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Integrated Prediction Model for Normal and Recycled Aggregate Concrete Strength Using Ensemble Learning Techniques

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***Abstract*—Recycled aggregate concrete (RAC) is a sustainable alternative construction material to reduce natural resource exploitation and manage construction and demolition waste. However, predicting the mechanical performance of RAC remains a challenge due to the high variability of recycled aggregate properties. The purpose of this study is to develop a machine learning model to predict the compressive strength of recycled aggregate-based concrete and compare its performance with normal concrete. The dataset used consists of 2165 samples (1600 normal concrete and 565 recycled aggregate concrete) collected from various scientific publications. Three tree-based machine learning algorithms (Random Forest, XGBoost, and LightGBM) were implemented and optimized using RandomizedSearchCV with 5-fold cross-validation. The results showed that LightGBM provided the best performance with R^2 = 0.92, MAE = 2.45 MPa, and RMSE = 3.52 MPa on the test set. This model is able to predict the compressive strength of normal concrete (R^2 = 0.92) and recycled aggregate concrete (R^2 = 0.91) with almost the same accuracy, indicating strong generalization. Feature importance analysis revealed that curing age, cement content, and water content are the most important factors in compressive strength prediction, while for RAC, recycled aggregate water absorption (WRCA) also makes a significant contribution. Error analysis shows that residuals are random and normally distributed without systematic bias. This model can reliably predict concrete compressive strength in the range of 20-60 MPa with an average error of ±3-4 MPa and can be integrated into mix proportioning design software to improve the efficiency of the design process and support the use of sustainable construction materials.**

***Index Terms*—Recycled aggregate concrete, compressive strength prediction, machine learning, LightGBM.**

I. Introduction

The global construction industry faces increasingly pressing environmental challenges related to the management of construction and demolition waste (CDW). The construction sector contributes approximately one-third of global greenhouse gas emissions and generates enormous volumes of waste, with an estimated 35% of CDW still being disposed of in landfills worldwide [1]. In the United States, over 600 million tons of CDW were generated in 2018, an amount twice that of municipal solid waste [2]. Improper CDW management not only results in land depletion for landfills and environmental pollution but also leads to overexploitation of natural resources for new aggregates [3]. In this context, the use of recycled aggregates from CDW as a substitute for virgin aggregates in concrete production is an important strategy in supporting sustainable construction practices and a circular economy [4].

Recycled aggregate concrete (RAC) has been the focus of intensive research in the last decade as an environmentally friendly alternative construction material. RAC offers dual benefits: reducing the need for virgin aggregate mining while providing a solution for construction waste management [5]. Recycled aggregate derived from waste concrete, when properly processed, can retain most of the mechanical characteristics required for structural applications [6]. However, the implementation of RAC in construction practice still faces significant obstacles, primarily related to the variability in the quality of recycled aggregates, which is influenced by factors such as the strength of the parent concrete, residual mortar content, water absorption rate, and processing method [7]. This heterogeneity of properties leads to uncertainty in predicting the mechanical performance of RAC, particularly compressive strength, which is the most critical design parameter in structural applications.

Concrete compressive strength prediction, for both conventional and RAC concrete, has traditionally relied on laboratory testing requiring a 28-day curing period, a time-consuming and costly process. Conventional empirical approaches and analytical models often have limitations in capturing the complex nonlinear relationship between concrete mix composition and its mechanical performance, especially when dealing with the high variability inherent in recycled aggregates [8]. In the context of RAC, additional parameters such as the replacement rate of recycled aggregates, the quality of recycled aggregates (including density, water absorption, and crushing value), and interactions with other constituents (cement, water, admixtures) complicate predictive modeling [9]. Therefore, the development of accurate, efficient, and reliable prediction methods is an urgent need to support the wider adoption of RAC in the construction industry.

Rapid developments in machine learning (ML) and artificial intelligence have opened up new opportunities to address the challenges of predicting complex construction material properties. ML algorithms, with their ability to identify complex patterns and nonlinear relationships in multidimensional data, have proven effective in predicting various concrete properties, including compressive strength, tensile strength, elastic modulus, and durability [10]. Several recent studies have demonstrated the

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superiority of tree-ensemble-based algorithms, such as Random Forest, XGBoost, and LightGBM, in predicting concrete compressive strength with a high degree of accuracy [11]. A study by Jaglan & Singh [12] demonstrated that Gradient Boosting Machine (GBM) was able to achieve an R^2 value of 0.989 in predicting the mechanical properties of RAC containing ground granulated blast furnace slag (GGBS). Meanwhile, a study by Demirturk et al. [13] confirmed that the LightGBM and XGBoost algorithms optimized with Bayesian optimization can provide highly accurate predictions for high-performance concrete.

The application of machine learning to predict the compressive strength of RAC has become a rapidly growing research area in recent years. Several studies have applied various ML algorithms with promising results. A study by Zhang et al. [9] used a Bayesian optimization-based prediction model for RAC and successfully identified key factors affecting compressive strength, including the recycled aggregate replacement ratio and the water-cement ratio. A comparative study by Ahmad et al. [14] evaluated the performance of various ensemble learning algorithms, including Random Forest, Gradient Boosting, and XGBoost, for predicting the compressive strength of RAC and found that the gradient boosting method consistently outperformed the bagging method. Furthermore, the application of interpretability techniques such as SHapley Additive exPlanations (SHAP) has enabled researchers to not only predict the compressive strength but also understand the relative contribution of each input parameter to the prediction [15]. However, most existing studies focus on limited datasets or specific types of RAC, and there is still a need to develop more general and robust models that can handle the wide variability in RAC composition.

Despite significant progress in the application of machine learning for concrete property prediction, several research gaps remain to be addressed. First, most existing studies develop models separately for conventional concrete and RAC, thus underexploring the model's generalizability for both types of concrete simultaneously [16]. Second, comprehensive comparisons between state-of-the-art tree-based algorithms (Random Forest, XGBoost, and LightGBM) on large and diverse RAC datasets are still limited. Third, in-depth analysis of feature importance and model interpretability in the RAC context is rarely systematically conducted [17]. Fourth, validation of model performance at various curing ages has not been thoroughly explored, despite its importance for practical applications in quality control and construction process acceleration. Finally, the integration of ML prediction results with practical mix proportioning design systems still requires further development to facilitate industrial adoption.

This study aims to develop and evaluate an accurate and robust machine learning model for predicting the compressive strength of recycled aggregate-based concrete, and compare its performance with conventional concrete prediction. Specifically, this study will collect and curate a comprehensive dataset covering normal and RAC concrete from various literature sources, apply systematic data preprocessing including handling of missing values, outlier detection based on curing age groups, and feature engineering, implement and optimize three state-of-the-art tree-based machine learning algorithms (Random Forest, XGBoost, and LightGBM) using hyperparameter tuning with RandomizedSearchCV, conduct a comprehensive comparative analysis of the model performance on normal and RAC concrete, as well as at various curing ages, identify the most influential factors on compressive strength using feature importance analysis and SHAP values; and conduct a thorough error analysis to understand the characteristics and limitations of the model.

The main contribution of this research is the development of a predictive model that can handle both conventional concrete and RAC in one integrated framework, with high accuracy and good interpretability. The results of this study are expected to provide in-depth insights into the factors that control the compressive strength of RAC, as well as provide a practical tool that can be integrated into the mix proportioning design process and quality control. More broadly, this research supports global efforts to improve the sustainability of the construction industry through the utilization of construction waste and reduced exploitation of natural resources [18]. The developed model has the potential to accelerate the adoption of RAC in construction practice by reducing uncertainty in its performance prediction, thereby contributing to the achievement of sustainable development goals and a circular economy in the construction sector [19].

II. Materials and Method

A. Data Collection and Preprocessing

This study uses secondary datasets collected from various scientific publications related to normal concrete (NC) and recycled aggregate-based concrete (RAC). The NC dataset is sourced from Ke and Ming [20] with an initial number of 1,670 data, while the RAC dataset is sourced from Rahman and Aayaz [21] with an initial number of 584 data. After going through the preprocessing stage, the number of data becomes 1,600 for NC and 565 for RAC. Each sample includes information on the composition of the concrete mixture material as well as the results of compressive strength tests at various curing ages.

The data preprocessing stage was carried out systematically to ensure data quality and model reliability. This stage included handling missing values, removing duplicate data, and detecting outliers. Numeric columns with a missing value ratio greater than or equal to 30% were removed from the dataset, as they were deemed to not adequately represent the data. After merging the NC and RAC datasets, a recheck was performed for the presence of NaN values, and all remaining NaN values were filled with 0 to ensure no missing values interfered with the modeling process.

Outliers in the target variable (concrete compressive strength) were identified and removed using the Interquartile Range (IQR) method applied separately for each curing age group (stratified outlier removal). This approach was chosen because the distribution of concrete

compressive strength is highly dependent on curing age, so outliers need to be detected within the context of each age group. For each curing age group, the Q1 (first quartile) and Q3 (third quartile) values of compressive strength were calculated, then IQR = Q3 - Q1. The lower and upper limits of outliers were determined by the formula: Lower limit = Q1 - 1.5 × IQR and upper limit = Q3 + 1.5 × IQR. Samples with compressive strength values outside the range (lower limit, upper limit) were considered as outliers and removed from the dataset. For modeling purposes, the categorical variable "Type" that distinguishes between normal concrete (NC) and recycled aggregate-based concrete (RAC) was coded numerically using label encoding. The value “NC” is encoded as 0, and “RAC” is encoded as 1. This encoding allows the machine learning model to process the concrete type information as numeric features.

B. Dataset

Statistical descriptions of the input and output parameters for the NC and RAC datasets are presented in Table I and Table II, respectively. These tables provide comprehensive information on the mean, standard deviation, minimum, quartile, and maximum values for each variable, providing insight into the distribution and variability of the data.

TABLE I. THE STATISTICAL DESCRIPTION OF THE INPUT AND OUTPUT PARAMETERS OF NORMAL CONCRETE

Variable	Type	Unit	Mean	Std	Min	25%	50%	75%	Max
Cement	Input	kg/m³	362.28	100.77	194	300	354	400	958
Sand	Input	kg/m³	867.88	211.39	631	774	818.5	861.25	1712
NCA	Input	kg/m³	944.16	310.92	0	999	1046	1086	1398
Water	Input	kg/m³	178.74	39.13	110	162	168	173	476
SP	Input	kg/m³	5.41	4.71	0	3.79	5.1	6.2	39.2
FlyAsh	Input	kg/m³	23.69	35.21	0	0	0	54	195
Accelerating_Agent	Input	kg/m³	0.75	4.93	0	0	0	0	50
SilicaFume	Input	kg/m³	0.19	2	0	0	0	0	25
Age	Input	hari	17.62	10.5	7	7	28	28	28
Strength	Output	Mpa	37.58	12.72	4.3	28.7	38.03	45.35	71.8

Table 1 presents the statistical characteristics of the normal concrete (NC) dataset consisting of 565 samples after preprocessing. The cement content has an average of 362.28 kg/m³ with a standard deviation of 100.77 kg/m³, indicating a fairly high variation in mix composition across literature sources. The minimum value of 194 kg/m³ represents a low-cement mix, while the maximum value of 958 kg/m³ indicates the presence of high-strength concrete in the dataset. Fine aggregate (sand) has an average of 867.88 kg/m³ with a range of 631-1712 kg/m³, reflecting differences in mix design proportions. Natural coarse aggregate (NCA) shows an average of 944.16 kg/m³ and a standard deviation of 310.92 kg/m³; The minimum value of 0 kg/m³ indicates the presence of mortar or concrete samples without coarse aggregate, while the maximum value of 1398 kg/m³ indicates a mixture with a dominant proportion of coarse aggregate. The water content is relatively more controlled with an average of 178.74 kg/m³ and a standard deviation of 39.13 kg/m³, while the superplasticizer (SP) has an average of 5.41 kg/m³ with a range of 0 to 39.2 kg/m³, indicating variations in workability requirements in certain mixtures.

Pozzolanic additives such as fly ash, accelerating agent, and silica fume had a median value of 0, indicating that more than half of the samples did not use these additives. However, their respective maximum values were quite high, indicating that some mixtures utilized these materials in significant amounts to improve concrete performance. The Age variable was dominated by tests at 7 and 28 days, with a median of 28 days being the common standard for compressive strength testing. As an output variable, compressive strength had a mean of 37.58 MPa with a standard deviation of 12.72 MPa and a wide range from 4.3 MPa to 71.8 MPa, reflecting the diversity of concrete quality in the dataset.

TABLE II. THE STATISTICAL DESCRIPTION OF THE INPUT AND OUTPUT PARAMETERS OF RECYCLED AGGREGATE CONCRETE

Variable	Type	Unit	Mean	Std	Min	25%	50%	75%	Max
Age	Input	hari	27.43	26.17	1	7	28	28	90
Metakaolin	Input	kg/m³	4.66	14.69	0	0	0	0	58.8
Water	Input	kg/m³	192.44	38.31	116	180	206	220	271
Cement	Input	kg/m³	406.22	83.54	147.5	350	401	420	600
Sand	Input	kg/m³	642.66	121.23	400	611	666	705	895
NCA	Input	kg/m³	519.88	350.68	0	368	524	782	1261
RCA	Input	kg/m³	446.15	366.24	0	153	324	585	1119
SP	Input	kg/m³	2.31	34.97	0	0	0	0.23	700
Dmax_RCA	Input	mm	18.9	2.94	12.5	20	20	20	25.4
Density_RCA	Input	kg/m³	2437.91	102.75	2232	2350	2390	2570	2750
WRCA	Input	%	4.08	1.31	0.79	3.51	3.9	4.81	8.8
Strength	Output	Mpa	40.29	12.02	4.3	33.32	39.9	49	78.1

Table II presents the statistical characteristics of the recycled aggregate concrete (RAC) dataset consisting of 1,600 samples after preprocessing and shows a number of differences compared to normal concrete. The average

cement content of RAC is 406.22 kg/m³, higher than that of NC, indicating a tendency to increase the cement dosage to compensate for the relatively lower quality of recycled aggregate; on the other hand, the standard deviation is smaller, resulting in more homogeneous compositional variations. The water content of RAC is also higher (average 192.44 kg/m³), in line with the characteristics of recycled aggregate, which has a greater absorption capacity. The proportion of fine aggregate is lower because some of the volume is replaced by recycled coarse aggregate (RCA), which has an average of 446.15 kg/m³ with very large variations. The minimum RCA value of 0 kg/m³ indicates the presence of a control sample without substitution, while the maximum value of 1,119 kg/m³ represents the full replacement of natural coarse aggregate.

The RAC dataset also contains physical parameters of RCA, such as the maximum aggregate size (average 18.9 mm), density (average 2437.91 kg/m³), which is generally lower than that of natural aggregates, and water absorption (WRCA) of an average of 4.08% with a maximum value reaching 8.8%, indicating high porosity due to residual old mortar. The use of superplasticizer is relatively lower, and its distribution tends to be skewed to the right, while metakaolin appears in some samples to improve the quality of the interfacial transition zone (ITZ). The test age variable has a wider range (1-90 days), reflecting a wider variation in curing age compared to NC. In terms of mechanical performance, the compressive strength of RAC has an average of 40.29 MPa with a maximum value of 78.1 MPa, exceeding NC, indicating that with appropriate mix design and RCA quality, RAC is capable of achieving or even exceeding the performance of normal concrete; its quartile distribution confirms that most samples are in the medium- to high-quality category.



Fig. 1. Data distribution. (A). Natural Concrete, (B). Recycled Aggregate Concrete

Fig. 1 illustrates the distribution patterns of input and output variables for the NC and RAC datasets. The histogram provides a visual representation of the frequency distribution for each parameter, revealing the characteristics and potential skewness in the data. This visualization is crucial for understanding the underlying data structure before model development.

C. Correlation Analysis

Correlation analysis was performed to identify relationships between input variables and between input variables and the target variable (compressive strength). The Spearman correlation method was used because it can capture both linear and non-linear monotonic relationships, making it more robust for datasets that may not follow a normal distribution.

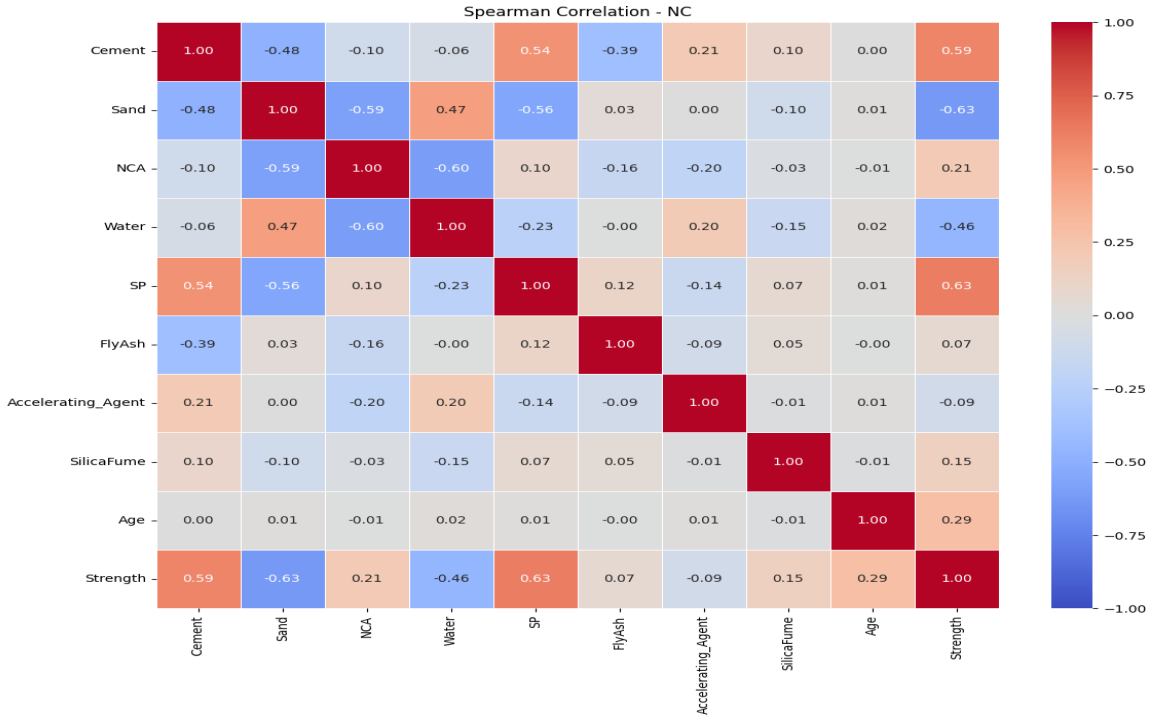


Fig. 2. Correlation analysis Normal Concrete

The correlation analysis results for the NC dataset (Fig. 2) revealed several important relationships. Cement content showed a strong positive correlation with compressive strength, indicating that increasing cement content generally increases concrete strength. Age also showed a significant positive correlation with compressive strength, confirming the well-known fact that concrete gains strength over time through the hydration process. Water content showed a negative correlation with compressive strength, in line with the fundamental principle that higher water-cement ratios reduce concrete strength. Natural coarse aggregate (NCA) showed a moderate correlation with compressive strength, while additional pozzolanic materials (fly ash, silica fume) showed varying degrees of influence depending on their dosage.

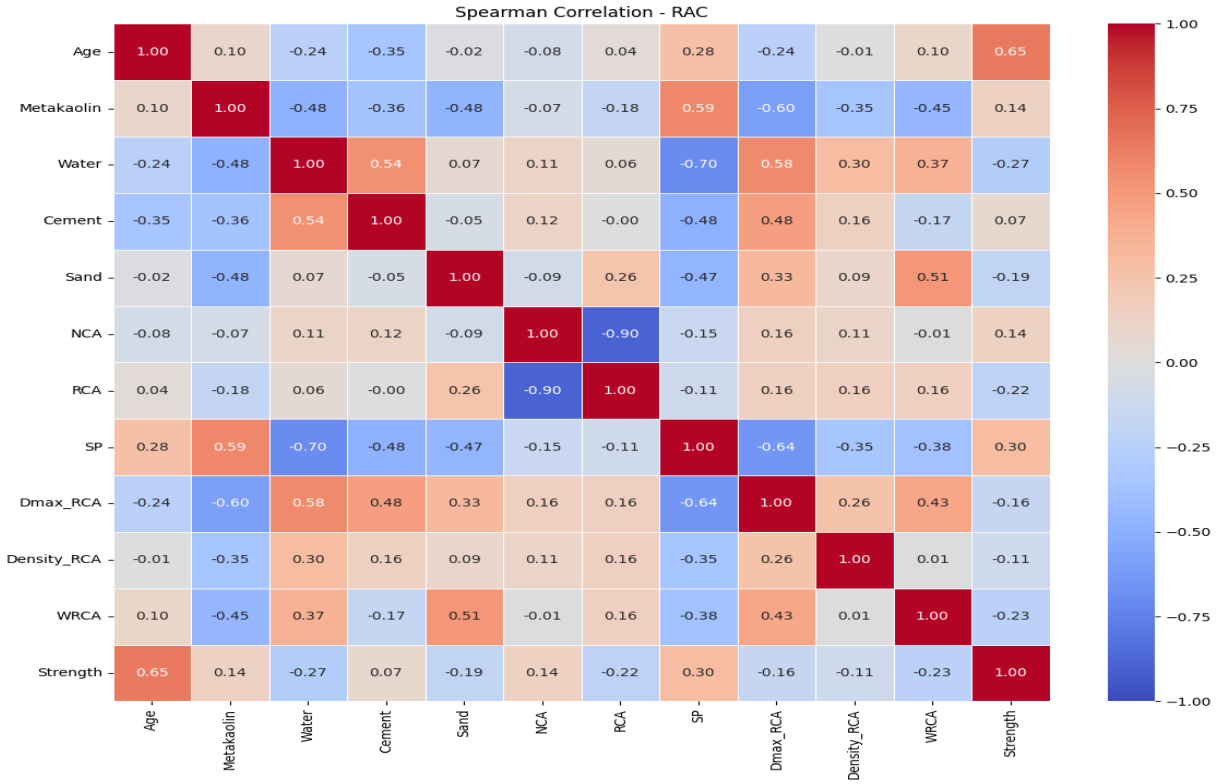


Fig. 3. Correlation analysis recycled aggregate concrete

In the RAC dataset (Fig. 3), the correlation pattern is more complex due to the presence of recycled coarse aggregate (RCA) and its associated properties. Cement content maintains a strong positive correlation with compressive strength, similar to NC. However, the RCA replacement ratio introduces additional complexity to the relationships between variables. RCA properties, including maximum size (Dmax_RCA), density (Density_RCA), and water absorption (WRCA), exhibit correlations with compressive strength, reflecting the inherent characteristics of recycled aggregate. The negative correlation between WRCA and compressive strength indicates that higher water absorption in RCA may adversely impact concrete strength, likely due to a reduced effective water-cement ratio and a weaker interfacial transition zone.

D. Machine learning models

1) Random Forest

Random Forest is an ensemble learning method developed from the Decision Tree algorithm with the principle of building multiple decision trees and combining their prediction results to improve model accuracy and stability. This method has two main sources of randomness, namely in the data and in the features. Data randomness is obtained through the bootstrap sampling technique, namely taking n random samples (with replacement) from the original dataset to form a new subset of training data, where each subset is used to train a decision tree. Meanwhile, feature randomness is done by randomly selecting a number of m features at each tree node, with m much smaller than the total number of features, and then from these features, the most optimal is selected to perform node separation. This process is repeated until the tree is fully grown, and the entire stage is replicated B times to produce B decision trees that form a forest. Mathematically, the prediction generated by the b-th tree for an input data x is expressed as:

$$\hat{y}_b(x) = T_b(x) \tag{1}$$

where $T_b(x)$ represents the prediction function of the b-th tree. The final prediction of the Random Forest is obtained by calculating the average of all B trees, which is formulated as:

$$\hat{y}(x) = \frac{1}{B}\sum_{b=1}^{B} \widehat{y_b}(x) \tag{2}$$

In classification, this aggregation can be done using a majority voting mechanism, while in regression, the average value is used. Furthermore, feature importance in Random Forest can be calculated based on impurity reduction, such as Gini impurity or Mean Squared Error (MSE). In general, the importance for the jth feature is formulated as:

$$FI(j) = \sum_{b=1}^{B} \sum_{t \in T_b(j)} \Delta MSE(t) \tag{3}$$

where $T_b(j)$ represents the set of all nodes in the b-th tree that use the j-th feature as a splitting variable, and $\Delta MSE(t)$ indicates the magnitude of the error reduction due to the splitting process at the t-th node. With the prediction aggregation approach and evaluation of the feature contribution, Random Forest is able to improve the model's generalization capability while providing an interpretation of the influence of each variable in the prediction process.

2) Extreme Gradient Boosting (XGBoost)

XGBoost is an extension of the Gradient Boosting Decision Tree (GBDT) algorithm designed to improve prediction accuracy, computational efficiency, and model regularization capabilities. Unlike conventional boosting, XGBoost optimizes the objective function using first- and second-order gradient approaches, resulting in a more stable learning process and faster convergence.

In general, the prediction at the tth iteration is expressed as the sum of the previous model and the new tree function:

$$\hat{y}_i^{(t)} = \hat{y}_i^{(t-1)} + f_t(x_i) \tag{4}$$

where $f_t(x_i)$ is the decision tree at iteration t. The objective function of XGBoost is formulated as a combination of the loss function and model complexity regularization:

$$Obj^{(t)} = \sum_{i=1}^{n} l\left(y_i, \hat{y}_i^{(t)}\right) + \sum_{k=1}^{t} \Omega(f_k) \tag{5}$$

With $l(\cdot)$ as the loss function and $\Omega(f_k)$ as the regularization function that controls the complexity of the tree. The regularization function is generally expressed as:

$$\Omega(f) = \gamma T + \frac{1}{2}\lambda \sum_{j=1}^{T} w_j^2 \tag{6}$$

where T is the number of leaves in the tree, w_j is the weight at the j-th leaf, and γ and λ are regularization parameters. This approach allows XGBoost to reduce the risk of overfitting by penalizing overly complex tree structures.

Optimization is performed using a second-order Taylor expansion of the loss function to obtain a computationally efficient quadratic approximation. Furthermore, XGBoost implements shrinkage techniques, column subsampling, and automatic missing data handling. With this combination, XGBoost demonstrates high and stable predictive performance on various regression and classification problems.

E. Model Training and Hyperparameter Optimization

The preprocessed dataset was divided into a training set (80%) and a testing set (20%) using stratified sampling based on the "Age" variable. Stratified sampling ensured that the age distribution in the training and testing sets was proportional and representative of the overall dataset. The random state was set at 42 to ensure reproducibility of the data division results. Hyperparameter optimization was performed using Randomized Search Cross-Validation (RandomizedSearchCV) with 5-fold cross-validation and 20 random sampling iterations. The R^2 score was used as an evaluation metric to maximize the model's predictive ability.

TABLE III. HYPERPARAMETER TUNING

Model	Hyperparameter	Search Space	Best Value
RandomForest	n_estimators	200, 400, 600, 800	400
	max_depth	None, 10, 20, 30	None
	bootstrap	True, False	False
XGBoost	n_estimators	300, 500, 700	700
	max_depth	3, 6, 9	6
	subsample	0.6, 0.8, 1.0	0.6
	learning_rate	0.01, 0.05, 0.1	0.05
LightGBM	n_estimators	300, 500, 700	700
	num_leaves	31, 50, 70	31
	colsample_bytree	0.6, 0.8, 1.0	0.8

The hyperparameter search space was defined to balance model complexity and computational efficiency. For Random Forest, the number of estimators ranged from 200 to 800 trees, with varying maximum depths, including infinite depth (None). For XGBoost and LightGBM, the number of estimators ranged from 300 to 700, with learning rates ranging from conservative (0.01) to more aggressive (0.1). Subsampling ratios were explored to prevent overfitting while maintaining predictive power.

F. Metrix Evaluation Model

Model performance is evaluated using three statistical metrics commonly used in regression analysis: the Coefficient of Determination (R^2), Mean Absolute Error (MAE), and Root Mean Squared Error (RMSE).

The Coefficient of Determination (R^2) measures how much variation in the target variable the model can explain. R^2 values range from 0 to 1, with values closer to 1 indicating better predictive ability. Mathematically, R^2 is formulated as:

$$R^2 = 1 - \frac{SS_{res}}{SS_{tot}} = 1 - \frac{\sum_{i=1}^{n}(y_i - \hat{y}_i)^2}{\sum_{i=1}^{n}(y_i - \bar{y})^2} \quad (7)$$

where SS_{res} is the sum of squared residuals and SS_{tot} is the total sum of squares. The Mean Absolute Error (MAE) represents the average absolute difference between the predicted and actual values. This metric provides an overview of the magnitude of the prediction error in the same units as the target variable (e.g., MPa for concrete compressive strength), making it easier to interpret in practice. MAE is formulated as

$$MAE = \frac{1}{n}\sum_{i=1}^{n}|y_i - \hat{y}_i| \quad (8)$$

Meanwhile, the Root Mean Squared Error (RMSE) measures the root of the average square of the difference between the predicted and actual values. Because it uses the squared error, RMSE imposes a greater penalty on errors with high deviations than MAE. The formula for RMSE is

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2} \quad (9)$$

These three metrics are calculated on both the training and testing data sets to detect potential overfitting or underfitting. Using multiple evaluation indicators simultaneously allows for a more comprehensive and objective assessment of model performance.

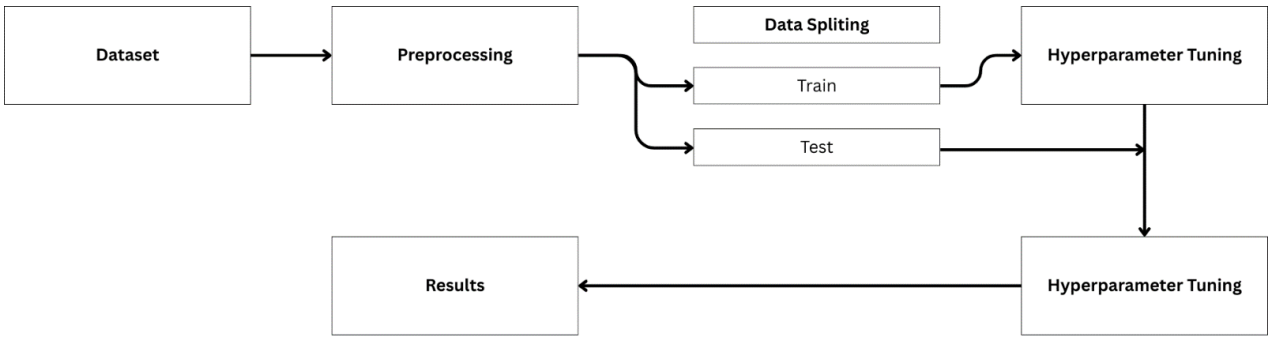


Fig. 4. Framework

The research framework shown in Fig. 4 illustrates the comprehensive and structured methodology flow, from the initial stage to the final documentation. The process begins with the collection of normal concrete (NC) and recycled aggregate concrete (RAC) datasets from various credible scientific sources, including material composition and compressive strength test results at several curing ages. Next, the data preprocessing stage is carried out, which includes handling missing values (using the median for missing values <30% and deleting columns with missing values ≥30%), removing duplicate data, detecting and eliminating outliers using the IQR method based on curing age groups, and encoding categorical variables into numeric types (NC=0, RAC=1). The exploratory data analysis (EDA) stage is then carried out through descriptive statistical calculations, Spearman correlation analysis, and visualization of distributions and relationships between variables to obtain a comprehensive understanding of the data characteristics before modeling.

The cleaned dataset was then divided into a training set (80%) and a testing set (20%) using stratified sampling based on the Age variable to maintain proportionality in the curing age distribution. The model development stage involved three tree-based algorithms, namely Random Forest, XGBoost, and LightGBM, which were selected for their ability to handle nonlinear relationships and their resilience to overfitting. Hyperparameter optimization was performed using RandomizedSearchCV with 5-fold cross-validation and 20 iterations, with R^2 as the objective metric. The best model was then evaluated using R^2, MAE, and RMSE on the training and test data, including performance analysis based on NC-RAC groups and curing age variations. Model interpretation was performed through feature importance and SHAP analysis to understand the contribution of each variable.

III. Result and Discussion

A. Model Evaluation

The performance of the three machine learning models (Random Forest, XGBoost, and LightGBM) was evaluated using three standard metrics: coefficient of determination (R^2), mean absolute error (MAE), and root mean square error (RMSE). The evaluation was performed on the training and testing sets to identify the model's generalization ability and potential overfitting. The model performance evaluation results are presented in Table IV.

TABLE IV. Model Performance Evaluation on Training and Testing Sets

Model	Train R^2	Test R^2	Train MAE	Test MAE	Train RMSE	Test RMSE
RandomForest	0.96	0.87	1.82	3.05	2.63	4.44
XGBoost	0.98	0.91	1.33	2.4	1.86	3.55
LightGBM	0.98	0.92	1.18	2.45	1.76	3.52

Table IV shows that all three models performed very well in predicting concrete compressive strength, with R^2 values in the testing set ranging from 0.87 to 0.92. LightGBM recorded the highest performance with an R^2 of 0.92, followed by XGBoost (0.91) and Random Forest (0.87). These high R^2 values indicate that more than 87% of the variation in concrete compressive strength can be explained by the input variables used in the model. In terms of error metrics, LightGBM and XGBoost demonstrated very competitive accuracy, with MAE testing values of approximately 2.45 MPa and 2.40 MPa, respectively, and RMSE values of 3.52 MPa and 3.55 MPa, respectively. Meanwhile, Random Forest had larger MAE and RMSE values of 3.05 MPa and 4.44 MPa. The relatively low error values in the two boosting models confirm that the resulting predictions are very close to the actual values, with an average error of around 2.4-3.0 MPa.

The differences in the performance of the three models are also related to their algorithmic characteristics. Random Forest builds decision trees independently through bootstrap sampling and combines it with an averaging method, thus providing stability but is less than optimal in capturing complex nonlinear patterns. In contrast, XGBoost and LightGBM build trees sequentially by minimizing errors from previous iterations, allowing for more precise capture of the relationship between concrete composition and compressive strength. LightGBM slightly outperforms XGBoost because it uses a more aggressive, leaf-wise tree growth strategy oriented towards maximum gain, although it potentially increases the risk of overfitting. With appropriate hyperparameter tuning, this risk can be controlled, making LightGBM the best model based on the highest R^2 testing (0.92) and the lowest RMSE (3.52 MPa), and it is the most suitable for applications predicting the compressive strength of both conventional and recycled aggregate-based concrete.

Fig. 5 presents a Taylor Diagram that provides a comprehensive representation of the performance of the three models (Random Forest, XGBoost, and LightGBM) in one polar graph. The Taylor Diagram displays three statistical metrics simultaneously: (1) the correlation coefficient indicated by the polar angle (azimuth angle), (2) the standard deviation indicated by the radial distance from the origin, and (3) the centered root mean square error (RMSE) indicated by the distance from the observation reference point.

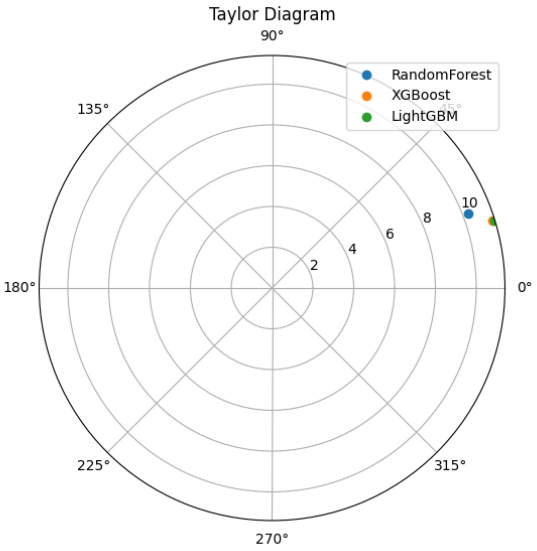


Fig. 5. Taylor diagram

In the Taylor Diagram, the reference point (observed data) is located on the horizontal axis with the observation standard deviation value. The closer the model's position to the reference point, the better its performance because it indicates: (1) the correlation coefficient is close to 1 (angle close to 0°), (2) the predicted standard deviation is close to the observation standard deviation, and (3) the minimum centered RMSE.

From Fig. 5, it can be observed that all three models are positioned relatively close to the reference point, indicating good predictive performance. LightGBM and XGBoost are closest to the reference point, showing very high correlation coefficients (>0.95) and standard deviations that are nearly identical to the observations. The close proximity of the two models confirms their performance is nearly equivalent, with a marginal advantage for LightGBM. Random Forest is slightly further from the reference point, with a slightly lower correlation coefficient and a larger centered RMSE, consistent with the lower R^2 and RMSE values in Table 4.

The predicted standard deviations, which are close to the observed standard deviations for LightGBM and XGBoost, indicate that both models are not only accurate in their mean predictions but also capture the variability in the data very well. This is important because it shows that the models do not underpredict or overpredict variance, which will result in reliable prediction intervals for practical applications. The Taylor diagram clearly visualizes the superiority of the gradient boosting algorithms (XGBoost and LightGBM) compared to the bagging approach (Random Forest) for the task of predicting concrete compressive strength.

B. Comparison of NC vs. RAC Performance

To evaluate whether machine learning models are capable of predicting the compressive strength of normal concrete (NC) and recycled aggregate concrete (RAC)

with comparable accuracy, a comparative analysis was conducted on subsets of the testing data based on concrete type. The best model, LightGBM, was used to generate predictions for each subset, and its performance was evaluated using the R^2 score metric. A summary of the comparison results is presented in Table 5.

TABLE V. COMPARISON PERFORMANCE

Group	R^2	Samples
NC	0.92	298
RAC	0.91	135

Table V shows that the LightGBM model is able to predict the compressive strength of normal concrete (NC) and recycled aggregate concrete (RAC) with a very high and almost identical level of accuracy. In the NC subset, the model produces an R^2 value of 0.92 from 298 test samples, while in RAC it obtained an R^2 of 0.91 from 135 samples. The very small difference, namely 0.01, confirms that the model's generalization ability is consistent across both types of concrete. Although the number of NC samples is larger than RAC, reflecting the dominance of normal concrete research in the literature, the RAC sample size is still sufficient for representative statistical evaluation, and the almost identical R^2 results indicate that the model is not biased by differences in dataset size.

This finding is significant because RAC generally has more complex characteristics than NC, such as variations in recycled aggregate quality, higher water absorption rates, and lower densities. Nevertheless, the model still captures the relationship between material composition and compressive strength with comparable accuracy. This indicates that the input variables used, including cement content, water content, aggregate content, superplasticizer content, RCA properties, and curing age, are sufficiently representative in describing the factors influencing compressive strength in both types of concrete.

The ability to predict RAC with NC-equivalent accuracy has significant practical implications. The machine learning approach can be utilized as a reliable tool in RAC mix design, which has traditionally tended to require a more intensive trial-and-error process. Furthermore, the consistent model performance strengthens support for the use of RAC as a more sustainable construction material. Further analysis of the residual distributions in both groups can provide additional validation regarding potential bias; if the errors are symmetrically distributed and centered around zero, this further confirms the robustness and generalizability of the model developed in this study.

Beyond predictive accuracy, the practical translation of the proposed model into an engineering decision-support tool involves several considerations. The trained LightGBM model imposes minimal computational demands, requiring only milliseconds to generate a prediction on standard office hardware, in marked contrast to the 28-day curing period required for conventional compressive strength testing; this characteristic renders near-instantaneous strength estimation feasible during the mix design stage. A form-based interface accepting readily available mix proportioning parameters cement, water, and aggregate content, superplasticizer dosage, and curing age and returning predicted compressive strength as output would allow engineers without machine learning expertise to operate the model directly. Within a practical workflow, the model is most appropriately positioned as a rapid screening and preliminary optimization tool employed iteratively during early-stage mix design, enabling engineers to evaluate multiple mix compositions before narrowing candidates for standard laboratory verification, rather than as a substitute for physical testing in final design approval. Several implementation challenges nevertheless remain, including the need for periodic recalibration as new mix design and material data become available, rigorous quality control of input data to prevent prediction errors arising from out-of-range or erroneous entries, and local validation against regional materials prior to application in contexts where recycled aggregate characteristics differ substantially from those represented in the training data. A pilot deployment conducted in collaboration with industry partners represents a promising avenue for addressing these challenges in future work.

C. Influence of Concrete Age

Curing age is one of the most important factors influencing concrete compressive strength due to the continuous cement hydration process over time. To evaluate the model's ability to predict compressive strength at various stages of concrete strength development, model performance was analyzed for each curing age group. The results are presented in Table 6.

TABLE VI. COMPARISON PERFORMANCE

Age	R^2	MAE	Samples
1	0.81	1.58	7
3	0.25	3.9	9
4	0.83	3.14	6
7	0.88	2.45	185
28	0.91	2.36	201
56	0.75	2.71	11
90	0.74	3.56	10

Table 6 shows an interesting variation in model performance across various curing age groups. The best performance was achieved at 28 days with an R^2 of 0.91 and an MAE of 2.36 MPa from 201 samples, followed by 7 days with an R^2 of 0.88 and an MAE of 2.45 MPa from 185 samples. The high accuracy at these two ages can be explained by the dominant data representation, as 7 and 28 days are the most common compressive strength testing standards in the literature and industrial practice. Furthermore, at these ages, the cement hydration process has reached a relatively stable state, so the relationship between material composition and compressive strength becomes more consistent. The large number of samples also provides sufficient information for the model to optimally learn the pattern.

At very early ages, namely 1 and 4 days, the model showed moderate to good performance with R^2 of 0.81 and 0.83, respectively, despite the very limited number of samples (7 and 6 samples). The relatively low MAE value at 1 day (1.58 MPa) indicates that the predictions are still quite accurate in absolute terms, although data variation causes the R^2 to be lower than at 28 days. This capability is important in the context of quality control, especially for evaluating the early strength of concrete and making

decisions such as when to remove formwork (stripping formwork).

The lowest performance occurred at 3 days with an R^2 of only 0.25 and an MAE of 3.9 MPa. This low accuracy is likely due to the very limited number of samples (9 samples), so the model did not obtain a sufficiently robust pattern. Furthermore, 3 days is a critical transition phase in the hydration process, where compressive strength development is strongly influenced by cement type, curing temperature, and environmental conditions. The heterogeneity of data sources from various literatures also has the potential to increase variability, making predictions less stable in this age group.

At later ages, namely 56 and 90 days, there was a decrease in performance with R^2 of 0.75 and 0.74, respectively, which can be attributed to the limited number of samples (11 and 10 data) and the influence of long-term factors such as prolonged curing, carbonation, and subsequent microstructural development that may not be fully represented in the model features. Although the MAE at 56 days is still relatively low (2.71 MPa), the MAE value at 90 days increases to 3.56 MPa, indicating greater prediction uncertainty at very late ages. Overall, the results of the analysis of the effect of curing age indicate that the machine learning model is most reliable for predicting concrete compressive strength at standard test ages (7 and 28 days) that have good data representation. For very early ages (<7 days) or very late ages (>56 days) with a limited number of samples, model predictions need to be interpreted more cautiously and should be accompanied by wider confidence intervals. These results provide important guidance for the practical application of the model: optimal use is at 7-28 days of age for mix proportion design and quality control, while for extreme ages it needs to be combined with laboratory testing or additional data.

D. Feature Importance and Interpretability

To understand the factors that most influence the prediction of concrete compressive strength, a feature importance analysis was performed using the built-in feature importance of the best LightGBM model and a SHAP (SHapley Additive exPlanations) analysis for a more in-depth interpretation. The results of the feature importance analysis are presented in Fig. 6, and the SHAP analysis is presented in Fig. 7.

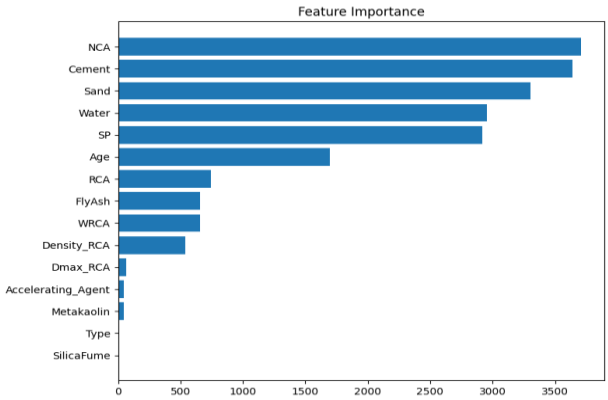


Fig. 6. Feature Importance

Fig. 6 displays the feature importance ranking, indicating the relative contribution of each input variable to the LightGBM model prediction. Feature importance is calculated based on the total gain generated by each feature in the splitting process across all decision trees in the ensemble. Features with high importance indicate that they consistently make a large contribution to reducing the model's prediction error. Based on the feature importance analysis, the curing age (Age) shows the highest importance, confirming the critical role of time in concrete compressive strength development through the cement hydration process that continues over time. This is consistent with cement hydration theory, which suggests that concrete strength develops logarithmically over time, with a significant increase in the early weeks and a gradual slowdown later in life. The high importance of age also reflects that the model has successfully captured the temporal pattern in concrete strength development.

Cement content showed very high importance, ranking second or third depending on the data subset analyzed. This makes sense because cement is the primary active component in concrete responsible for strength development through hydration. The relationship between cement content and compressive strength is generally positive and nearly linear within a certain range, making cement a very strong and consistent predictor. Water content also showed significant importance, which can be explained by its role in determining the water-cement ratio, one of the most important parameters in concrete mix proportioning design. A lower water-cement ratio generally produces concrete with higher compressive strength due to lower porosity and a denser microscopic structure. The model successfully captured this negative relationship between water content and compressive strength.

Natural coarse aggregate (NCA) and recycled coarse aggregate (RCA) showed moderate importance. For RAC, physical properties of RCA such as density (Density_RCA), water absorption (WRCA), and maximum size (Dmax_RCA) also contributed to the prediction, reflecting the influence of recycled aggregate quality on the mechanical performance of concrete. A high WRCA may indicate high porosity and lower aggregate quality, which negatively impacts compressive strength. Superplasticizer (SP) showed relatively lower importance compared to the main material components, which is consistent with its role as an admixture that affects workability more than direct strength. However, SP can have an indirect effect on compressive strength by allowing water reduction without compromising workability, thereby increasing the effective water-cement ratio.

Fig. 7 displays a SHAP summary plot that provides a comprehensive visualization of the influence of each feature on the model's predictions for each individual observation. Unlike conventional feature importance, which only presents a global ranking of influence, SHAP values can show both the magnitude and direction of each feature's contribution to the model's output.

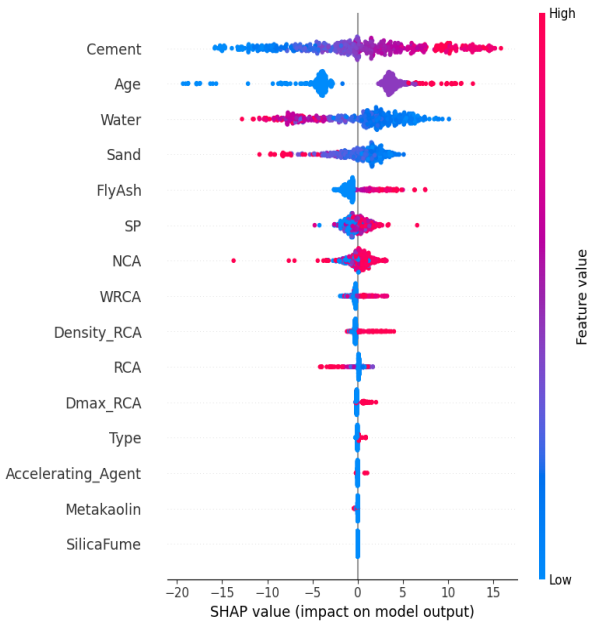


Fig. 7. SHAP analysis

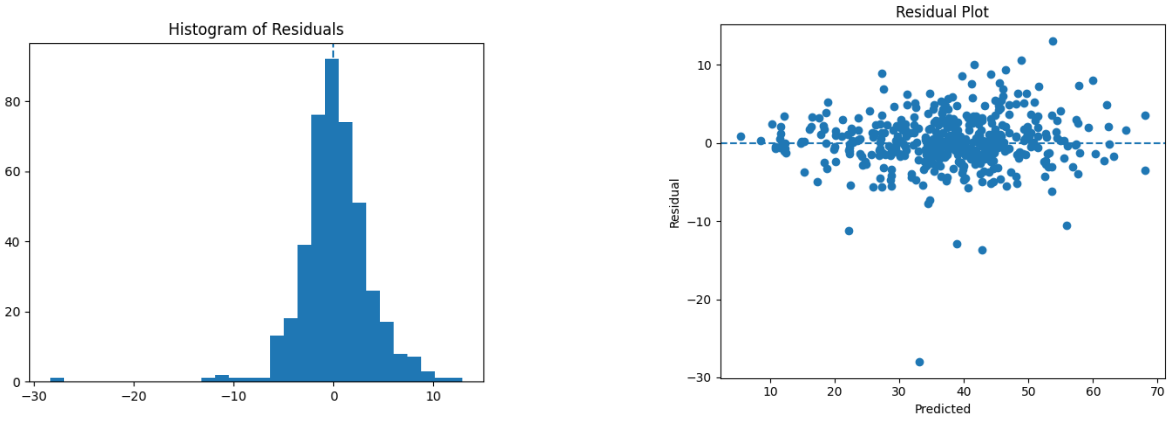
Each point on the plot represents a single sample, with the horizontal position indicating the SHAP value (contribution to the compressive strength prediction) and the color indicating the feature value (red for high values and blue for low values). This approach allows for a more in-depth interpretation of how the model makes decisions at both the individual and global levels.

The analysis results show that age is the most dominant feature, where high curing age values consistently provide a large positive contribution to the predicted compressive strength, confirming a strong positive relationship between concrete age and strength development. Cement also shows an almost monotonic positive pattern, with high cement content increasing the predicted compressive strength, although the effect can be influenced by the water-cement ratio. Conversely, water tends to provide a negative contribution when its value is high, confirming that excess water has the potential to reduce compressive strength, although its effect remains contextual depending on the combination of other variables in the mixture.

For aggregate variables, both NCA and RCA show a more complex and contextual contribution pattern, reflected in the fairly wide distribution of SHAP values due to the interaction between proportion, quality, and aggregate substitution ratio. Specifically in RAC, high WRCA values tend to contribute negatively to the prediction of compressive strength, in accordance with the characteristics of highly porous recycled aggregates. The combination of feature importance and SHAP analysis not only improves model interpretability but also provides practical guidance in mix design optimization, such as controlling the water-cement ratio, using adequate cement content, optimal curing, and selecting recycled aggregates with low water absorption to achieve maximum compressive strength.

E. Error Analysis

Error analysis was performed to understand the characteristics and distribution of model prediction errors, identify systematic patterns in the errors, and evaluate the underlying assumptions of the regression model. Error visualizations are presented in Fig.s 8 and 9.



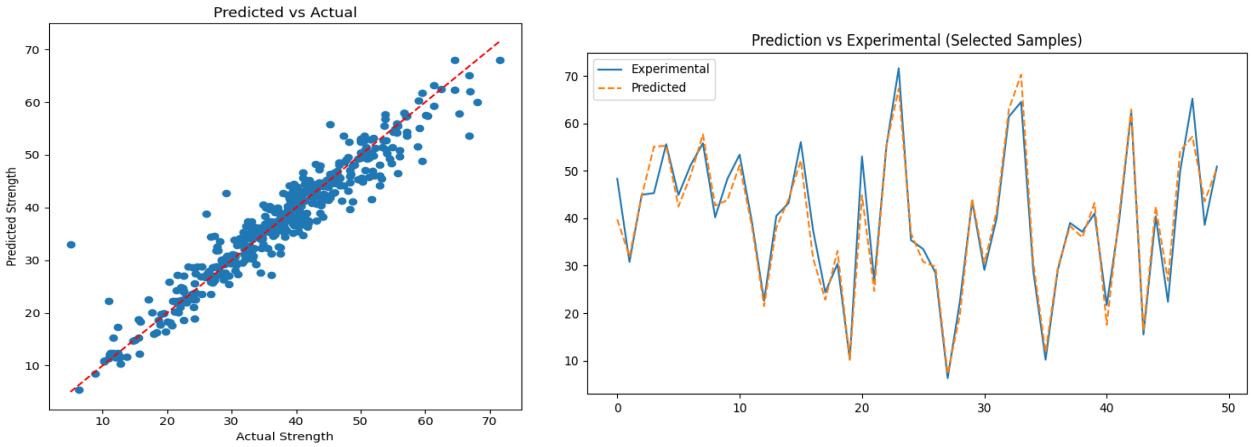
A **B**

Fig. 8. (A) histogram residual, (B) scatter plot residual vs predicted values

Fig. 8 displays two types of error visualizations: (A) a residual histogram and (B) a scatter plot of residuals vs. predicted values. The residual histogram (Fig. 8A) shows the frequency distribution of the residuals (the difference between actual and predicted values). The ideal residual distribution for a regression model is a normal (Gaussian) distribution centered around zero, indicating that the errors are random and unbiased. From Fig. 8A, it can be observed that the residual distribution approaches a normal shape with a peak around zero and a relatively symmetric shape. This indicates that the model does not have significant systematic bias in predictions, there is no tendency to consistently over- or under-predict compressive strength. Most of the residuals are concentrated within the ±5 MPa range, with only a few outliers having very large absolute errors. The near-normal shape of the distribution also confirms that the assumption of homoscedasticity (constant error variance) is largely met.

The scatter plot of residuals vs. predicted values (Fig. 8B) provides additional insight into error patterns. This plot displays residuals on the Y-axis and predicted values on the X-axis. The ideal pattern is a random scatter around the horizontal line y=0, with no clear pattern or trend. From Fig. 8B, it can be observed that residuals are spread relatively randomly around zero, with some observations in the 20-30 MPa predicted range showing a relatively

constant spread and distributed around zero, indicating good predictive performance in the low compressive strength range. The 30-50 MPa predicted range is the range with the largest number of samples (based on point density), and the residuals show a very consistent spread. There is no clear funnel pattern or trend, confirming that the model is very reliable in the most common compressive strength range. The predicted range of >50 MPa has a tendency for slight underprediction (positive residuals) in some samples with very high compressive strength.



A **B**

Fig. 9. (A) Scatter plot actual vs predicted strength, (B) line plot comparison of prediction and actual strength

Fig. 9 presents two additional error visualizations: (A) a scatter plot between predicted and actual values and (B) a line plot comparing predicted and actual values for a selected sample. The scatter plot in Fig. 9A is a fundamental method for evaluating regression models, with observed values on the X-axis and predicted values on the Y-axis. The diagonal line (y = x) represents a perfect prediction condition. The closer the data points are to this line, the higher the model accuracy. The graph shows that most of the points are concentrated very close to the diagonal line, confirming the R^2 value of 0.92 previously described. In the compressive strength range of 20-70 MPa, which is most common in construction practice, the point deviation is very small, indicating that the model is highly reliable over the most practically relevant strength range.

A more detailed analysis of the scatterplot reveals several important patterns. In the compressive strength range of 10-30 MPa, the points remain close to the diagonal line without any systematic overprediction or underprediction patterns. In the 30-50 MPa range, which has the highest data density, the points closely follow the diagonal line, reflecting optimal model accuracy. Meanwhile, at compressive strengths >60 MPa, a slight underprediction trend is observed, with several points falling below the diagonal line. This is likely due to the limited number of samples in the training data at these extremes.

Fig. 9B displays a line plot comparing predicted and actual values across a number of random samples from the testing set. The graph shows two linessolid lines for actual values and dashed lines for predictionswith the sample index as the X-axis and the compressive strength (MPa) as the Y-axis. Both lines exhibit a very similar pattern, with peaks and valleys appearing at similar locations. This indicates that the model consistently captures fluctuations in compressive strength values. The vertical differences between the lines are relatively small for most samples, while larger deviations only appear at specific points corresponding to previously identified outliers. It is important to note that these deviations are not systematic, as the model returns to the actual pattern in subsequent samples.

The error analysis using scatter plots and line plots confirms that the LightGBM model has excellent predictive performance with random and unbiased errors. The consistency of these results, which is also in line with the previous residual analysis, indicates the absence of systematic error patterns that indicate fundamental problems with the model. In practical applications, the model can reliably predict concrete compressive strengths in the range of 20-60 MPa with a high level of confidence and relatively small deviations (approximately ±3-4 MPa for most samples). However, for very unusual compositions or target compressive strengths >70 MPa, the prediction results should be validated through laboratory testing or supplemented with additional safety margins in the structural design.

The present evaluation is based on a held-out test split (20%) derived from the same combined dataset used for model training, rather than an independent external dataset or newly cast physical specimens; this constitutes a limitation common to machine learning studies of concrete properties that rely on literature-compiled data. The underlying NC and RAC datasets, however, were each aggregated from multiple independent scientific publications, such that the training and testing samples inherently span a range of mix designs, material sources, and testing conditions. This heterogeneity partially compensates for, though does not substitute, formal external validation. Strengthening confidence in the generalization capability of the proposed model for practical engineering applications therefore requires validating the model against an independent dataset

excluded from training and hyperparameter tuning, as well as against experimentally cast concrete specimens incorporating locally sourced recycled aggregates, prior to recommending the model for field deployment.

IV. Conclusion

This study successfully developed and evaluated machine learning models based on tree-based algorithmsRandom Forest, XGBoost, and LightGBMto predict the compressive strength of recycled aggregate concrete (RAC) and normal concrete (NC). The analysis was conducted on 2165 samples (1600 NC and 565 RAC) that had undergone systematic preprocessing stages. In general, all three models showed excellent predictive performance on the test data. LightGBM provided the best results with an R^2 value of 0.92, MAE of 2.45 MPa, and RMSE of 3.52 MPa, followed by XGBoost ($R^2 = 0.91$) and Random Forest ($R^2 = 0.87$). The gradient boosting approach proved more effective than the bagging method in capturing the nonlinear relationship between material composition and concrete compressive strength.

The model's generalization capability also demonstrated high consistency across both types of concrete. LightGBM was able to predict the compressive strength of both normal concrete ($R^2 = 0.92$) and recycled aggregate concrete ($R^2 = 0.91$) with very little difference. This indicates that the model has robust generalization capability and that the input variables used are sufficiently representative in describing the factors affecting compressive strength. Analysis based on curing age showed that the model's performance was most optimal at 7 days ($R^2 = 0.88$) and 28 days ($R^2 = 0.91$), while accuracy decreased slightly at very early (<7 days) and very late (>56 days) ages due to limited data and the complexity of the hydration process at that stage.

The results of feature importance and SHAP analysis indicate that curing age (Age), cement content (Cement), and water content (Water) are the most dominant factors in determining the compressive strength of concrete. In RAC concrete, additional parameters such as recycled aggregate water absorption (WRCA) also provide a significant contribution. The identified relationship shows that age and cement have a positive effect on increasing compressive strength, while water and WRCA tend to have a negative effect. Residual analysis indicates that prediction errors are random, unbiased, and mostly within the range of ±5 MPa, with a slight tendency to underpredict in very high-quality concrete (>70 MPa).

Practically, the developed model can be relied upon to predict compressive strength in the range of 20-60 MPa with a good level of confidence (±3-4 MPa for most samples). This model has the potential to be integrated into mix proportioning and quality control design systems to accelerate compressive strength estimation without having to wait for 28 days of laboratory testing. In addition, the model's success in predicting RAC with NC-equivalent accuracy provides an important contribution to sustainable construction practices. Going forward, the development of a broader dataset, the addition of new variables, the exploration of deep learning approaches, experimental validation, and the development of web-based or mobile applications are further research directions.

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