AUIQ Technical Engineering Science

Volume 1 | Issue 1 Article 10

2024

Enhancing Predictive Accuracy of Compressive Strength in Recycled Concrete Using Advanced Machine Learning Techniques with K-means Clustering

Ziaul Haq Doost
Department of Civil and Environmental Engineering, King Fahd University of Petroleum and Minerals, Dhahran, Saudi Arabia, ziaulhaq.doost@gmail.com

Leonardo Goliatt
Computational and Applied Mechanics Department, Federal University of Juiz de Fora, 36036-900, Brazil, leonardo.goliatt@ufjf.br

Mohammed Suleman Aldlemy
Department of Mechanical Engineering, Collage of Mechanical Engineering Technology, Benghazi, Libya, AND Libyan Center for Solar Energy Research and Studies, Benghazi Branch, Benghazi, Libya, maldlemy@ceb.edu.ly

Mumtaz Ali
UniSQ College, University of Southern Queensland, QLD 4305, Australia; AND Faculty of Sustainable Design Engineering, University of Prince Edward Island, Charlottetown, PE C1A4P3, Canada, mumtazali7288@gmail.com

Bruno da S. Macêdo
Department of Systems Engineering and Automation, Federal University of Lavras, Lavras, MG, 37200-000, Brazil, bruno.macedo2@estudante.ufla.br

Follow this and additional works at: https://ates.alayen.edu.iq/home

Part of the Engineering Commons

Recommended Citation

Doost, Ziaul Haq; Goliatt, Leonardo; Aldlemy, Mohammed Suleman; Ali, Mumtaz; and Macêdo, Bruno da S. (2024) "Enhancing Predictive Accuracy of Compressive Strength in Recycled Concrete Using Advanced Machine Learning Techniques with K-means Clustering," *AUIQ Technical Engineering Science*: Vol. 1: Iss. 1, Article 10.
DOI: https://doi.org/10.70645/3078-3437.1009

This Research Article is brought to you for free and open access by AUIQ Technical Engineering Science. It has been accepted for inclusion in AUIQ Technical Engineering Science by an authorized editor of AUIQ Technical Engineering Science.

AUIQ TECHNICAL ENGINEERING SCIENCE 2024;1:116–128

Scan the QR to view the full-text article on the journal website

ORIGINAL STUDY

Enhancing Predictive Accuracy of Compressive Strength in Recycled Concrete Using Advanced Machine Learning Techniques with K-means Clustering

Ziaul Haq Doost [a,*], Leonardo Goliatt [b], Mohammed Suleman Aldlemy [c,d], Mumtaz Ali [e,f], Bruno da S. Macêdo [g]

[a] Department of Civil and Environmental Engineering, King Fahd University of Petroleum and Minerals, Dhahran, Saudi Arabia
[b] Computational and Applied Mechanics Department, Federal University of Juiz de Fora, 36036-900, Brazil
[c] Department of Mechanical Engineering, Collage of Mechanical Engineering Technology, Benghazi, Libya
[d] Libyan Center for Solar Energy Research and Studies, Benghazi Branch, Benghazi, Libya
[e] UniSQ College, University of Southern Queensland, QLD 4305, Australia
[f] Faculty of Sustainable Design Engineering, University of Prince Edward Island, Charlottetown, PE C1A4P3, Canada
[g] Department of Systems Engineering and Automation, Federal University of Lavras, Lavras, MG, 37200-000, Brazil

ABSTRACT

The urgent need to mitigate environmental impacts in the construction industry drives the exploration of sustainable practices, such as the use of recycled materials in concrete production. The primary objective of this study was to enhance the predictability of compressive strength in the concrete through the application of advanced machine learning (ML) techniques, specifically Gradient Boosting Regression (GBR) and Random Forest Regression (RFR). Using a comprehensive dataset of 353 eco-friendly concrete samples, the study carefully developed and validated these models to evaluate their performance. The findings exposed that the GBR model outperformed the RFR model, obtained an R^2 of 0.97 in training phase and 0.96 in testing phase, the findings supported further with root mean squared error (RMSE) of 1.99 and 3.06, and by mean absolute error (MAE) of 1.44 and 2.38 for training and testing phases respectively, where indicating high predictive accuracy. Conclusively, the broader adoption of GBR model for similar applications recommended by the study and points towards future research directions to integrate more diverse datasets and investigate more predictive models to improve sustainable construction practices.

Keywords: Sustainable construction, Data clustering techniques, Sustainable materials, AI in construction, Sustainable environment, Machine learning

1. Introduction

Global climate change continues to influence many countries around the world, demanding a unified global response to thrive sustainable development and reduce its effects [1, 2]. This global initiative helps to tackle this challenge through technics that foster low-carbon growth [3]. The construction sector cannot be excluded from these efforts, which is known for its significant contributions to global carbon emissions [4, 5]. For example, strategies like incorporating recycled materials from construction and demolition waste into new concrete mixes not only help mitigate carbon emissions but also manage

Received 30 July 2024; accepted 8 August 2024.
Available online 27 August 2024

* Corresponding author.
E-mail addresses: ziaulhaq.doost@gmail.com (Z. Haq Doost), leonardo.goliatt@ufjf.br (L. Goliatt), maldlemy@ceb.edu.ly (M. Suleman Aldlemy), mumtazali7288@gmail.com (M. Ali), bruno.macedo2@estudante.ufla.br (B. da S. Macêdo).

https://doi.org/10.70645/3078-3437.1009
3078-3437/© 2024 Al-Ayen Iraqi University. This is an open-access article under the CC BY-NC-ND license (https://creativecommons.org/licenses/by-nc-nd/4.0/).

waste effectively [6–8]. While there are extensive research emphasizing on how the construction industry can reduce the effects of global warming, the use of recycled materials remained less explored [7]. These alternative materials provide a sustainable solution by substituting traditional concrete constituents, increasing environmental benefits and sustainability.

In response to the urgent need for sustainable construction practices, recent advancements in ML applications offer promising solutions for optimizing material properties and enhancing eco-efficiency. For instance, scientific research utilized a hybrid K-means clustering with different ML methods, including REG, CART, GENLIN, CHAID, ANN, and SVM, to optimize the workability of concrete mixtures [9]. The study included 103 datasets for the modeling and prediction [9]. The results demonstrating a significant improvement in slump and flow tests for sustainable mixes [9]. Similarly, another research developed models using ANNs and Decision Trees (DT) to enhance the efficiency of using Blast Furnace Slag (BFS) and Fly Ash in concrete. Incorporated a comprehensive 1030 datasets, which contributed to both material and environmental sustainability by accurately predicting compressive strength [10]. Further, a study used an innovative approach involved a hybrid AI model that integrated Least Squares Support Vector Regression (LSSVR) with Grey Wolf Optimization (GWO) to address the empirical limitations in predicting the compressive strength of foamed concrete, a crucial factor for structural design [11]. Furthermore, another study adopted a comprehensive data-driven approach employing multiple ML techniques including DT, RF, GB, SVM, and MLP to predict the compressive strength of fiber-reinforced polymer confined concrete, showcasing enhanced prediction accuracy and methodology that could be applied to various environmental conditions [12]. These studies collectively signify the potential of ML in revolutionizing sustainable practices in the construction sector by providing more accurate, efficient, and environmentally friendly solutions. For a detailed review of additional ML applications in sustainable construction materials, refer to Table 1.

The construction industry faces significant challenges in reducing its environmental impact while maintaining the structural integrity of buildings [17, 18]. Traditional methods for predicting the compressive strength of concrete are often limited in their ability to account for the complex interactions between various materials [13], especially in sustainable concrete mixes that include recycled or alternative materials [13]. These limitations can lead to inaccurate predictions, which in turn affect the safety, durability, and sustainability of construction projects [12, 19]. As the demand for eco-friendly construction materials grows, there is a pressing need for more advanced and accurate methods to predict the performance of these materials [20, 21]. Thus, this study aimed to apply advanced ML models, specifically GBR and RFR. To improve the predictability of compressive strength in concrete. These models were selected for their proven ability to deliver high accuracy predictions and their power in handling complex, non-linear data often found in concrete compositions. As evidenced by their successful application in different contexts (Table 2), such as predicting compressive and tensile strength in sustainable geopolymer concrete [22], forecasting real GDP growth [23], and predicting daily confirmed COVID-19 cases [24]. The research question guiding this study was: How can the predictability of compressive strength in sustainable concrete mixes be improved using advanced ML models? This study addresses this question by demonstrating that both GBR and RFR models not only improve prediction accuracy but also offer a reliable approach to managing the complexities associated with sustainable concrete mixtures, thereby contributing to more effective and sustainable construction practices.

The primary objective of this study is: (i) To evaluate and compare the predictive ability of GBR and RFR models by obtaining the compressive strength of concrete. This will determine which model offers precise, and efficient accuracy and reliability. (ii) To increase the existing models for compressive strength of concrete prediction by synthesizing advanced ML models. (iii) To perform sensitivity analysis to identify the most influential variables in predicting the compressive strength of concrete, thereby enhancing the understanding of which factors most significantly impact model accuracy and reliability. Therefore, contributing to the development of more effective, accurate, and dependable predictive tools for sustainable construction materials.

2. Methodology

2.1. Models' development

The model development began with the collection of data, where a comprehensive dataset containing variables that are suitable for the compressive strength of concrete (Fig. 1). In the next stage the dataset underwent a shuffling or randomization process to avoid any biases. Therefore, ensuring the integrity of the training process. Then, the data was divided into training and testing sets. Where 70% was used for training to make a strong model learning, and the remainder (30%) for testing to assess the models'

Table 1. Comparative analysis of ML applications for sustainable construction materials across various studies.

Reference	Year	Problem	Data input	Data output	No. of data points	AI methods used	Methodology
[9]	2020	Optimizing workability of concrete mixtures	Cement, slag, fly ash, water, superplasticizer, coarse aggregate, fine aggregate	Slump test, flow test	103	REG, CART, GENLIN, CHAID, ANN, SVM	Hybrid K-means clustering with an ensemble of ML methods for prediction
[10]	2022	Enhancing efficiency in using BFS and Fly Ash for eco-friendly concrete production	OPC, F. Ash, BFS, water, days, SP, CA, FA	CS	1030	(ANNs), (DT)	Use of ANNs and DTs to model and predict CS based on material composition and cure time
[11]	2020	Limitations of empirical methods in comprehensively accounting for all influencing factors when predicting the compressive strength of sustainable foamed concrete materials, which is essential for structural design.	Density, cement content, sand content, water/cement ratio, sand size, foaming agent, foam, and cure time	CS	150	(LSSVR), (GWO)	Hybrid AI model using LSSVR optimized with GWO for early prediction of compressive strength
[12]	2021	Problem is the need to predict the CS of cementitious composites in varying environmental conditions for safety reasons, using ML approaches.	Cement, fly ash, superplasticizer, coarse aggregate, fine aggregate, water, days (age of concrete)	CS	98	GEP, DT, ANN, BR	Using ML algorithms to predict compressive strength and comparing various ML techniques
[13]	2022	Problem is the inefficiency and inaccuracy of traditional empirical and statistical methods in developing new materials for construction, due to complex relationships in concrete properties, mixture composition, and curing conditions.	Specimen geometry, mechanical properties of FRP and concrete, FRP layer thickness, unconfined concrete strength	CS	1476	DT, RF, GB, SVM, MLP	Data preprocessing, ML model training, and validation of models
[14]	2023	The problem addressed is the need for accurate models to predict the mechanical strength of sustainable concrete with novel mixtures for consistent and predictable outcomes.	Cement, SCMs, recycled aggregate, mineral admixtures, water, superplasticizer	CS	370	Hybrid ML with RF and Bagging, SVR, DT	Developing a hybrid ML model to predict CS and compare different ML techniques.
[15]	2024	The problem is the need to predict the properties of Vibrocentrifuged concrete under aggressive environmental conditions using specialized machine learning algorithms.	Data on freeze-thaw cycles, chloride content, sulfate content, number of wet-dry cycles, cement, crushed stone, sand, water, density, slump	CS	600 samples (1800 cubes)	LR, SVR, RF, CatBoost	Data-driven modeling using ML to predict compressive strength, with model validation and performance metrics
[16]	2023	The problem is predicting the CS of eco-friendly concrete containing GGBFS and RCA, which is challenging.	Recycled Aggregate (RA%), GGBFS%, superplasticizer (kg), water to binder ratio (W/B), age of concrete (days)	CS	Not specified	XGBoost optimized with Bayesian Optimization, compared with SVR and KNN	Developing an optimized XGBoost model using Bayesian Optimization to predict compressive strength, evaluated using RMSE, MAE, and R^2, and analyzed using PDP.

Table 2. Summary of studies suing GBR and RFR models in various application contexts.

Reference	Year	Model used	Application context	Data input	Advantages	Limitations
[22]	2024	GBR, ABR, XGBR	Predicting compressive and tensile strength of sustainable geopolymer concrete	Slag, Corncob Ash, Fine Aggregate, Concrete Grade, Water, Curing Days, Sodium Silicate Gel, Molar Concentration	High predictive accuracy with R^2 values > 0.90; Effective in handling complex interactions	Computational complexity; Susceptibility to noisy data; Requires meticulous hyperparameter tuning
[25]	2018	GBR	Predicting human age based on DNA methylation	DNA methylation data from blood and saliva samples	High predictive accuracy with $R^2 = 0.97$ for healthy datasets; mean absolute deviation (MAD) as low as 2.72 years	Computational complexity
[23]	2020	GBR, RFR	Forecasting real GDP growth in Japan	Economic indicators such as GDP, CPI, employment, trade data, inflation statistics	High predictive accuracy; benchmarks with RMSE as low as 0.35 for GBR and 0.79 for RF	Complex model tuning required for optimal results
[24]	2021	GBR	Predicting daily confirmed COVID-19 cases worldwide	Time-series data of daily confirmed cases from January 22 to May 30, 2020	High predictive accuracy with RMSE as low as 0.00686; Effective in handling time-series data	Computational complexity; Requires large datasets for robust training
[26]	2022	RFR	Detecting fault location and predicting duration in power systems	Voltage magnitude, phase angle, frequency from a simulated power grid	High accuracy (84% for fault location), effective in real-time applications, handles missing data well	Computationally intensive, performance may vary with the complexity of the power grid scenario
[27]	2021	RFR, GEP	Predicting compressive strength of fly ash-based geopolymer concrete	Curing temperature, age, molarity of NaOH, SiO2/Water ratio, aggregate ratios, plasticizer percentage	High accuracy with RF ($R^2 = 0.9826$), provides empirical formula with GEP for practical use	GEP model is more complex; RF does not provide an empirical equation, limiting practical application

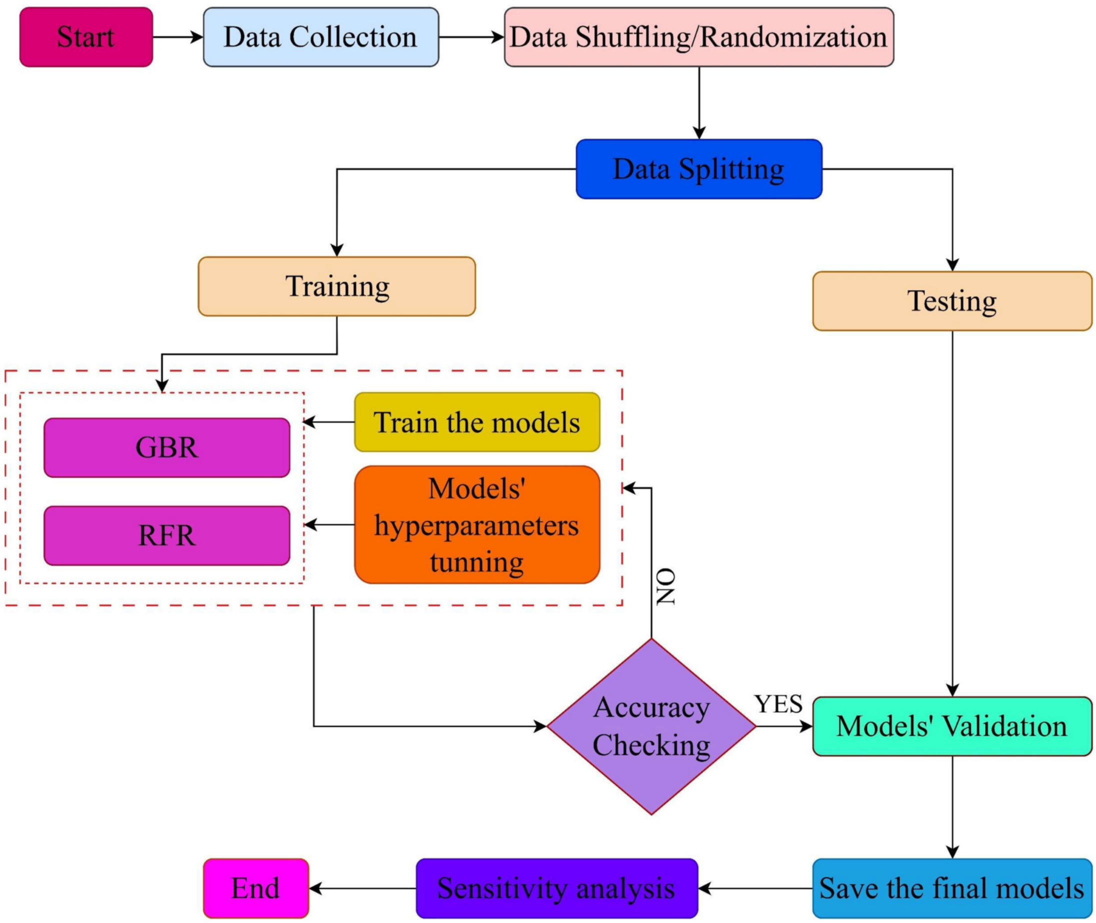


Fig. 1. Model's development flowchart.

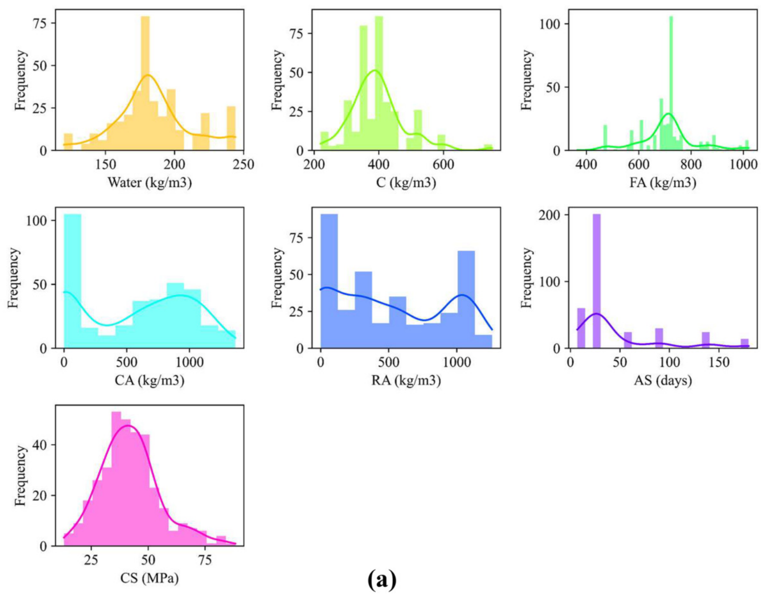
predictive performance. Next, the GBR and RFR models were trained. Subsequently, models underwent a process called 'tuning the hyperparameters' to optimize their performance. Afterward, the models were used to check their accuracy. So, if the accuracy was found to be not appropriate then more tuning was applied. Once the models fit the desired accuracy conditions they were validated. Subsequently, the models that passed all evaluation stages were saved as the final models. Finally, a sensitivity analysis was performed to assess the influence of different input variables.

2.2. Data collection and analysis

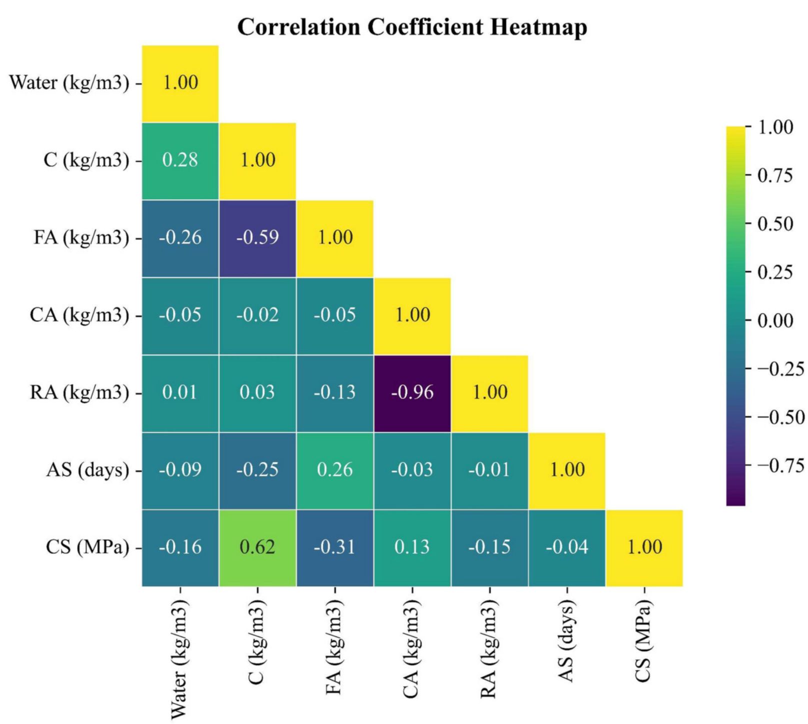
For the development of the AI models, datasets were obtained from open-source records [28]. These datasets consist of 353 instances of eco-friendly concrete samples, detailing their compressive strength. The data encompasses various parameters including the content of water (W), cement (C), fine aggregate (FA), coarse aggregate (CA), recycled aggregate (RA), and the age of the samples (AS), along with the compressive strength (CS) values. The dataset is split into two subsets: a calibration subset and a validation subset. The calibration subset, which comprises 70% of the dataset (247 records), is utilized for the implementation and development of the regression models. The remaining 106 records form the validation subset, which is used to assess the performance of the proposed AI models. Statistical characteristics such as maximum value, minimum value, mean, standard deviation, skewness, and kurtosis are calculated for each variable and presented in Table 3. The data reveals a well distribution and follows approximately a normal distribution (Fig. 2a). The compressive strength values range from 13 to 88.3, with a mean of 42.11, which supports the normal distribution. These properties confirm that the dataset is robust enough for the predictive modeling of the compressive strength of concrete. Moreover, correlation coefficient matrix is evaluated for better understanding the relationships between the variables in the dataset and is presented in Fig. 2b.

Table 3. Data statistical characteristics.

Features	Count	Mean	StD	Min	Max	25%	50%	75%	Skewness	Kurtosis
Water (kg/m3)	353	184.14	27.14	120.00	244.00	172.43	180.00	195.00	0.29	0.39
C (kg/m3)	353	394.86	83.94	220.00	750.00	350.00	400.00	436.00	1.11	2.98
FA (kg/m3)	353	710.27	108.45	365.00	1020.00	685.00	720.00	730.00	0.32	1.50
CA (kg/m3)	353	564.83	438.71	0.00	1366.00	0.00	629.50	940.00	−0.10	−1.45
RA (kg/m3)	353	504.27	414.59	0.00	1259.00	0.00	443.71	972.00	0.22	−1.41
AS (days)	353	45.25	43.96	7.00	180.00	28.00	28.00	56.00	1.78	2.25
CS (MPa)	353	42.11	13.13	13.00	88.30	33.60	41.20	48.50	0.65	0.78



(a)



(b)

Fig. 2. (a) Frequency distribution of features using histograms, (b) Correlation coefficient relationship matrix.

2.3. Employed ML models

In this study, two advanced ML models (RFR and GBR), were used to predict the compressive strength of concrete. These models were selected for their ability to handle complex, robustness, and their non-linear relationships within the data. Both models were trained and validated using the obtained and described datasets in the above section, with hyper-parameter tuning applied to optimize their predictive performance.

2.3.1. Random Forest Regression (RFR)

RFR is an ensemble learning method that operates by constructing multiple decision trees during training and outputting the mean prediction of each tree separately [23]. It decreases overfitting by averaging the results. Therefore, improving accuracy, and efficiency. The RFR model was trained using the available dataset to predict compressive strength of concrete. The general formula for RFR is given in the following equation [23]:

$$F_m(x) = \frac{1}{M}\sum_{m=1}^{M} f_m(x) \tag{1}$$

Where, $f_m(x)$ is the prediction of the m^{th} tree and M is the total number of trees in the forest. This integration aims to minimize the discrepancy of the predictions, decreasing the danger of overfitting typically merged with decision trees.

2.3.2. Gradient Boosting Regression (GBR)

GBR algorithm (model) is an advanced ensemble method that builds models sequentially. where each new model correcting errors created by the previous ones. This method reduces the loss function by consolidating the predictions of multiple weak models [24].:Generally decision trees, to create a robust predictive model. GBR was employed to predict the compressive strength using the same dataset [24, 29, 30]. The general formula for GBR is given by:

$$F(x) = \sum_{m=1}^{M} \gamma_m h_m(x) + \text{const} \tag{2}$$

where $h_m(x)$ are the weak learners (decision trees), γ_m are the coefficients, and M is the number of boosting stages. At each stage m, a new tree $h_m(x)$ is fitted on the negative gradient of the loss function evaluated at the current model $F_{m-1}(x)$, effectively reducing the residual errors of the model. The update rule for adding new learners can be described by [23]:

$$F_m(x) = F_{m-1}(x) + \gamma_m h_m(x) \tag{3}$$

where γ_m is chosen to minimize the overall loss L. This is typically done by solving [23]:

$$\gamma_m = \arg\min_{\gamma} \sum_{i=1}^{N} L(y_i, F_{m-1}(x_i) + \gamma_m h_m(x_i)) \tag{4}$$

GBR model encompasses multiple hyperparameters like the number of trees M, the learning rate (which scales the contribution of each tree), the depth of each tree, and the loss function [31].

2.4. K-means clustering

The dataset was stratified into distinct groups by K-means clustering, which boosted the explicitness of the ML models. By categorizing the dataset into clusters on their similarity, the approach allowed a more detailed analysis, adopting the predictive algorithms to the patterns built-in within each cluster [32, 33]. Clusters numbers were optimally identified through the method of elbow, confirming that the segmentation accurately caught the inherent variations in the prediction efficiencies [34, 35]. This approach offered understanding into the condition dependencies of environmental and treatment within the data, enhancing the accuracy and relevance for each unique cluster of the model's predictions [32, 33].

2.5. Models' performance assessment

Accuracy, precision, and efficacy of all ML models in rainfall prediction employed in this study is quantitatively evaluated through error metrics. These metrics provide a statistical measure of the performance of models [36]. These metrics are mandatory as they display the predictions' performance in comparison to the observed data, directing the better tunning of models for increased precision [37]. In this section the main error metrics used in this study were discussed. They are including R-Squared (R^2), Root Mean Squared Error (RMSE), Mean Absolute Error (MAE), and Median Absolute Error (MedAE). Each of them offers a specific perspective on the predictive ability of models.

(i) R-Squared (R^2): Reflects the proportion of variance in the dependent variable explained by the independent variables, indicating the goodness of fit. A value closer to 1 suggests a model with minimal error in prediction

[38, 39].

$$R^2 = 1 - \frac{\text{Sum of squares of residuals}}{\text{Total sum of squares}} \tag{5}$$

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

(ii) Root Mean Squared Error (RMSE): Measures the square root of the average of the squares of the errors, providing insight into the typical size of the errors. Like MSE, lower RMSE values signify more accurate predictions [38, 40].

$$\text{RMSE} = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(yi - \hat{y}i)^2} \tag{7}$$

(iii) Mean Absolute Error (MAE): Computes the average of the absolute differences between predicted and actual observations, providing a straightforward measure of prediction error without emphasizing outliers. Lower MAE values reflect more accurate predictions [40, 41].

$$\text{MAE} = \frac{1}{n}\sum_{i=1}^{n}|yi - \hat{y}i| \tag{8}$$

(iv) Median Absolute Error (MedAE): Identifies all absolute differences of the median. Thus, providing a strong measure less impacted by skewed data, and outliers. It expose a central point of errors' prediction [42].

$$\text{MedAE} = \text{median}(|yi - \hat{y}i|) \tag{9}$$

where y_i represents the observed values, $\hat{y}i$ is the predicted values, $\bar{y}$ indicates the mean of the observed values, and n stands for the number of observations. These metrics collaboratively aim to evaluate the accuracy, precision, and effectiveness of each model. Therefore, helping in the improvement of model's performance.

2.6. Sensitivity analysis

The sensitivity analysis was performed to determine the influence of different input variables on the compressive strength predictions of the used models. By systematically eliminating one input at a time, while keeping others constant, the analysis determined which factors had the most significant impact on the model's output. This process helped to understand the strength and reliability of the models. So, confirming that the predictions were not inappropriately influenced by any single variable. The insights obtained from the sensitivity analysis contributed to refining of the models and improving their overall accuracy and applicability.

3. Results representation

3.1. Analysis of model performance in predictive accuracy

The performance metrics of the RFR and GBR models across both training and testing phases were examined, as illustrated in Fig. 3. For the RFR model, during the training phase, the model achieved an R^2 of 0.96 with an RMSE of 2.48, a MAE of 1.83, and a MedAE of 1.34. In the testing phase, the RFR model's performance declined drastically, recording an R^2 of 0.90, an RMSE of 4.27, MAE of 3.24, and MedAE of 2.40 compared to its training phase. Conversely, the GBR model demonstrated a stronger consistency between the training and testing phases. In the training phase, the GBR model reported an R^2 of 0.97, RMSE of 1.99, MAE of 1.44, and MedAE of 0.99. During testing phase, the performance metrics recorded as an R^2 of 0.96, RMSE of 3.06, MAE of 2.38, and MedAE of 1.94. These results demonstrate the robust predictive capabilities of GBR model, where it is showing significantly superior accuracy and lower error metrics compared to the RFR model across different phases of model evaluation.

3.2. Comparative evaluation of GBR and RFR model efficiencies

A detailed comparison of the performance metrics for both models GBR and RFR is presented in the current section, as shown in the bar charts of Fig. 4. In the training phase, the GBR model exhibits profoundly high $R^2 = 0.97$ compared to the RFR model's as $R^2 = 0.96$, indicating slightly more accurate predictions. The GBR model also achieved lower error rates with a RMSE = 1.99 and a MAE = 1.44, vs the RFR's RMSE = 2.48 and MAE = 1.83. The MedAE follows a similar pattern, with the GBR model recorded as 0.99 compared to the RFR's of 1.34.

In the testing phase, the GBR model continues to outperform the RFR model drastically. The GBR model maintained a high $R^2 = 0.96$, while the RFR model drops to 0.90. The disparity in RMSE and MAE further illustrates the GBR model's robustness, with values of 3.06 and 2.38 respectively, compared to the RFR's 4.27 and 3.24. The MedAE for GBR is 1.94, sig-

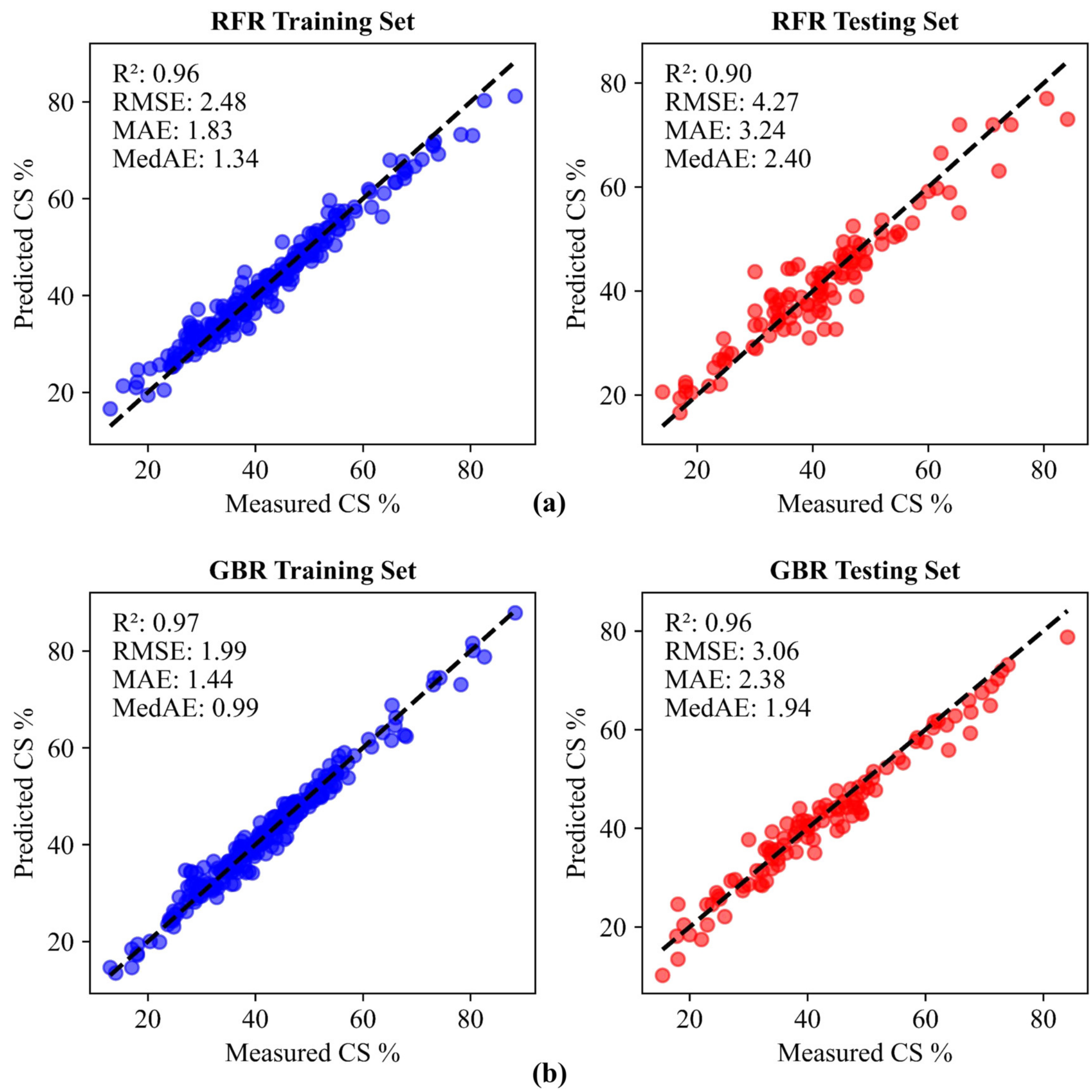


Fig. 3. Performance metrics of predictive modeling on training and testing phases; (a) RFR model, (b) GBR model.

nificantly lower than RFR's 2.40. Conclusively, these metrics indicated that the GBR model not only performed better consistently across both the training and testing phases but also demonstrated superior stability in its predictive accuracy. The evidence strongly supports the use of the GBR model for more reliable and precise predictions in practical applications of compressive strength modeling in eco-friendly concrete.

3.3. Enhancing result reliability with Taylor diagram analysis

The Taylor diagram provides a concise visual representation of how closely the predictions from the GBR and RFR models align with observed data by plotting correlation coefficients (CC), and standard deviations (StD). In this diagram, the GBR model exhibits a smaller StD, and a higher CC compared to the RFR model, particularly in the testing phase. This indicates that the GBR model predictions are not only more accurate but also more consistent with the observed data, showing less variability and greater predictive reliability (Fig. 5).

These findings from the Taylor diagram supports the findings provided earlier in the paper. The robust performance of the GBR model, as evidenced by its closer proximity to the observed data point in the diagram, validates the model's superior performance metrics discussed in Sections 3.1 and 3.2. Specifically, the GBR model's higher R^2, and lower RMES, MAE, and MedAE across both training and testing phases demonstrate its effectiveness and stability as a predictive tool. This visual and statistical validation through

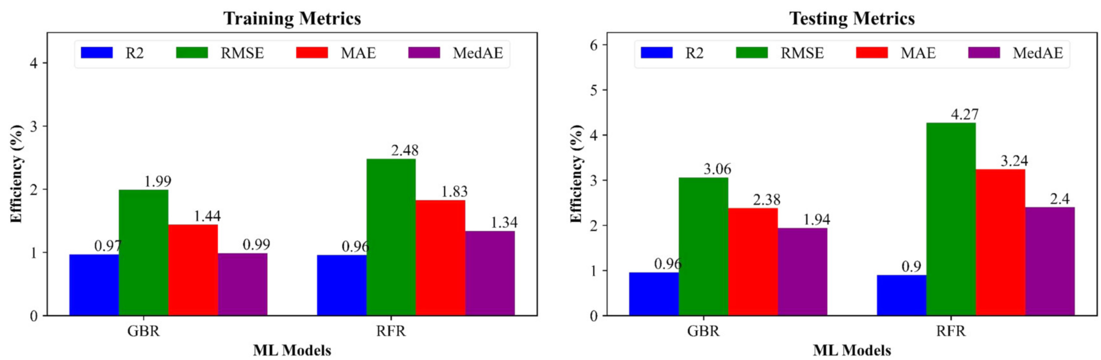


Fig. 4. Performance comparison of GBR and RFR across training and testing phases.

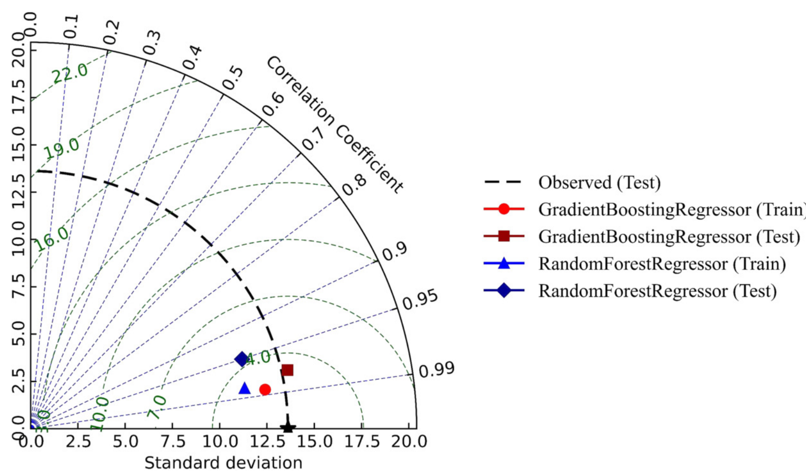


Fig. 5. Model evaluation through Taylor diagram: GBR vs. RFR.

the Taylor diagram analysis enhances the reliability of the results, confirming the GBR model as a more reliable choice for predicting compressive strength of concrete.

3.4. Sensitivity analysis results

For the RFR model, the exclusion of water significantly degraded performance, with the R^2 dropping from 0.96 to 0.87 in training and from 0.90 to 0.79 in testing (Table 4). This change corresponded with an increase in RMSE from 2.48 to 4.56 in training and from 4.27 to 6.24 in testing. Similarly, excluding cement saw the training R^2 decrease to 0.84 and the testing R^2 to 0.73, alongside increases in RMSE to 5.19 and 7.08, respectively. The removal of fine aggregate (FA) and recycled aggregate (RA) also adversely affected both training and testing metrics but to a lesser degree compared to water and cement. In contrast, the GBR model exhibited resilience to the exclusion of inputs but still showed variability in performance metrics. The exclusion of water resulted in a decrease in training R^2 from 0.97 to 0.89 and in testing R^2 from 0.96 to 0.84, along with increases in RMSE to 3.86 and 5.87, respectively. Notably, excluding cement had a profound impact, with training RMSE rising to 4.68 and testing RMSE to 5.36. However, excluding coarse aggregate (CA) had minimal impact on the GBR model's performance compared to other inputs. Overall, the sensitivity analysis highlights the critical roles that water and cement play in the predictive accuracy of both models. Their exclusion leads to significant decreases in performance metrics, indicating that these components are crucial for accurate predictions. The analysis also demonstrates the GBR model's generally stronger robustness against input exclusion compared to the RFR model, suggesting its superior handling of missing or incomplete data scenarios.

4. Discussion

The analysis presented in this study on the predictive accuracy of GBR and RFR models for compressive strength of Concrete provided important insights into the effectiveness of advanced ML techniques in the

Table 4. Comparative impact of input removal on model efficacy for RFR and GBR.

RFR model													
Inputs						Training				Testing			
Water (kg/m^3)	C (kg/m^3)	FA (kg/m^3)	CA (kg/m^3)	RA (kg/m^3)	AS (days)	R^2	RMSE	MAE	MedAE	R^2	RMSE	MAE	MedAE
						0.96	2.48	1.83	1.34	0.9	4.27	3.24	2.4
Excluded						0.87	4.56	2.89	1.63	0.79	6.24	4.66	3.17
	Excluded					0.84	5.19	3.28	1.8	0.73	7.08	5.04	3.53
		Excluded				0.94	3.02	2.14	1.33	0.85	5.21	3.9	2.61
			Excluded			0.96	2.47	1.76	1.23	0.91	4.12	3.2	2.83
				Excluded		0.96	2.58	1.89	1.32	0.9	4.29	3.34	2.67
					Excluded	0.91	3.9	3.02	2.62	0.86	5.17	4.22	3.44
GBR model													
Inputs						Training				Testing			
Water (kg/m^3)	C (kg/m^3)	FA (kg/m^3)	CA (kg/m^3)	RA (kg/m^3)	AS (days)	R^2	RMSE	MAE	MedAE	R^2	RMSE	MAE	MedAE
						0.97	1.99	1.44	0.99	0.96	3.06	2.38	1.94
Excluded						0.9	3.86	2.26	1.18	0.84	5.87	4.04	2.73
	Excluded					0.86	4.68	2.87	1.57	0.86	5.36	3.69	2.57
		Excluded				0.97	2.3	1.75	1.35	0.94	3.59	2.79	2.5
			Excluded			0.96	2.34	1.7	1.22	0.95	3.18	2.58	2.39
				Excluded		0.96	2.4	1.75	1.23	0.95	3.28	2.48	1.9
					Excluded	0.92	3.57	2.75	2.3	0.87	5.31	4.48	4.15

context of sustainable construction materials. This section compares our findings with those from other studies, which have similarly employed ML models to predict the mechanical properties of eco-friendly concrete materials. In the current research, the GBR model demonstrated superior performance with an R^2 of 0.97 in training and 0.96 in testing phases, accompanied by RMSE of 1.99 and 3.06, respectively, significantly outperforming the ANN model of [43] on prediction of CS of concrete with (R^2 for training phase ranging 0.917-0.945, and R^2 for testing phase ranging 0.814-0.922), and the Fuzzy Polynomial Neural Networks (FPNN) of [44], the model 6 achieved an R^2 of 0.8194 in training and 0.8209 in testing, with corresponding RMSE values of 14.4463 MPa in training and 9.5555 MPa in testing phase. Where it indicates a significant low R^2 with very high RMSE for both training and testing compared to our study. Similarly, while the best performing model (M5P tree model) in [45] achieved an R^2 of 0.8872, and accompanied with its higher RMSE of 7.1874 suggests less precise predictions than our GBR model. Compared to the Multiple Additive Regression Trees (MART) used in [46], which reported an R^2 of 0.9543, our models not only show higher accuracy but also better consistency between training and testing phases, emphasizing the robustness and potential of advanced ensemble methods like GBR for enhancing predictive performance in eco-friendly concrete applications.

5. Conclusion

The construction industry faces significant environmental challenges, particularly in managing waste and reducing carbon emissions. This study aimed to enhance the predictability of compressive strength in recycled concrete through advanced ML techniques, specifically GBR and RFR models. Employed a dataset of 353 eco-friendly concrete samples, these models were developed and trained, rigorously testing their performance. The findings indicated that the GBR model exhibited superior predictive accuracy, obtained an R^2 of 0.97 in training phase and 0.96 in testing phase, with corresponding RMSE values of 1.99 and 3.06 respectively. These results underscore the effectiveness of GBR model in handling complex, non-linear relationships in recycled concrete data. The study recommends the adoption of GBR model for similar applications and suggests further exploration into integrating additional predictive variables and testing alternative ML algorithms to broaden the understanding and applications of sustainable construction materials.

Ethical approval

The manuscript is conducted within the ethical manner advised by the targeted journal.

Consent to participate

Not applicable.

Consent to publish

The research is scientifically consented to be published.

Funding

The research did not receive any types of funds.

Competing interests

The authors declare no conflict of interest.

Acknowledgement

The authors would like to acknowledge the funding supported by KFUPM University for the PhD's degree scholarship.

Abbreviations

ML: Machine Learning; GBR: Gradient Boosting Regression; RFR: Random Forest Regression; RMSE: Root Mean Squared Error; MAE: Mean Absolute Error; MedAE: Median Absolute Error; ANN: Artificial Neural Networks; DT: Decision Trees; LSSVR: Least Squares Support Vector Regression; GWO: Grey Wolf Optimization; FPNN: Fuzzy Polynomial Neural Networks; MART: Multiple Additive Regression Trees; XGBR: XGBoost; BO: Bayesian Optimization; KNN: Knowledge Nearest Neighbor; PCA: Principal Component Analysis; PDP: Partial Dependence Plot; GGBFS: Ground Granulated Blast-Furnace Slag; RA: Recycled Aggregate; W/B: Water to Binder ratio; OPC: Ordinary Portland Cement; F. Ash: Fly Ash; SP: Superplasticizer; CA: Coarse Aggregate; FA: Fine Aggregate; CART: Classification and Regression Tree; GENLIN: Generalized Linear Model; CHAID: Chi-squared Automatic Interaction Detector; SVM: Support Vector Machines; MLP: Multilayer Perceptron; ABR: Adaptive Boosting Regression; GEP: Gene Expression Programming; CS: Compressive Strength; GDP: Gross Domestic Product; CPI: Consumer Price Index; MAD: Mean Absolute Deviation.

Conflict of interest

The authors declare no conflict of interest to any party.

References

1. M. Yazdani, M. Mojtahedi, and M. Loosemore, "Enhancing evacuation response to extreme weather disasters using public transportation systems: a novel simheuristic approach," *J. Comput. Des. Eng.*, vol. 7, no. 2, pp. 195–210, 2020, doi: 10.1093/jcde/qwaa017.
2. M. Yazdani, M. Mojtahedi, M. Loosemore, and D. Sanderson, "A modelling framework to design an evacuation support system for healthcare infrastructures in response to major flood events," *Prog. Disaster Sci.*, vol. 13, p. 100218, 2022, doi: 10.1016/j.pdisas.2022.100218.
3. W. Wei, M. Mojtahedi, M. Yazdani, and K. Kabirifar, "The Alignment of Australia's National Construction Code and the Sendai Framework for Disaster Risk Reduction in Achieving Resilient Buildings and Communities," *Buildings*, vol. 11, no. 10, p. 429, 2021, doi: 10.3390/buildings11100429.
4. A. A. Shahmansouri, M. Yazdani, M. Hosseini, H. Akbarzadeh Bengar, and H. Farrokh Ghatte, "The prediction analysis of compressive strength and electrical resistivity of environmentally friendly concrete incorporating natural zeolite using artificial neural network," *Constr. Build. Mater.*, vol. 317, p. 125876, 2022, doi: 10.1016/j.conbuildmat.2021.125876.
5. K. Kabirifar, M. Mojtahedi, C. Changxin Wang, and V. W. Y. Tam, "Effective construction and demolition waste management assessment through waste management hierarchy; a case of Australian large construction companies," *J. Clean. Prod.*, vol. 312, p. 127790, 2021, doi: 10.1016/j.jclepro.2021.127790.
6. K. Kabirifar, M. Mojtahedi, C. Wang, and V. W. Y. Tam, "Construction and demolition waste management contributing factors coupled with reduce, reuse, and recycle strategies for effective waste management: a review," *J. Clean. Prod.*, vol. 263, p. 121265, 2020, doi: 10.1016/j.jclepro.2020.121265.
7. A. De Luca, L. Chen, and K. Gharehbaghi, "Sustainable utilization of recycled aggregates: robust construction and demolition waste reduction strategies," *Int. J. Build. Pathol. Adapt.*, vol. 39, no. 4, pp. 666–682, 2021.
8. T. M. Hashim et al., "Evaluating rutting resistance of rejuvenated recycled hot-mix asphalt mixtures using different types of recycling agents," *Materials (Basel).*, vol. 15, no. 24, p. 8769, 2022.
9. D. Wijaya, D. Prayogo, D. I. Santoso, T. Gunawan, and J. A. Widjaja, "Optimizing prediction accuracy of concrete mixture behavior using hybrid k-means clustering and ensemble machine learning," in *Journal of Physics: Conference Series*, IOP Publishing, 2020, p. 12022.
10. S. A. R. Shah, M. Azab, H. M. Seif ElDin, O. Barakat, M. K. Anwar, and Y. Bashir, "Predicting compressive strength of blast furnace slag and fly ash based sustainable concrete using machine learning techniques: an application of advanced decision-making approaches," *Buildings*, vol. 12, no. 7, p. 914, 2022.
11. A.-D. Pham, N.-T. Ngo, Q.-T. Nguyen, and N.-S. Truong, "Hybrid machine learning for predicting strength of sustainable concrete," *Soft Comput.*, vol. 24, no. 19, pp. 14965–14980, 2020.
12. H. Song et al., "Predicting the compressive strength of concrete with fly ash admixture using machine learning algorithms," *Constr. Build. Mater.*, vol. 308, p. 125021, 2021.
13. F. Sofos, C. G. Papakonstantinou, M. Valasaki, and T. E. Karakasidis, "Fiber-reinforced polymer confined concrete: data-driven predictions of compressive strength utilizing

machine learning techniques," *Appl. Sci.*, vol. 13, no. 1, p. 567, 2022.
14. B. A. A. Almahameed and H. R. Sobuz, "The role of hybrid machine learning for predicting strength behavior of sustainable concrete," *Civ. Eng. Archit.*, vol. 11, no. 4, pp. 2012–2032, 2023.
15. A. N. Beskopylny et al., "Prediction of the compressive strength of vibrocentrifuged concrete using machine learning methods," *Buildings*, vol. 14, no. 2, p. 377, 2024.
16. S. R. Al-Taai, N. M. Azize, Z. A. Thoeny, H. Imran, L. F. A. Bernardo, and Z. Al-Khafaji, "XGBoost prediction model optimized with bayesian for the compressive strength of eco-friendly concrete containing ground granulated blast furnace slag and recycled coarse aggregate," *Appl. Sci.*, vol. 13, no. 15, p. 8889, 2023.
17. P. O. Akadiri, E. A. Chinyio, and P. O. Olomolaiye, "Design of a sustainable building: A conceptual framework for implementing sustainability in the building sector," *Buildings*, vol. 2, no. 2, pp. 126–152, 2012.
18. W. Jing, H. I. Naji, R. N. Zehawi, Z. H. Ali, N. Al-Ansari, and Z. M. Yaseen, "System dynamics modeling strategy for civil construction projects: The concept of successive legislation periods," *Symmetry (Basel)*., vol. 11, no. 5, p. 677, 2019.
19. M. C. Liejy et al., "Prediction of the bending strength of a composite steel beam–slab member filled with recycled concrete," *Materials (Basel)*., 2023, doi: 10.3390/ma16072748.
20. J. Zhao et al., "Eco-friendly geopolymer materials: A review of performance improvement, potential application and sustainability assessment," *J. Clean. Prod.*, vol. 307, p. 127085, 2021.
21. E. Ghafari, H. Costa, and E. Júlio, "Critical review on eco-efficient ultra high performance concrete enhanced with nano-materials," *Constr. Build. Mater.*, vol. 101, pp. 201–208, 2015.
22. J. Zhou, Q. Tian, A. Ahmad, and J. Huang, "Compressive and tensile strength estimation of sustainable geopolymer concrete using contemporary boosting ensemble techniques," *Rev. Adv. Mater. Sci.*, vol. 63, no. 1, p. 20240014, 2024.
23. J. Yoon, "Forecasting of real GDP growth using machine learning models: gradient boosting and random forest approach," *Comput. Econ.*, vol. 57, no. 1, pp. 247–265, 2021.
24. A. Gumaei, M. Al-Rakhami, M. M. Al Rahhal, F. R. Albogamy, E. Al Maghayreh, and H. AlSalman, "Prediction of COVID-19 confirmed cases using gradient boosting regression method," *Comput Mater Contin*., vol. 66, no. 66, pp. 315–329, 2021.
25. X. Li, W. Li, and Y. Xu, "Human age prediction based on DNA methylation using a gradient boosting regressor," *Genes*, vol. 9, p. 424, 2018.
26. Z. El Mrabet, N. Sugunaraj, P. Ranganathan, and S. Abhyankar, "Random forest regressor-based approach for detecting fault location and duration in power systems," *Sensors*, vol. 22, no. 2, p. 458, 2022.
27. M. A. Khan, S. A. Memon, F. Farooq, M. F. Javed, F. Aslam, and R. Alyousef, "Compressive strength of fly-ash-based geopolymer concrete by gene expression programming and random forest," *Adv. Civ. Eng.*, vol. 2021, pp. 1–17, 2021.
28. A. Ashrafian, N. S. Hamzehkolaei, N. K. A. Dwijendra, and M. Yazdani, "An evolutionary neuro-fuzzy-based approach to estimate the compressive strength of eco-friendly concrete containing recycled construction wastes," *Buildings*, vol. 12, no. 8, p. 1280, 2022.
29. G. De'Ath, "Boosted trees for ecological modeling and prediction," *Ecology*, vol. 88, no. 1, pp. 243–251, 2007.
30. J. Cai, K. Xu, Y. Zhu, F. Hu, and L. Li, "Prediction and analysis of net ecosystem carbon exchange based on gradient boosting regression and random forest," *Appl. Energy*, vol. 262, p. 114566, 2020.
31. A. Israeli, L. Rokach, and A. Shabtai, "Constraint learning based gradient boosting trees," *Expert Syst. Appl.*, vol. 128, pp. 287–300, 2019.
32. D. N. Ouedraogo, "Interpretable machine learning model selection for breast cancer diagnosis based on K-means clustering," *Appl. Med. Informatics*, vol. 43, no. 3, pp. 91–102, 2021.
33. D. Ranti, A. J. Warburton, K. Hanss, D. Katz, J. Poeran, and C. Moucha, "K-means clustering to elucidate vulnerable subpopulations among medicare patients undergoing total joint arthroplasty," *J. Arthroplasty*, vol. 35, no. 12, pp. 3488–3497, 2020.
34. C. Guo, M. Liu, and M. Lu, "A dynamic ensemble learning algorithm based on K-means for ICU mortality prediction," *Appl. Soft Comput.*, vol. 103, p. 107166, 2021.
35. K. Mittal, G. Aggarwal, and P. Mahajan, "Performance study of K-nearest neighbor classifier and K-means clustering for predicting the diagnostic accuracy," *Int. J. Inf. Technol.*, vol. 11, pp. 535–540, 2019.
36. D. Chakraborty and H. Elzarka, "Performance testing of energy models: are we using the right statistical metrics?" *J. Build. Perform. Simul.*, vol. 11, no. 4, pp. 433–448, 2018.
37. J. Dessain, "Machine learning models predicting returns: why most popular performance metrics are misleading and proposal for an efficient metric," *Expert Syst. Appl.*, vol. 199, p. 116970, 2022.
38. D. Chicco, M. J. Warrens, and G. Jurman, "The coefficient of determination R-squared is more informative than SMAPE, MAE, MAPE, MSE and RMSE in regression analysis evaluation," *Peerj Comput. Sci.*, vol. 7, p. e623, 2021.
39. A. C. Cameron and F. A. G. Windmeijer, "An R-squared measure of goodness of fit for some common nonlinear regression models," *J. Econom.*, vol. 77, no. 2, pp. 329–342, 1997.
40. T. O. Hodson, "Root mean square error (RMSE) or mean absolute error (MAE): When to use them or not," *Geosci. Model Dev. Discuss.*, vol. 2022, pp. 1–10, 2022.
41. G. Brassington, "Mean absolute error and root mean square error: which is the better metric for assessing model performance?" in *EGU General Assembly Conference Abstracts*, 2017, p. 3574.
42. J.-M. Sánchez-González, C. Rocha-de-Lossada, and D. Flikier, "Median absolute error and interquartile range as criteria of success against the percentage of eyes within a refractive target in IOL surgery," *J. Cataract Refract. Surg.*, vol. 46, no. 10, p. 1441, 2020.
43. I.-C. Yeh, "Modeling of strength of high-performance concrete using artificial neural networks," *Cem. Concr. Res.*, vol. 28, no. 12, pp. 1797–1808, 1998.
44. M. H. F. Zarandi, I. B. Türksen, J. Sobhani, and A. A. Ramezanianpour, "Fuzzy polynomial neural networks for approximation of the compressive strength of concrete," *Appl. Soft Comput.*, vol. 8, no. 1, pp. 488–498, 2008.
45. C. Deepa, K. SathiyaKumari, and V. P. Sudha, "Prediction of the compressive strength of high performance concrete mix using tree based modeling," *Int. J. Comput. Appl.*, vol. 6, no. 5, pp. 18–24, 2010.
46. J.-S. Chou, C.-K. Chiu, M. Farfoura, and I. Al-Taharwa, "Optimizing the prediction accuracy of concrete compressive strength based on a comparison of data-mining techniques," *J. Comput. Civ. Eng.*, vol. 25, no. 3, pp. 242–253, 2011.