from 38 previous investigations as presented in Table 1.

Table 1: Datasets of experimental studies in literature

#	Reference	Parameters			
		w/c	E	l/d	V_f(%)
1	Usman, et al. [28]				✓
2	Marcalikova, et al. [29]			✓	✓
3	Al Marahla and Garcia-Taengua [30]	✓	✓	✓	✓
4	Zhang, et al. [31]	✓	✓	✓	✓
5	Rostami, et al. [32]		✓		
6	Buratti, et al. [33]	✓	✓	✓	✓
7	Jain and Negi [34]	✓		✓	✓
8	Galeote, et al. [35]	✓			✓
9	Zhang, et al. [36]				✓
10	Hasani, et al. [37]	✓	✓	✓	✓
11	Choi, et al. [38]			✓	
12	Folino, et al. [39]				✓
13	Kuppala, et al. [40]	✓		✓	✓
14	Xu, et al. [41]	✓	✓	✓	✓
15	Raza, et al. [42]	✓	✓	✓	
16	Sabapathy, et al. [43]				✓
17	More and Subramanian [44]	✓	✓	✓	✓
18	Ali, et al. [45]	✓	✓	✓	
19	Grzesiak, et al. [46]				✓
20	Yang, et al. [47]			✓	✓
21	Ramesh and Eswari [48]				✓
22	Azandariani, et al. [49]	✓	✓	✓	
23	Hedjazi and Castillo [50]	✓	✓	✓	
24	Iyer, et al. [51]		✓	✓	✓
25	Abbass, et al. [52]	✓		✓	✓
26	Ahmed, et al. [53]				✓
27	Kizilkanat, et al. [54]		✓	✓	✓
28	Okeola, et al. [55]				✓
29	Eidan, et al. [56]			✓	✓
30	Caggiano, et al. [57]		✓	✓	✓

31	Wang, et al. [58]		✓	✓	✓
32	Liu, et al. [59]		✓	✓	✓
33	Elsaid, et al. [60]				✓
34	Daneshfar, et al. [61]				✓
35	Wang, et al. [62]	✓			✓
36	Zhang, et al. [63]	✓		✓	✓
37	Noushini, et al. [64]			✓	✓
38	Hilles and Ziara [65]			✓	✓

In this analysis, the independent variables affecting the compressive strength of FRC as assessed experimentally by literature are water-to-cement ratio (w/c), type of fibers used through the modulus of elasticity in GPa (E), percentage (volume fraction), and aspect ratio (l/d). Whereas the dependent variable in this study is the concrete compressive strength (f'c). The descriptive statistics of the variables are presented in Table 2. The categorical variable referred to as the modulus of elasticity (E) in Table 2 represents the type of fibers. Literature employed in this analysis investigated eight types of metallic and non-metallic fibers (Steel fibers (SF), Basalt fibers (BF), Polypropylene or Polyethylene fibers (PP/PE), Glass fibers (GF), Aluminium fiber (AF), Polyvinyl Alcohol fibers (PAF), Carbon fibers (CF), and Sisal fibers (SF)).

Table 2: Descriptive statistics of the gathered dataset.

	w/c	E(GPa)	Percentage	Aspect ratio	f'c
Mean	0.38	148.14	1.11	215	72.13
Standard Error	0.01	7.09	0.06	22.12	3.11
Standard deviation	0.15	103	0.82	321	45.13
Kurtosis	-1.36	9.72	1.76	3.40	-0.24
Skewness	-0.11	1.73	1.18	2.16	0.94
Minimum	0.16	0.35	0	24.7	17.5
Maximum	0.6	750	4.5	1388	182

According to the statistics of variables presented in Table 2, compressive strength of concrete ranged between 17.5-182 MPa with a 3.11 standard deviation which indicates the variety of compressive strength values in literature. Skewness and Kurtosis were calculated to demonstrate the distribution of each parameter with compressive strength. Unlike the other variables, w/c parameter with a standard deviation of 0.15 shows a negative skewness value of -0.11 which means the left tail for the distribution of the compressive strength values. Moreover, excess of Kurtosis (value above 3) is detected by the E (GPa) parameter which reflects thin bell shape of its normal distribution. It is worth mentioning that the higher negative value of Kurtosis parameter indicates shorter distribution tails compared to the normal distribution, whereas positive values are associated with longer tails. Due to the non-normal distribution of the variables, ordinary least squares regression may yield unreliable results.

4 Methodology

Regression tree analysis is utilized to create partitions in predictors at which the more important variables in predicting the target parameters are displayed employing both numeric and categorical data [66]. The methodology followed in this study adapts the Classification and Regression Tree (CART) to explain and classify the main contributors to concrete mechanical properties, and further the influence of different input parameters on the outcome factor, i.e., compressive strength is analyzed.

CART method was introduced by Gordon, et al. [67], which employs the Gini index to measure the dispersion among the parameters resulting in a binary tree. The decision tree is a non-linear regression model that uses a supervised machine learning algorithm to both predict and classify a regressor that has been introduced in a variety of engineering disciplines [67-69]. Moreover, supervised machine learning reduces the approximation error to approximate the connection between input variables and one or more dependent numerical outputs by using optimization methods. Marani and Nehdi [70] asserted that training requires labelled data to predict variables and data in supervised machine learning. Currently, algorithms adopted in machine learning for civil engineering applications are trained for several properties of concrete including compressive strength, tensile strength, and the modulus of elasticity.

The decision tree is based on decision rules to map the most important influencing factors related to the investigation process. The process of extracting decision rules from a decision tree is constrained by the structure of the tree. This technique does not need any certain assumption or predefined hypothesis regarding the relationship between dependent and independent variables, which is required in the case of traditional regression techniques. Hence the data in this study fits well with this framework.

The tree construction recursively partitioning the target variable to minimize the impurity in the terminal nodes using the Gini index criterion. The partitioning is done by searching for all possible threshold values for all input variables (splitters) to find the threshold that leads to the greatest improvement in the purity score of the resultant nodes and a saturated tree is obtained. In this research, the CART-based decision tree method is used to define decision rules from compressive strength data available in the literature. To facilitate the application of the classification tree method, numerical values of the compressive strength are converted to categorical using the clustering technique. Clustering has divided the compressive strength into three groups ($f'c_1$, $f'c_2$, and $f'c_3$) in which the difference between groups is maximal as presented in Table 3.

Table 3. Clustering of concrete compressive strength values.

	$f'c_1$	$f'c_2$	$f'c_3$
Min.	38	64	168
Max.	51	88	182
Count	116	56	38

5 Results, Analysis and Discussions

5.1. Sensitivity Analysis Results

The predictor variables considered in this analysis were analyzed in terms of concrete compressive strength, which was classified under three qualitative target variables (i.e., $f'c_1$, $f`c_2$, $f'c_3$), to detect the change in compressive strength patterns and explain the main contributing factors. The CART decision tree and the Gini splitting criterion were employed to construct the tree and select the best features. By using the R package, results were classified, and the tree was constructed as presented in

.

As shown in

, the CART tree obtained from the dataset presented in Table 1 has five terminal nodes with five decision rules. It can be noticed that w/c, type of fibers, and modulus of elasticity E (GPa) are the primary selected splitter variables described by the tree. The first splitter, w/c appeared at the top of the tree as the most influential parameter in identifying the concrete compressive strength (f′c).

illustrates that the values in the terminal boxes represent the compressive strength character of the given group referring to the majority of the given rule in the top row. The following line represents the number of specimens classified into f'_{c1}, f'_{c2}, or f'_{c3} from left to right (concrete with the lowest strength values to the highest values). The last row describes the weighted percentage of compressive strength by each rule.

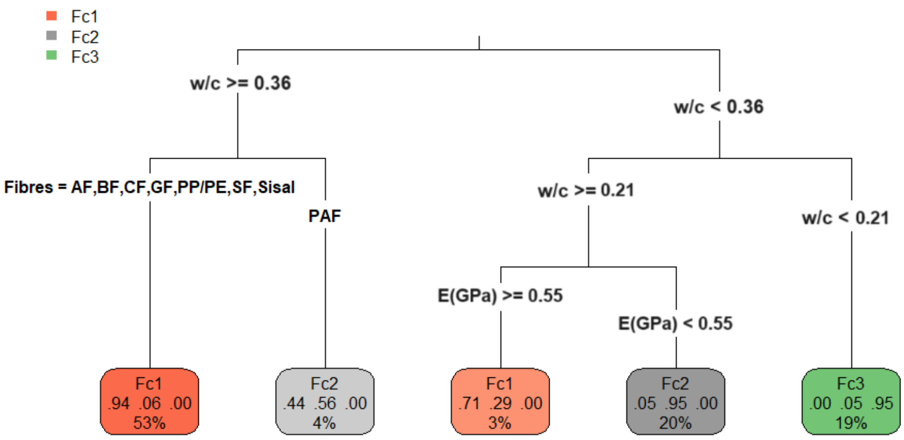

Fig. 1. The output of CART tree.

The CART results showed that the first group associated with the lowest compressive strength values ($f'c_1$) constitutes 53% for all fibers except PAF when the w/c is above or equal to 0.36. Considering FRC concrete mixes with the same w/c ratio but having PAF fibers, results displayed higher compressive strength, however, concrete strength still did not reach the group with the highest strength ($f'c_3$). This is attributed to the improvement in the strength of the engineered cementitious composite when reinforced with the optimum PAF fiber content, PAF fibers contributed to efficiently limiting the development, enlargement, and spread of fractures in concrete mixes. Findings are in good agreement with the observations reported by the predictive model conducted by Pal, et al. [71], results of importance evaluation showed that w/c ratio and nominal aggregate size are the most important critical parameters that significantly influence the compressive strength of fiber-reinforced concrete mixes containing rubber-based fiber. Results of sensitivity analysis as presented in

are in good agreement with the results obtained from importance analysis conducted by Han, et al. [25] where random forest algorithm was utilized to evaluate the influence of concrete age and water-to-binder ratio of concrete compressive strength, and results indicated the significance impact of w/c ratio on the compressive strength prediction.

Further, Khan, et al. [72] developed different regression models to predict compressive strength with steel fibers considering several input variables: cement content, water, fine and coarse aggregates, fly ash, silica fume, superplasticizer, fiber diameter and length. Researchers employed radient boosting, random forest, and XGBoost. Results of the analysis revealed that cement content was the most significant parameter that positively influences the compressive strength of SFRC. On the contrary, regression tree analysis of the impact of the water-to-cement ratio and curing time on concrete compressive strength was evaluated by Zhang, et al. [73], results of the gradient boosting regression tree algorithm indicated that compressive strength values are most sensitive to the curing time when compared to the influence of the variation in the w/c ratio. Comparison of the findings of sensitivity analysis reported by previous investigations are presented in Table 4.

Table 4: Comparison of importance/sensitivity results of literature models.

Investigation	Parameters	Model	Significant Parameter
Han et al. [25]	Concrete age and water-to-binder ratio	Random forest algorithm	Water-to-cement ratio
Ren et al. [26]	Cement, fly ash, silica fume, blast slag, stone powder, and age	Gaussian process regression, random forest, and support vector	Age of concrete, the stone powder content
Albostami et al. [27]	Cement content, w/c ratio, superplasticizer recycled plastic aggregate, natural fine aggregate content, natural coarse aggregate content, curing time	Multi-objective genetic algorithm evolutionary polynomial regression and gene expression	Recycled plastic aggregate content, superplasticizer dosage, and binder content
Zhang et al. [36]	Curing time, w/c ratio	Gradient boosting regression tree algorithm	Curing time
Pal et al. [71]	Water to cement ratio, percentage of rubber, replacement level of recycled concrete aggregate, percentage of fiber, and fiber type	Linear regression, ridge regression, lasso regression, support vector machine, k-nearest Neighbors, artificial neural network, decision tree, random forest, AdaBoost, Voting Regressor, Gradient Boost, CatBoost, and XGBoost.	w/c ratio, aggregate size
Khan et al. [72]	Cement content, water, fine and coarse aggregates,	Radient boosting, random forest, and XGBoost	Cement content

	fly ash, silica fume, fiber diameter and length		
Alyami, et al. [74]	Fine aggregate, water-to-cement, superplasticizer, rice husk ash	Random forest, light gradient boosting machine, ridge regression, and extreme gradient boosting (XGBoost)	Water-to-cement ratio

Previous study [75] highlighted one of the disadvantages of applying decision tree, researchers reported that the individual decision trees tend to overfit training data. However, comparing the results of sensitivity analysis adopted in this study with the findings of previous models in literature presented in Table 4 indicated that the employing the simple model of decision tree can be competitive to the other models (i.e., random forests method which is considered as an effective tool for prediction without overfit). However, to assess the predictive performance of individual decision trees and the degree of overfitting, extensive work is required to be carried out considering complex models.

Further reduction in water-to-cement ratio (values between 0.2 and 0.36), resulted in the classification of the concrete strength value based on the modulus elasticity (E) of the fibers used in concrete mixes. It is worth mentioning that concrete mixes having fibers with higher values of E (above 0.55) resulted in a medium to low compressive strength with a higher probability of fitting in the first group ($f'c_1$). Whereas concrete mixes with a modulus of elasticity E (GPa) less than 0.55 resulted in medium compressive strength values. It was noticed that with any further increase in Fiber's elasticity, the compressive strength of the FRC increased. Although several experimental studies have investigated fibers and their different properties that contribute to the compressive strength of concrete, no strong arguments supported by statistical evidence were found about the impact of fiber's modulus of elasticity on the compressive strength of concrete subjected to compression loads. It can be noticed from

that the far right of the tree represents the high compressive strengths that fit in the third group of compressive strength ($f'c_3$). In other words, when w/c content is less than 0.21, the concrete specimens are likely to have high compressive strength values.

Unlike previous studies that primarily utilized linear regression models or correlation-based methods to identify influencing factors, this study employs Classification and Regression Trees (CART), which offer a distinct advantage in capturing complex, the nonlinear relationships and interactions among variables. Unlike traditional approaches that often assume linearity and struggle with multicollinearity, CART recursively splits the data to uncover hierarchical structures and decision rules, making it possible to isolate and rank key influencing factors with greater clarity. This interpretability and ability to handle variable interactions make CART a powerful alternative for identifying and predicting dominant drivers in the system.

Sensitivity analysis offered valuable insights for optimizing FRC mix designs to achieve the desired mechanical properties and durability performance. Among the parameters, the water-to-cement (w/c) ratio was found to be the most influential. While increasing the w/c ratio can help mitigate the loss of workability caused by fiber addition, it also leads to higher porosity and microcrack formation, reducing bond performance and, ultimately, the compressive strength. Therefore, careful selection of mix proportions - including a well-balanced w/c ratio- is essential for enhancing flexural strength while maintaining adequate fiber dispersion. Additionally, sensitivity models for predicting mechanical properties can significantly reduce material testing costs and time by streamlining evaluation and minimizing the number of required trial mixes.

5.2. Limitations and Challenges

Accurately analyzing and predicting the influence of these parameters on concrete compressive strength of FRC using ML applications involves addressing several key challenges and limitations associated with relatively small datasets. The following points outline the main considerations:

- Poor generalizability: relatively small datasets may not capture the diverse input and variability which might lead to poor generalizability. Further, models corresponding to training data in such cases may perform well whereas those for real world data and unseen ones perform poorly.
- Inadequate validation: this can result in high variability in evaluation metrics like precision, making it challenging to reliably assess model performance.
- Overturning risk: models developed with limited data points are more prone to memorizing patterns or noise instead of learning generalizable trends. This often results in high accuracy during training but poor performance on validation or test data due to overfitting.
- limited models: small datasets constrain models' complexity (i.e., expressive models) as they require developing simple models.

6 Conclusion

The accurate prediction of the compressive strength of fiber-reinforced concrete has proved to be a cumbersome process where different factors (water-to-cement ratio (w/c), modulus of elasticity (E), percentage, and aspect ratio of fiber) contribute to its strength. This study presents a regression tree analysis of a dataset containing 210 observations aimed at evaluating the sensitivity of concrete compressive strength to these factors. Classification and Regression Tree (CART) was utilized to explain the main contributors to concrete compressive strength. Based on the presented results and discussions, the conclusions drawn from this study can be summarized as follows:

- Review of the published literature revealed the inconsistent impact of fibers on the compressive strength of concrete.
- Regression tree analysis indicates that w/c ratio is the most significant parameter affecting the compressive strength of fiber-reinforced concrete for the dataset considered in this analysis.
- The model on the effect of predictor revealed that the performance of concrete compressive strength was positively influenced by the modulus of elasticity (type of fibers). Whereas compressive strength values were less influenced by fiber aspect ratio.
- The comparison of the results of the sensitivity analysis conducted in this study using the CART model with the results of the importance analysis models developed by previous studied using radient boosting, random forest, and XGBoost indicated the efficiency of employing CART model to evaluate the sensitivity of concrete compressive strength to different parameters.

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