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Optimized XGBoost-Based Framework for Robust Prediction of the Compressive Strength of Recycled Aggregate Concrete Incorporating Silica Fume, Slag, and Fly Ash

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ABSTRACT: Accurately predicting the compressive strength of recycled aggregate concrete (RAC) incorporating supplementary cementitious materials (SCMs) remains a critical challenge due to the heterogeneous nature of recycled aggregates (RA) and the complex interactions among multiple binder constituents. This study advances the field by developing the most extensive and rigorously preprocessed database to date, which comprises 1243 RAC mixtures containing silica fume, fly ash, and ground-granulated blast-furnace slag. A hybrid, domain-informed machine-learning framework was then proposed, coupling optimized Extreme Gradient Boosting (XGBoost) with civil engineering expertise to capture the complex chemical and microstructural mechanisms that govern RAC performance. Systematic grid-search optimization ($n_estimators = 50$, $learning_rate = 0.2$, $max_depth = 7$) produced superior predictive accuracy (training $R^2 = 0.9923$, testing $R^2 = 0.937$; $MAE = 2.378$ MPa; $RMSE = 3.591$ MPa), which outperformed Extra Trees, Light Gradient Boosting, and traditional regressors. Beyond prediction, model interpretability was achieved using Shapley additive explanations and partial dependence analyses, which revealed curing age as the dominant strength driver, while water-to-binder ratio and recycled aggregate water absorption exhibited strong negative influences. Three-dimensional interaction plots further demonstrated how optimal superplasticizer dosages reduce the strength loss associated with high recycled aggregate content. In summary, this work provides a novel, explainable, and data-driven framework that achieves high predictive accuracy with mechanistic transparency and offers a powerful, interpretable tool for the design and optimization of sustainable RAC mixtures.

KEYWORDS: Compressive strength; machine learning; modeling; recycled aggregate concrete; supplementary cementitious materials

1 Introduction

Concrete remains one of the most extensively utilized materials in construction due to its notable advantages, including high strength, durability under corrosive conditions, cost-effectiveness, and ease of application. However, because natural aggregates (NA) constitute a primary component of concrete, the widespread use of concrete raises significant environmental concerns. These include the depletion of natural aggregate resources, substantial CO₂ emissions, and the accumulation of demolition waste leading to landfill overcapacity [1–3]. To address these issues, various alternatives have been explored, such as the incorporation of innovative materials (e.g., elastomeric composites), supplementary cementitious materials



(SCMs), alkali-activated materials (AAMs), and recycled constituents like glass particles [4–7]. Among these strategies, the reuse of recycled aggregate concrete (RAC) sourced from demolished reinforced concrete (RC) structures has garnered considerable attention. Utilizing RCA offers several environmental benefits: it reduces CO₂ emissions, conserves natural resources, minimizes construction and demolition waste [8–11], alleviates landfill space demands, and mitigates the broader environmental impacts associated with discarded concrete [12–14].

To conduct a systematic investigation of studies on RAC, the review began with the formulation of a precise research question: How can interpretable machine learning (ML) techniques be utilized to examine the role of SCMs in enhancing the mechanical strength of RAC, with a specific focus on silica fume, slag, and fly ash? This question guided the identification of relevant search terms, including: (“Recycled aggregate (RA)” and “concrete”) and (“compressive strength (CS)” or “mechanical properties” or “structural performance”) and (“optimization” or “prediction” or “modeling” or “machine learning”). A comprehensive search within the Web of Science Core Collection (<http://Clarivate.Com/Academia-Government/Scientific-and-Academic-Research/Research-Discovery-and-Referencing/Web-of-Science/Web-of-Science-Core-Collection/>, accessed on 11 November 2025) yielded 171 articles published between 2018 and March 2025. To refine the dataset, exclusion criteria were implemented, restricting the selection to English-language publications. The literature selection process is depicted in Fig. 1. To further enhance relevance, a secondary screening based on title significance (Fig. 1) reduced the pool to 18 key studies, which will be analyzed in detail in the following paragraphs.

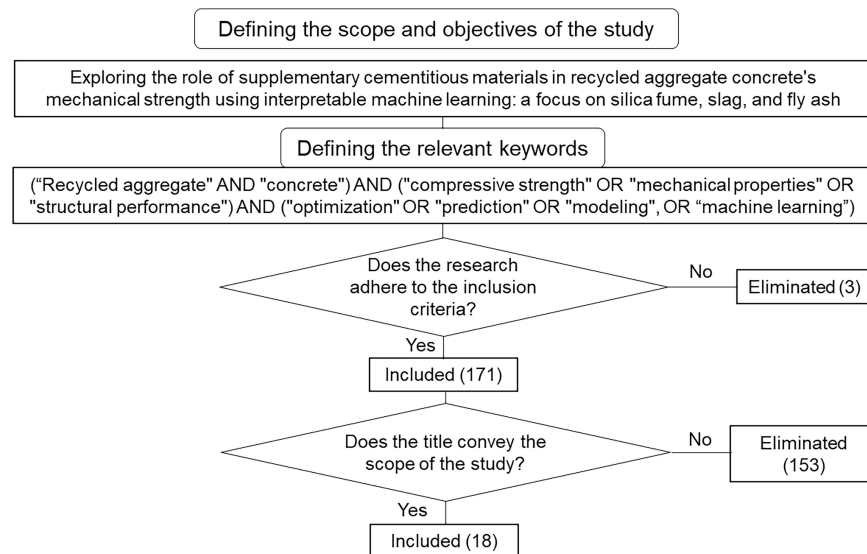


Figure 1: The systematic methodology employed for literature collection. (Inclusion Criteria: Only scientific articles written in English)

RAC has gained prominence as a sustainable alternative in modern construction due to its potential to mitigate environmental impacts by reducing both carbon emissions and construction waste. As its adoption increases, reliable prediction of its CS becomes essential for ensuring structural integrity. To this end, ML has been increasingly employed for modeling the mechanical behavior of RAC with high precision. Traditional empirical and semi-empirical models for RAC compressive strength prediction, developed through regression analysis on experimental datasets, have achieved moderate accuracy with correlation coefficients typically ranging from 0.50 to 0.80 [15–19]. However, these approaches face significant

limitations, including poor generalization beyond specific mix proportion ranges, inability to capture complex nonlinear interactions among multiple parameters, and sensitivity to dataset bias and experimental variability. These constraints are particularly pronounced in RAC systems incorporating SCMs, where multi-parameter interactions become increasingly complex and difficult to model through conventional regression techniques.

In the literature, a wide range of ML techniques, including regression-based models, neural networks, and ensemble learners, has been applied to capture the nonlinear relationships governing RAC properties. Unlike empirical equations that rely on simplified mathematical relationships, ML algorithms can effectively learn from heterogeneous datasets and identify complex patterns that govern material behavior. Among these, ensemble-based boosting approaches, particularly XGBoost, Gradient Boosting, and their hybrid variants, have consistently demonstrated the highest accuracy with correlation coefficients typically exceeding 0.94–0.99 due to their robustness and ability to model complex material interactions [20–24]. This superior performance stems from their capacity to handle nonlinear interactions among parameters such as water-binder ratio, recycled aggregate water absorption, superplasticizer content, and SCM compositions (relationships that conventional empirical models struggle to adequately represent). These models outperform conventional predictive methods across diverse datasets and input parameters, underscoring their suitability for RAC applications. Recent studies have demonstrated the potential of DL in predicting the mechanical performance of sustainable concretes. A chemistry-informed convolutional neural network (CNN) optimised with the enhanced bat algorithm accurately predicted the compressive strength of geopolymers using key mix and curing parameters ($R^2 = 0.997$ for training, 0.978 for testing) [25]. Likewise, a hybrid CNN–long short-term memory (LSTM) model with an attention mechanism and enhanced firefly optimisation effectively estimated the compressive strength of rubberised concrete ($R^2 = 0.967$ for training, 0.943 for testing) [26], as listed in Table 1. Both models, supported by SHapley Additive exPlanations (SHAP) analysis, identified critical mix parameters influencing strength, highlighting DL as a powerful and cost-effective tool for sustainable concrete design. Furthermore, modern ML frameworks offer interpretability through techniques such as SHAP and partial dependence plots, providing both predictive accuracy and mechanistic insights that empirical models typically cannot deliver. Despite these advancements, existing studies continue to face limitations related to dataset quality, model generalization, and the integration of parameters associated with SCMs. These challenges highlight the need for more comprehensive databases, robust model selection strategies, and interpretable ML frameworks that can reliably account for RAC's inherent heterogeneity.

Table 1: Comparison of various ML models used to predict RAC's compressive strength

Ref.	Database size	Input features	Input number	Used SCMs	Used ML models	Best ML model	Statistical index			
							RMSE	MAE	MAPE	R^2
Peng and Unluer [19]	607	PC, SP, W/C, SA, WA, ADRA, RA, NA	8	PC	GWO-SVR, ANN, SVR, PSO-SVR	GWO-SVR	4.549	2.401	6.608	0.9056

(Continued)

Table 1 (continued)

Ref.	Database size	Input features	Input number	Used SCMs	Used ML models	Best ML model	Statistical index			
							RMSE	MAE	MAPE	R ²
Yang et al. [21]	289	PC, CT, AG, FA, BF, SF, W/C, W/B, NA, RA, ADNA, ADRA, WA, RR, SA, MPS of RA, FMRA	18	PC, FA, SE, BF	RF, Bagging, RT, ANN	RF	4.516	3.523	NA	0.969
Das et al. [24]	465	PC, W/B, SA, NA, RA, Vf, Lf, Df	8	PC	GBRT, SVM, AdaBoost, BPANN	GBRT	3.872	2.624	5.277	0.924
Dabiri et al. [27]	234	PC, W/C, NA, FA, RA, FRA, SA, SP/C, AG	9	PC, FA	NLR, LR, RF	NLR	3.14	2.18	7.41	0.98
Duan et al. [28]	209	WA, WCR, FA, RCA, NCA, WTMR	6	PC, FA	ICA-XGBoost, ICA-SVR, ICA-ANN, ICA-ANFIS	ICA-XBoost	1.479	1.147	0.031	1.000
Pazouki et al. [29]	310	PC, W/C, RA, SA, NA, Binder, AG	7	PC, FA	ANN, RBFNN	ANN	3.2	2.4	NA	0.97
Pal et al. [30]	905	Nominal coarse aggregate size, RA, Rubber, Fiber, W/C	5	PC	ANN, VR, Cat-Boost, DT, RF, XGB, GBoost, KNN, SVR, AdaBoost, LR, Lasso, RR	ANN	5.651	4.046	22.023	0.896
Khan et al. [31]	638	W/C, ACR, RA, NSRA, ADRA, WA, Los Angeles index of RA	8	PC	DT, GB, Bagging	Bagging	5.693	4.258	NA	0.92

(Continued)

Table 1 (continued)

Ref.	Database size	Input features	Input number	Used SCMs	Used ML models	Best ML model	Statistical index			
							RMSE	MAE	MAPE	R ²
Hossein zadeh et al. [32]	500	W/C, PC, FA, RA, SA, NA, AG	7	PC, FA	XGBoost, Lasso, FR, KNN, DT, SVM, LGBost	XGBoost	NA	NA	NA	0.95
Huang et al. [33]	337	PC, AG, SP, Binder, W/B, RA, AS, NA, Cube size	9	PC, FA	AdaBoost, GEP, DT, SVM, KNN	ANN	3.07	1.93	NA	0.93
Miao et al. [34]	980	PC, FA, FB, SF, SP, W/B, W/C, FRA, SA, RA, NA, calcined caly	12	PC, FA, SF, BF	SSA-BPNN, SSA-RFR	SAA-XGBoost	4.7339	3.4897	NA	0.9353
Liu et al. [35]	1305	PC, W/C, SA, NA, FA, SGC, AG, RR, WA, MPSRA	10	PC, FA	XGBoost, BPANN, GPR, CART, RF, GBDT	XGBoost	2.030	NA	3.9	0.979
Wang et al. [36]	522	Cement strength grade, W/C, PC, SA, Sand ratio, MPSNA, WA, ADRA, RR, FA/C, AG	14	PC, FA	XGBoost, GPR, SVR, DT, RF, BPNN	XGBoost	2.710	1.523	NA	0.965

In light of the limitations identified in previous studies, the present research introduces a comprehensive, data-driven, and interpretable framework for predicting the CS of RAC that incorporates SCMs. The principal innovation of this work is the development and thorough preprocessing of the largest and most heterogeneous database to date, which includes 1243 RAC mixtures containing silica fume, fly ash, and ground-granulated blast-furnace slag. Building upon this foundation, an advanced hybrid machine-learning approach was established by integrating gradient-boosting algorithms, particularly an optimized

Extreme Gradient Boosting (XGBoost) model, with civil engineering domain expertise to capture the nonlinear chemical and microstructural interactions governing RAC performance. Through systematic hyperparameter tuning and interpretability analyses based on SHAP and partial dependence plots, the study not only achieves state-of-the-art predictive accuracy (testing $R^2 = 0.937$) but also provides mechanistic insights into the relative influence of mix parameters such as curing age, water-to-binder ratio, and recycled aggregate water absorption. The combination of robust predictive modeling, physical interpretability, and large-scale data integration represents a significant advancement over existing empirical and black-box ML models. Hence, this research offers both a methodological contribution through the development of a validated, explainable gradient-boosting framework and a practical contribution by providing an interpretable predictive tool that can guide the design of sustainable RAC mixtures with enhanced reliability.

2 Database of the Study

2.1 Variables of the Study

The performance of a ML model is highly dependent on the quality and comprehensiveness of its training dataset [37]. To enhance the accuracy of predictions, a well-curated and extensive database is essential. The database was systematically constructed through comprehensive literature searches of major academic databases, including Web of Science, Scopus, and Google Scholar, using targeted keywords such as “RAC”, “SCMs”, “SF”, “FA”, “slag”, “CS”, and their combinations. Only peer-reviewed experimental studies reporting complete mix design details and standardized compressive strength measurements under controlled laboratory conditions were considered for inclusion. Inclusion criteria required: (i) complete reporting of all mix design parameters, (ii) specified curing age and conditions, (iii) adherence to standard testing procedures (ASTM, EN, or equivalent), and (iv) clear documentation of RA properties. Exclusion criteria encompassed: (i) non-standard curing conditions (elevated temperature, accelerated curing), (ii) non-standard testing procedures deviating from established codes, and (iii) duplicate datasets from identical research programs.

In this study, a dataset comprising 1243 RACs mix designs including PC, BF, SF, and FA under standard curing conditions was compiled from 39 independent experimental studies (see [Appendix A, Table A1](#)). These sources were meticulously selected based on the richness of their data and their alignment with the study's objectives, ensuring that the dataset remains both robust and relevant. This rigorous curation process established a high-quality database that supports the reliability of the ML model training and validation procedures. Maintaining high-quality data is critical for validating the model's predictive reliability and practical applicability. The dataset includes 14 input variables and one target variable (CS). [Table 2](#) presents a detailed statistical summary of the key parameters influencing the mechanical behavior of RAC, encompassing 14 independent variables and one dependent variable (i.e., the CS). The binder components, PC, SF, FA, and BF, exhibit significant variability, with PC showing the highest mean (364.57 kg/m^3) and a substantial standard deviation (85.79 kg/m^3), indicating diverse cement dosages across mix designs. The inclusion of SCMs, such as SF (mean: 3.02 kg/m^3) and FA (mean: 51.64 kg/m^3), suggests a wide range of blended cementitious systems. The WB varies between 0.28 and 0.69, with a mean of 0.44 and a standard deviation of 0.09, reflecting its critical role in workability and strength development. Aggregate properties exhibit notable dispersion, particularly for NA, which has a high standard deviation (401.79 kg/m^3), and RA, which varies from 0 to 1240 kg/m^3 with a mean of 459.42 kg/m^3 , highlighting different levels of aggregate replacement. The RA's WA remains relatively stable (mean: 5.01%, std. dev.: 1.15%), reinforcing the known porosity concerns of RA. The CS demonstrates a broad range from 4.76 to 108.51 MPa (mean: 39.86 MPa, StdDev.: 18.26 MPa), capturing the inherent variability in RAC performance. This extensive variation in material composition and mechanical properties underlines the complexity of RAC mix design and suggests

that ML models could be instrumental in identifying nonlinear relationships and optimizing mixtures for enhanced performance.

Table 2: Description and fundamental statistical measures of the study's variables

#	Variable	Definition	Unit	Min.	Max.	Mean	Std. Dev.
1	PC	Portland cement content	kg/m ³	78.00	554.70	364.57	85.79
2	SF	Silica fume	kg/m ³	0.00	100.00	3.02	10.51
3	FA	Fly ash content	kg/m ³	0.00	332.80	51.64	72.47
4	BF	Ground granulated blast furnace slag	kg/m ³	0.00	214.50	9.38	34.06
5	RM	Reactivity modulus of cementitious materials, Eq. (1)	–	1.50	4.22	3.17	0.54
6	SM	Silica modulus of cementitious materials, Eq. (2)	–	1.26	10.45	2.30	0.95
7	AM	Alumina modulus of cementitious material, Eq. (3)	–	0.74	12.73	2.87	2.09
8	WB	Water-to-binder ratio	–	0.28	0.68	0.44	0.09
9	SP	High range water reducer content	kg/m ³	0.00	12.10	1.34	2.47
10	SA	Fine natural aggregate content	kg/m ³	203.70	1105.00	728.24	171.22
11	NA	Natural coarse aggregate content	kg/m ³	0.00	1366.00	505.67	401.79
12	RA	Recycled coarse aggregate content	kg/m ³	0.00	1240.00	459.42	382.04
13	WA	RCA Water absorption	%	2.20	7.80	5.01	1.15
14	AG	Age of curing	days	1	91	32	30
15	CS	Compressive strength	MPa	4.76	108.51	39.86	18.26

The dataset was curated to include the detailed oxide compositions of both the base cement and all SCMs, forming the basis for computing the concrete's equivalent cementitious modulus according to the procedure established by Abellan-Garcia et al. [38]. Establishing the relative modulus of each SCM is a critical step for determining the equivalent reactivity indices of the concrete mixture, as highlighted in [38]. To this end, the equivalent modulus for each constituent is evaluated independently by applying the method set out in Eqs. (1)–(3).

$$RM = \sum_{i=1}^n \left(\frac{CaO + MgO + Al_2O_3}{SiO_2} \right)_i w_i \quad (1)$$

$$SM = \sum_{i=1}^n \left(\frac{SiO_2}{Al_2O_3 + Fe_2O_3} \right)_i w_i \quad (2)$$

$$AM = \sum_{i=1}^n \left(\frac{Al_2O_3}{Fe_2O_3} \right)_i w_i \quad (3)$$

here, RM , SM , and AM represent the equivalent modulus of each mixture. The term n represents the total number of cementitious materials incorporated in the concrete mix. The term w_i denotes the weight fraction

of a specific cementitious material i , calculated as the ratio of its weight to the total weight of all cementitious components in the mixture.

2.2 Visualization of the Study Variables

The violin plots (Fig. 2) provide a detailed statistical analysis of key parameters influencing RACs' performance, illustrating their distribution, central tendency, and variability. CMs, such as PC, FA, BF, and SF, exhibit distinct patterns, with FA and SF showing right-skewed distributions indicative of their limited but strategic use as partial cement replacements. Admixtures like SP display multimodal distributions, reflecting their tailored incorporation to optimize workability and setting time. The relatively stable WB suggests controlled mix designs, while the broader distributions of NA and RA highlight material heterogeneity, particularly in WA. The equivalent modulus of each mixture, represented by RM, SM, and AM, varies depending on the material composition, influencing the overall stiffness and mechanical response of the mixture. The study label (CS) exhibits a dense central distribution with a wide range, influenced by mix composition and curing conditions, while the clustering of AG aligns with standard testing protocols. These trends emphasize the role of mixture optimization, material properties, and curing duration in defining RACs' performance, warranting further multivariate analysis to refine predictive modeling.

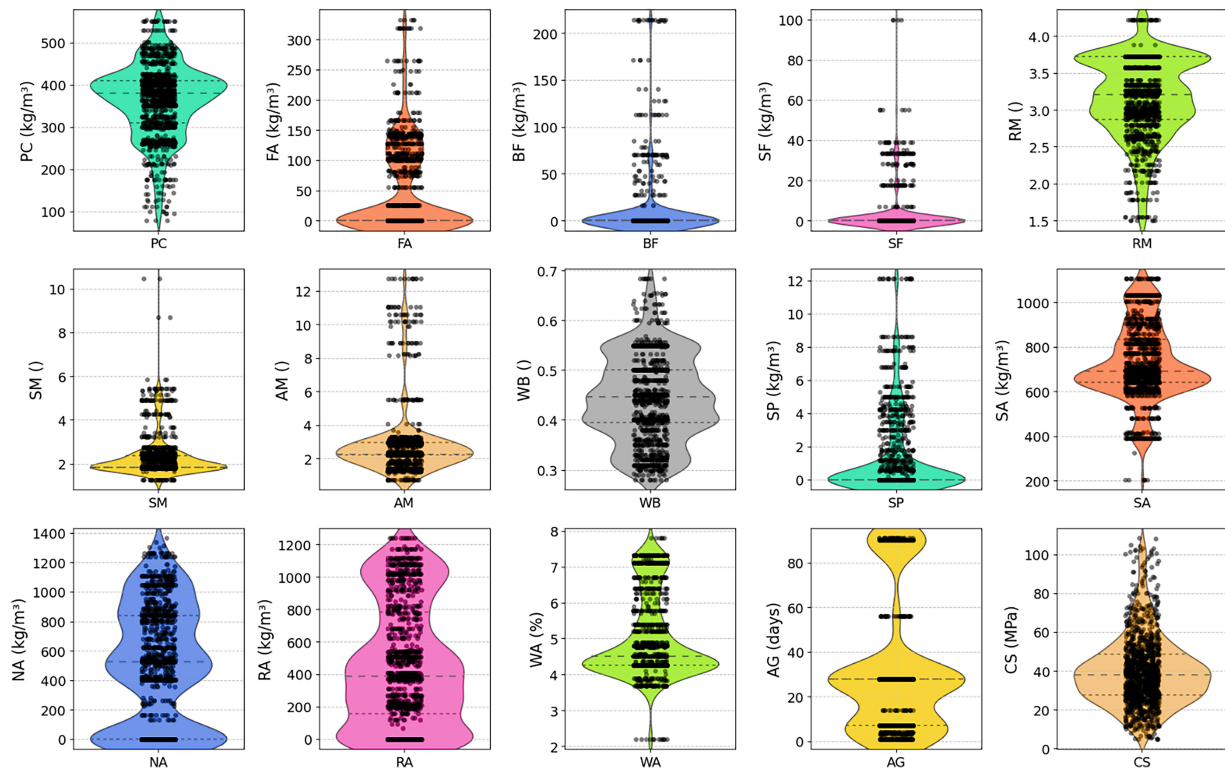


Figure 2: A violin plot visualizing the variables of the study

2.3 Correlation Analysis of Study Variables

To characterize how the input variables interact, the study explored both monotonic and strictly linear associations across the dataset. Two complementary statistical metrics were applied: (i) the Pearson product-moment coefficient r_p , defined in Eq. (4), and (ii) the Spearman rank coefficient r_s , given in Eq. (5). These measures capture the strength and direction of dependence along a covariance axis, with possible

values spanning from -1 to $+1$ (https://en.wikipedia.org/wiki/Pearson_correlation_coefficient, accessed on 11 November 2025). The resulting correlation map, illustrated in Fig. 3, highlights the intensity of these relationships, where progressively darker hues denote stronger positive or negative linkages.

$$r_p = \frac{\sum (x_i - \bar{x})(y_i - \bar{y})}{\sqrt{\sum (x_i - \bar{x})^2 \sum (y_i - \bar{y})^2}} \quad (4)$$

$$r_s = 1 - \frac{6 \sum d_i^2}{n(n^2 - 1)} \quad (5)$$

In the correlation formulas, each paired observation is indexed by i , and the term $(x_i - y_i)$ represents the difference between the corresponding values in the two datasets. The symbols $\bar{x}$ and $\bar{y}$ denote the respective arithmetic means of all x_i and y_i values. For the rank-based analysis, d_i signifies the discrepancy between the two ranks assigned to each observation, while n indicates the total number of paired samples considered in the computation.

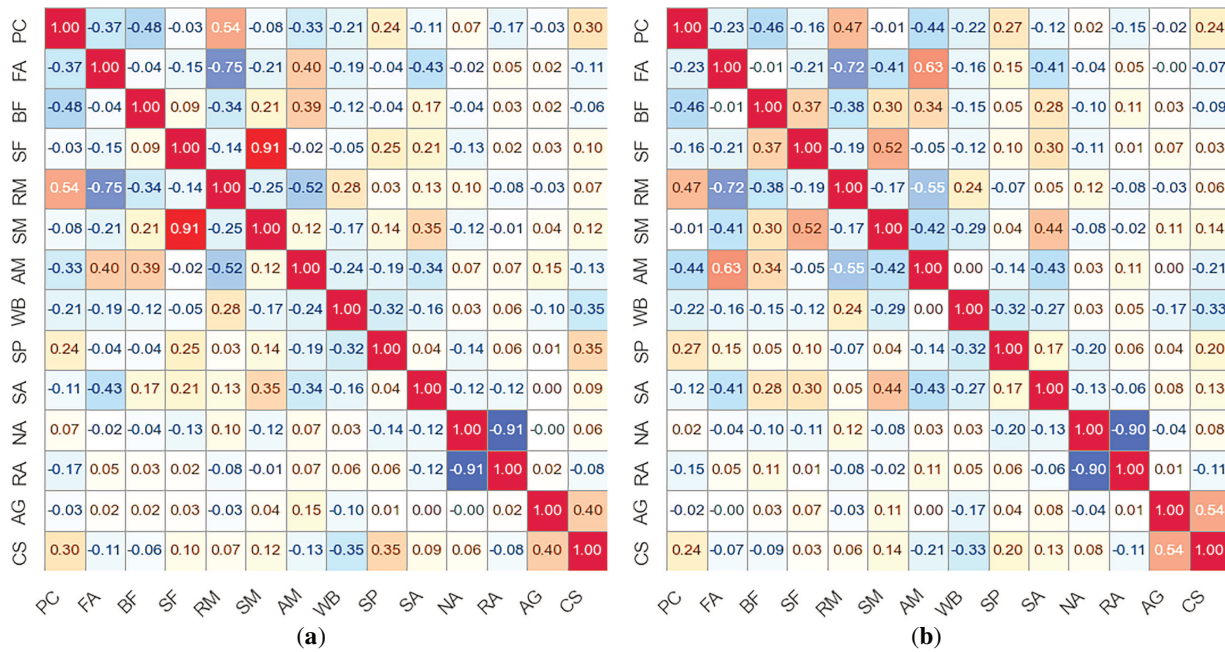


Figure 3: (a) Pearson's, and (b) Spearman's correlation heat maps

The correlation heat illustrates the relationships between key variables using Pearson's [Fig. 3a] and Spearman's [Fig. 3b] correlation coefficients. Pearson's correlation quantifies linear relationships, while Spearman's captures monotonic trends, offering complementary insights into the dataset's structure. The results indicate strong correlations among CMs, suggesting their simultaneous use in optimizing RACs' performance. Additionally, WB exhibits a negative correlation with CS, reinforcing the well-established principle that increased water content leads to higher porosity and reduced strength [39,40]. The relationship between RA and NA highlights the inverse balance in mix compositions incorporating varying aggregate types. The observed differences between Pearson's and Spearman's coefficients suggest potential nonlinear dependencies in admixtures and mechanical properties.

2.4 Data Preprocessing Protocols

Before model training, it was essential to screen the dataset for abnormal observations to preserve both the accuracy and the stability of subsequent regression models [41]. The study employed Cook's Distance, a well-established diagnostic that quantifies the influence of individual records on the regression model. This approach has been extensively documented in regression diagnostics literature [42–44] and remains a robust method for identifying influential or anomalous data points. Any data points exceeding the reference threshold in Fig. 4a were classified as highly influential and consequently treated as outliers. To confirm the robustness of this filtering process and to ensure that no valid high-strength data were unconsciously excluded, additional distribution-based methods were applied to the entire dataset. Specifically, Cook's Distance identified 82 influential observations (6.6%), whereas the Z-score ($|Z| > 3$) and Interquartile Range (IQR; $1.5 \times \text{IQR}$) techniques flagged 23 and 48 cases, respectively, with 19 observations being common across all three approaches. This robust overlap demonstrates the reliability of Cook's Distance in capturing genuine anomalies. Moreover, re-estimating the model after removing each outlier set produced stable or improved predictive performance (R^2 increased from 0.77 to 0.87, and RMSE decreased from 7.2 to 5.5 MPa), which supports that the exclusion of these points enhanced the model's robustness without discarding valid high-strength records. The refined dataset, illustrated in Fig. 4b, exhibits a clearer and more coherent relationship after outlier removal. The resulting dataset, reduced to 1161 valid entries, was then partitioned into training and testing subsets in an 80:20 ratio to maintain a representative balance for model calibration and performance evaluation.

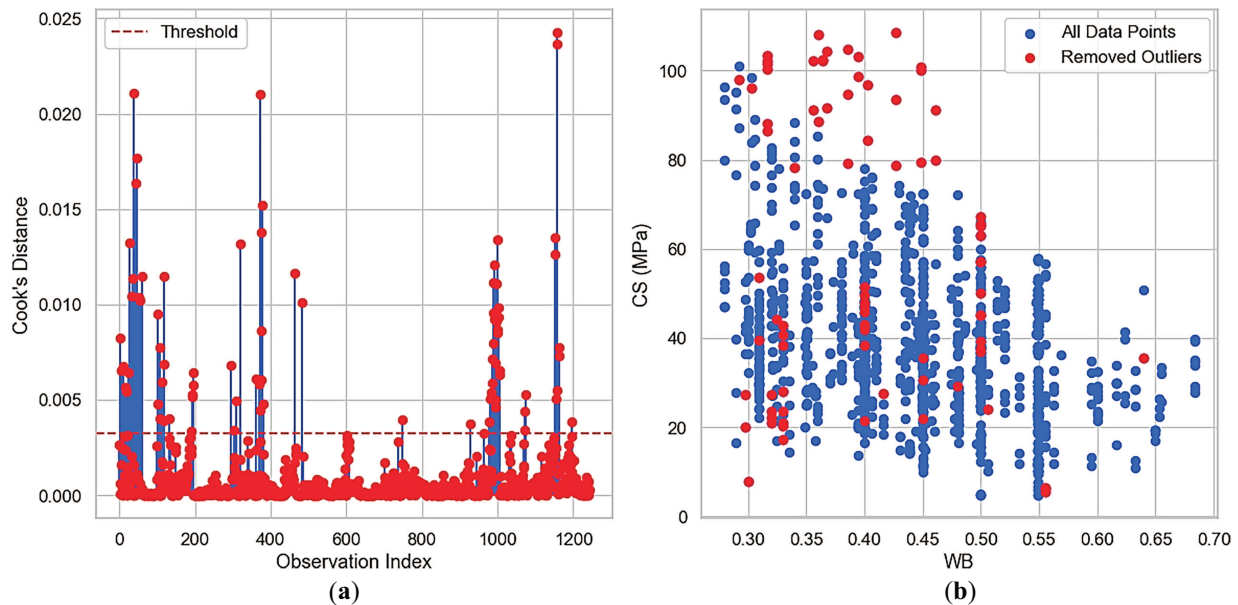


Figure 4: (a) Cook's distance for outlier detection, and (b) scatter plot illustrating the eliminated outlier

Figs. 5 and 6 illustrate the frequency distributions and corresponding boxplots of three selected variables, including PC, WB, and RA. Before preprocessing (Fig. 5), the distributions exhibit varying degrees of skewness and dispersion. PC is right-skewed, with a concentration around 400 kg/m³. WB has a multimodal distribution with peaks at distinct intervals and a relatively uniform spread, while RA is highly skewed, with a high concentration near zero and significant outliers. After preprocessing (Fig. 6), the key transformation observed is normalization, which maps all values onto a [0, 1] scale. The general shape of the distributions is retained, ensuring that intrinsic data structures remain intact. PC and WB show preserved patterns, while

RA still exhibits some skewness, suggesting that additional transformations, such as log-scaling, may be required. The primary objectives of preprocessing include ensuring comparability by scaling features to a common range, mitigating the effects of outliers, and preserving essential distribution characteristics. While normalization effectively standardizes the data, persistent skewness in RA suggests that more sophisticated transformations may be beneficial for optimizing data representation in ML applications. In this study, the min-max scaling approach was selected to ensure consistency across the diverse range of algorithms applied (refer to [Section 3](#)). This approach provided a uniform input range suitable for both scale-sensitive models (e.g., neural networks and support vector regression) and scale-invariant models (e.g., Random Forest, Extra Trees, and XGBoost). Although the RA variable remained moderately skewed after normalization, comparative trials using logarithmic and Yeo-Johnson power transformations [45] revealed negligible effects on model performance ($\Delta R^2 < 2.3\%$ and $\Delta RMSE < 0.8$ MPa). These findings confirm that the adopted scaling method effectively preserved predictive stability and interpretability across the developed ML framework, without requiring additional nonlinear transformations.

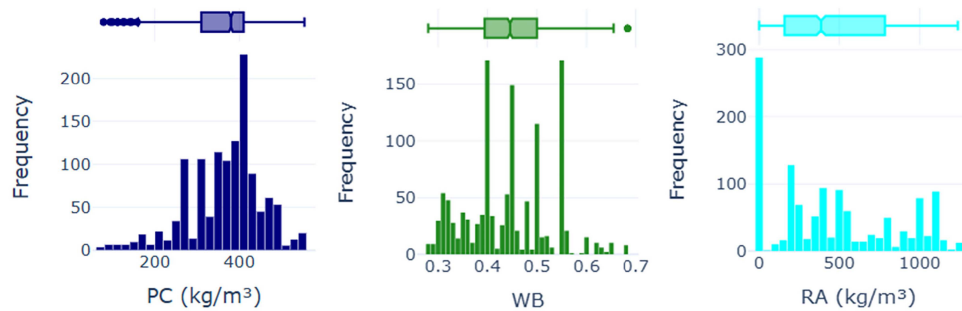


Figure 5: Distribution of some of the key features before preprocessing

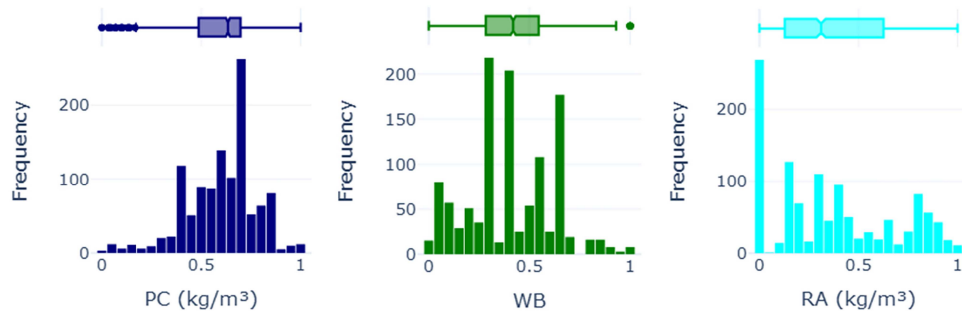


Figure 6: Distribution of some of the key features after preprocessing

Moreover, [Fig. 7](#) presents the distribution of the study label (CS) before and after preprocessing. Both histograms exhibit a roughly normal distribution, with a peak around 50 MPa and a spread extending up to approximately 100 MPa. The boxplots indicate the presence of outliers, particularly on the upper end, suggesting variability in high-strength samples. Notably, the preprocessing step does not significantly alter the overall shape of the distribution, indicating that the transformation applied primarily focused on standardization rather than structural modification. This suggests that the preprocessing method preserved the statistical properties of the CS data while ensuring consistency across the dataset, a crucial aspect for maintaining data integrity in predictive modeling applications.

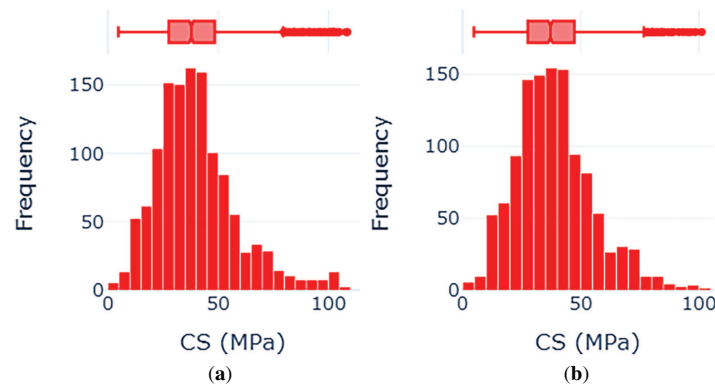


Figure 7: Distribution of the study label: (a) before-, and (b) after-preprocessing

3 Machine Learning Methodology

To enable a rigorous and unbiased evaluation of predictive performance, the dataset was first organized through a carefully planned partitioning procedure. The predictor variables (X) were separated from the response variable (y), after which 80% of the records were allocated for model development and the remaining 20% were set aside for independent testing. This split provided a clear distinction between training and validation phases, ensuring that the models' ability to generalize could be reliably assessed. A custom benchmarking routine was then constructed to compare a broad spectrum of regression approaches within a single, reproducible framework. The collection of models encompassed a wide methodological range:

- Classical linear estimators, namely Ordinary Least Squares, Ridge, Lasso, Elastic Net, and Bayesian Ridge, offered straightforward interpretability and efficient handling of linear trends. To capture more complex or non-linear patterns, the analysis incorporated K-Nearest Neighbors, Decision Trees, and Support Vector Regression.
- Ensemble approaches, such as Random Forests, Extra Trees, Gradient Boosting, AdaBoost, and Bagging Regressors, were added to exploit the strength of multiple base learners and to reduce both variance and bias.
- Advanced gradient-boosting implementations, specifically XGBoost and LightGBM, were included for their scalability and strong performance on high-dimensional data.
- Artificial Neural Networks (ANNs) with hidden layers ranging from 16 to 256 neurons and training horizons up to 200 iterations provided a deep-learning perspective capable of modeling intricate dependencies.

Most algorithms were implemented through the scikit-learn ecosystem, while XGBoost and LightGBM were accessed via their dedicated libraries. This modular design allowed consistent training, validation, and performance comparison across all candidate models, which facilitates the selection of the most suitable approach for the characteristics of the refined dataset and the study's predictive objectives.

4 Results and Discussion

4.1 Comprehensive Modeling Using the Full Feature Set

4.1.1 Performance of the Selected ML Algorithms

Table 3 presents the performance metrics of various ML algorithms applied to the dataset. The models were evaluated using multiple statistical indicators, including the coefficient of determination (R^2), mean absolute error (MAE), root mean square error (RMSE), and runtime. XGBoost exhibited the highest

predictive accuracy ($R^2 = 0.947$, MAE = 0.598, RMSE = 1.193), outperforming other ensemble techniques (Extra Trees and GBoost). Linear models (e.g., Ridge, Lasso) exhibited considerably weaker performance, which confirms that the underlying relationships are highly nonlinear. Ensemble-based learners generally outperformed traditional regressors, while MLP delivered moderate accuracy but at a substantially higher computational cost. Given its superior balance of accuracy and efficiency, XGBoost was selected as the primary predictive model; however, accuracy alone is not sufficient for engineering adoption. Therefore, the subsequent analysis prioritizes interpretability to ensure that model decisions align with known material behaviour and physical reasoning. It is noteworthy that default XGBoost parameters were used to establish a baseline comparison at the initial benchmarking stage. Subsequently, as will be discussed in [Section 4.1.3](#), a systematic hyperparameter optimization was conducted to refine model performance and control potential overfitting.

Table 3: Performance metrics for the employed ML algorithms using the complete feature set

Model	Mean R^2	STD R^2	MAE	RMSE	Runtime (s)
Linear Regression	0.553	0.0613	8.272	10.514	4.336
Ridge	0.551	0.0625	8.258	10.559	0.124
Lasso	0.258	0.0503	10.765	13.729	0.109
ElasticNet	0.089	0.0156	11.834	15.260	0.115
KNN	0.706	0.0409	4.644	6.675	0.156
SVR	0.531	0.0532	7.886	10.651	0.552
Random Forest	0.924	0.0189	1.111	1.801	2.958
Extra Trees	0.932	0.0174	0.227	1.052	2.099
GBoost	0.894	0.0184	2.997	4.140	0.847
AdaBoost	0.686	0.0248	7.231	8.664	0.730
Bagging	0.910	0.0263	1.314	2.142	0.347
XGBoost	0.947	0.0170	0.598	1.193	0.979
LGBoost	0.935	0.0156	1.420	2.161	19.034
MLP	0.671	0.0499	6.425	8.667	18.813

Note: Bold text indicates the best performance among the employed ML algorithms.

The superior performance of XGBoost can be attributed to its efficient handling of complex data patterns, regularization mechanisms that prevent overfitting, and an optimized gradient-boosting framework. In contrast, traditional regression models struggled due to their linear assumptions, and computationally expensive models like LGBoost and MLP did not provide a substantial performance advantage over XGBoost. Given the superior performance demonstrated by XGBoost, it was selected for subsequent analysis.

4.1.2 Ranking of Features

[Fig. 8](#) presents the feature importance ranking based on absolute SHAP values, offering insight into the contribution of each variable to the predictive model of CS. In [Fig. 8a](#), which considers the complete feature set, AG exhibits the highest influence with a mean absolute SHAP value of 7.25, followed by WA (3.2) and WB (2.92). Other significant contributors include SP with an absolute SHAP value of 2.24 and PC with 2.13, while features such as BF and SF show negligible impact. The cumulative importance curve indicates that approximately 95% of the total feature contribution is captured by the most influential variables. To reduce the model's complexity, the features AM, RM, FA, SF, and BF will be excluded. Consequently, only

the features demonstrating approximately 95% significance will be retained in the simplified model, referred to as the 'Pruned Model'. In Fig. 8b, after dimensionality reduction, the model retains the most relevant predictors, reducing redundancy while maintaining predictive performance. The top-ranked features remain largely unchanged, with AG (7.16), WA (3.26), and WB (3.05) maintaining dominance. However, the retained subset captures only 80% of the total importance, suggesting a trade-off between model simplification and information retention. The exclusion of lower-impact variables likely enhances model interpretability without significantly compromising accuracy. The relatively lower mean absolute SHAP value of PC (2.07) suggests that while cement content contributes to CS, other factors, such as aggregate and water proportions, play a more substantial role in determining strength variations.

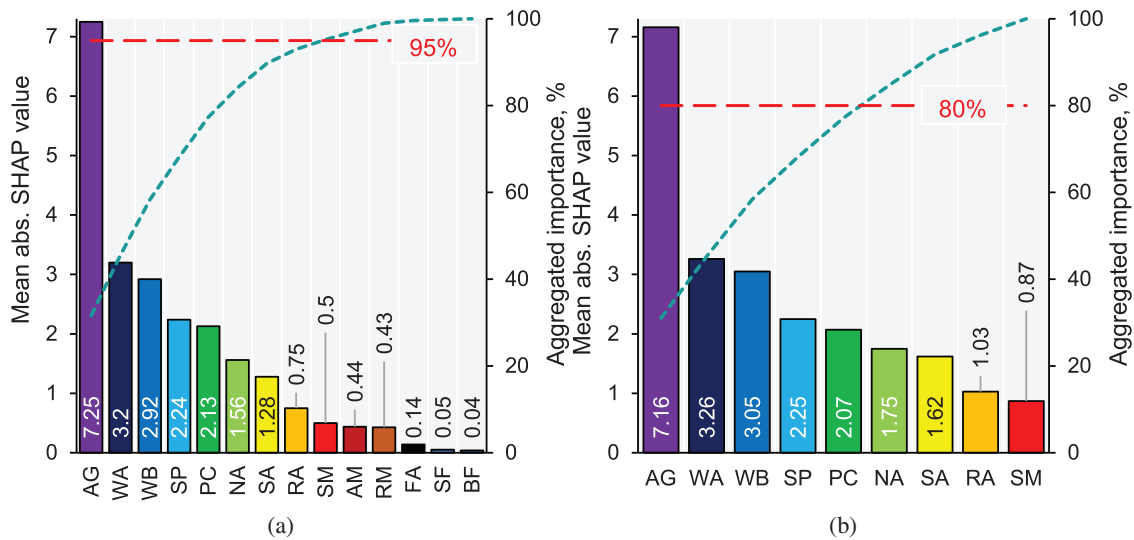


Figure 8: Feature importance ranking using the absolute SHAP values: (a) complete feature set and (b) selected features following dimensionality reduction

4.1.3 Enhancing the Efficiency of the XGBoost Model

This study implements a systematic hyperparameter optimization strategy to enhance the predictive performance of an XGBoost model. A comprehensive grid search was conducted to assess the influence of three critical hyperparameters: (i) the number of estimators (50–1000), (ii) the maximum tree depth (2–10), and (iii) the learning rate (0.01–1.0). The tuning process was performed in Python [46] (v3.13.2), leveraging NumPy (<https://numpy.org/>) for numerical computations and Pandas for structured data processing. The optimal configuration for the full feature set was determined as $n_estimators = 50$, $learning_rate = 0.2$, and $max_depth = 7$, whereas the reduced feature set achieved its best performance with $n_estimators = 500$, $learning_rate = 0.1$, and $max_depth = 4$. Fig. 9 presents the relationship between training and validation RMSE for different hyperparameter configurations, comparing models trained with the complete and reduced feature sets. Each point represents a model evaluated during optimization, with the best-performing model highlighted in red. In Fig. 9a, using the complete feature set, training RMSE ranges from approximately 0.5 to 8.0 MPa, while validation RMSE varies between 3.7 and 6.1 MPa. The optimal model, identified at (training RMSE $\approx$ 0.9 MPa, validation RMSE $\approx$ 3.7 MPa), achieves a balance between model complexity and generalization. In Fig. 9b, with the reduced feature set, training RMSE falls between 1.1 and 7.8 MPa, and validation RMSE spans 3.7 to 8.7 MPa. The best model, with training RMSE $\approx$ 1.7 MPa and validation RMSE $\approx$ 3.7 MPa, demonstrates improved generalization, likely due to reduced dimensionality and lower risk of overfitting. The dispersion of models with high training RMSE and widely varying validation

RMSE highlights the sensitivity of performance to hyperparameter selection, emphasizing the importance of rigorous tuning to optimize predictive accuracy while mitigating overfitting.

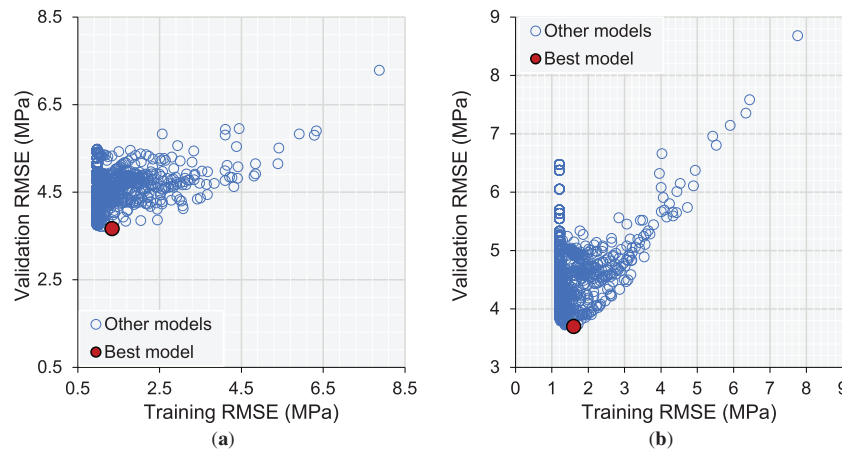


Figure 9: Training and validation loss trends observed during hyperparameter optimization: (a) utilizing the complete feature set and (b) employing the reduced feature set

Fig. 10 compares the predicted and actual CS values for the training and testing datasets. For the training set [Fig. 10a], the model shows an excellent fit ($R^2 = 0.9923$, MAE = 0.861 MPa, RMSE = 1.408 MPa), with points closely following the equality line. For the testing set [Fig. 10b], performance remains strong ($R^2 = 0.937$, MAE = 2.378 MPa, RMSE = 3.591 MPa), although the higher error indicates slight overfitting and reduced generalization to unseen data. Nonetheless, the close alignment between predicted and actual values confirms that the model maintains robust predictive capability, with the modest accuracy drop reflecting the normal balance between model complexity and generalization.

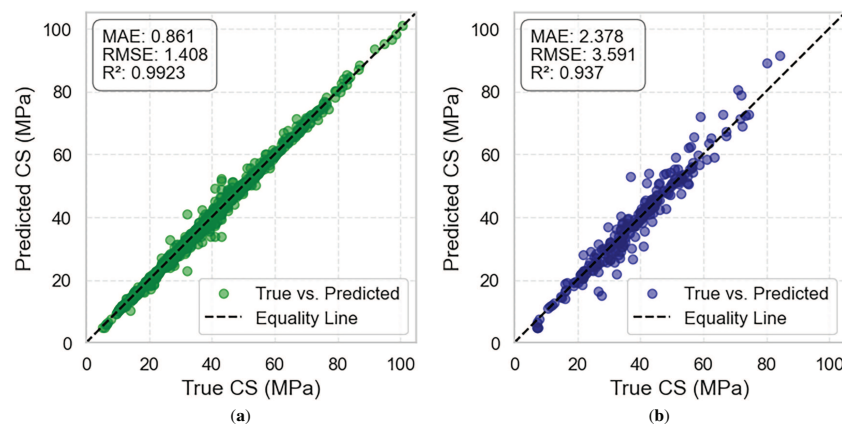


Figure 10: Comparison of predicted and actual values for: (a) the training dataset and (b) the testing dataset, using the model incorporating all variables

4.2 Performance of the Optimum Pruned Model

Fig. 11 presents the performance of the optimum Pruned model. In the training set [Fig. 11a], the predicted and measured CS values align closely, with $R^2 = 0.989$, MAE = 0.929 MPa, and RMSE = 1.602 MPa, which confirms excellent learning behavior. In the testing set [Fig. 11b], the model maintains strong generalization ($R^2 = 0.936$, MAE = 2.490 MPa, RMSE = 3.987 MPa), with only a modest drop in accuracy.

This small gap between training and testing results indicates limited overfitting and demonstrates that the model can reliably predict unseen data. The inclusion of chemically informed features further contributed to stable performance by better representing the underlying material behavior.

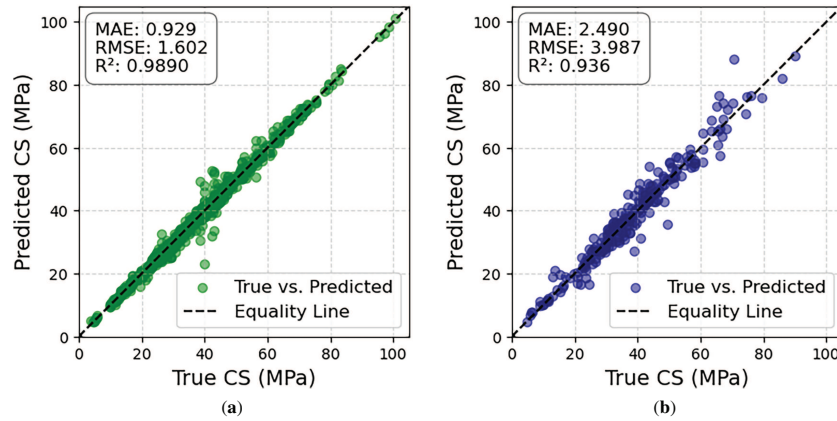


Figure 11: Predictions vs. true values for: (a) training and (b) testing datasets

4.3 Interpretation of the Optimum Pruned Model

4.3.1 Impact of Significant Features on the Model's Output

Fig. 12 shows the impact of key features on the Pruned model's outputs based on true SHAP values. Among all variables, AG exhibits the widest range of SHAP values, indicating a dominant influence on model predictions. Higher AG values are strongly associated with positive SHAP impacts, suggesting that increased AG significantly enhances the CS predicted by the model. This trend aligns with the well-established understanding that longer curing improves the hydration of cementitious materials, leading to denser microstructures and better mechanical performance [34,47–49]. WA and WB also exert substantial effects. For WB, higher values correspond to negative SHAP values, implying that an increased water-binder ratio reduces model outputs, likely reflecting a decrease in strength and durability due to higher porosity [50–52]. Conversely, lower WA values shift SHAP impacts positively, indicating that aggregates with lower water absorption contribute to better performance by minimizing internal water loss and shrinkage [53,54]. SP and PC show moderate but notable influences. Higher SP values are associated with positive SHAP effects, reflecting improved workability and reduced water demand. PC exhibits a more balanced SHAP distribution, suggesting that both excessive and insufficient cement contents can impact the output depending on the context of other mix design parameters. SA, NA, RA, and SM display narrower SHAP distributions, indicating relatively lower individual impacts. Notably, higher NA and RA values generally correspond to negative SHAP impacts, consistent with the notion that excessive replacement with RA can degrade mechanical properties if not carefully controlled [55,56]. It is noteworthy that AG was retained as a continuous variable between 1–91 days (Table 2) without transformation. This decision reflects the fundamental role of hydration kinetics in governing compressive strength evolution and enables the model to learn generalizable strength-age relationships across the full curing duration [57]. Despite AG's expected dominance, SHAP analysis confirmed that other features (WB, WA, SP, and PC) retained meaningful and mechanistically consistent influence, which demonstrates that the model captured multi-parameter interactions rather than collapsing into single-feature dependence.

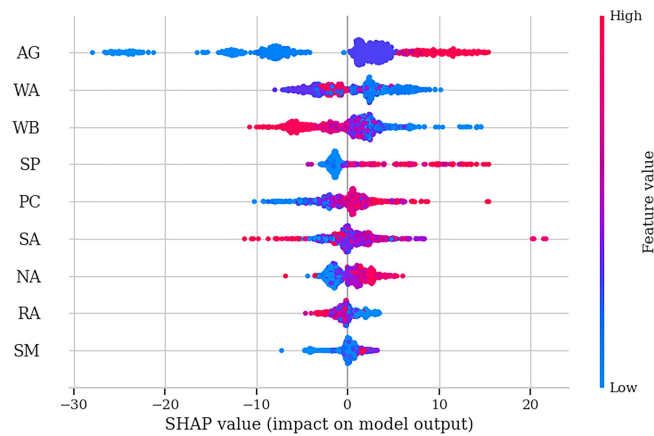


Figure 12: Influence of key features on the outputs of the Pruned model via true SHAP values

It is important to note that SHAP importance is derived from game-theoretic Shapley values [58], which quantify marginal contributions to predictions across all feature coalitions and are independent of feature frequency, occurrence count, or raw magnitude in physical units. In the present dataset (Table 2), SCMs [i.e., SF (mean 3.02 kg/m^3) and BF (mean 9.38 kg/m^3)] exhibit low absolute dosages and high dispersion relative to PC (mean 364.57 kg/m^3), which results in genuinely weak global influence as reflected by their narrow SHAP ranges. Subsequent pruning of these low-impact features (Section 4.2) preserved model accuracy (testing $R^2 = 0.937$), which confirms that their low SHAP importance represents true marginal influence rather than sampling or frequency artifacts. The stability of dominant features (AG, WB, WA) across folds and the alignment of SHAP directions with established physical mechanisms (e.g., increasing WB increases porosity and lowers CS) further validate the interpretability framework.

4.3.2 Partial Dependence Plots

Partial dependence plots (PDPs) offer an interpretable visualization of the marginal effect of individual features on an ML model's predictions [59–61]. By averaging the predictions over the dataset while varying a single feature, PDPs reveal how the model's output is influenced by changes in that specific feature, isolating its contribution from the interactions with other variables. In this study, PDPs are used to assess the effect of key input parameters on the predicted CS of RAC, as shown in Fig. 13. AG exhibits a strong positive and monotonic trend, with CS increasing sharply at early ages (up to 28 days) and continuing to rise at a slower rate thereafter. This behavior is consistent with the SHAP analysis depicted in Fig. 12. WB shows a clear negative trend, where higher values consistently reduce CS due to increased porosity and reduced matrix density [50–52]. PC demonstrates a nonlinear, threshold-based trend, remaining relatively stable at low contents but contributing positively beyond approximately 400 kg/m^3 , where additional binder enhances matrix cohesion. These observations align well with the findings of SHAP depicted in Fig. 12. SP displays a positive threshold effect, improving CS once dosage levels exceed about 4 kg/m^3 , where gains in workability and compaction become more pronounced. SA follows a non-monotonic trend, improving CS up to an optimal content ($\sim 800 \text{ kg/m}^3$), beyond which excessive sand disrupts aggregate skeleton stability and reduces strength. This finding suggests that an optimal sand content improves particle packing and reduces voids, but excessive sand may disrupt the coarse aggregate skeleton, weakening the concrete [55,56]. WA exhibits a negative trend, where CS generally decreases as WA increases beyond 3%–4%. Aggregates with higher water absorption introduce more internal porosity and weaken the interfacial transition zone, leading to reduced strength [55,56]. NA shows a positive trend, with higher contents improving CS due to the

superior mechanical properties of natural aggregates, whereas RA has a mildly negative trend, reflecting the detrimental effects of residual mortar and higher porosity. Increased RA content is associated with a modest decrease in strength, which is consistent with the understanding that RA often has attached mortar and greater porosity, reducing the quality of the concrete [50–52]. SM demonstrates no clear trend, indicating a negligible influence on CS within the tested range. These results collectively highlight that AG, water-related parameters (WB and WA), and aggregate composition exert the most pronounced effects.

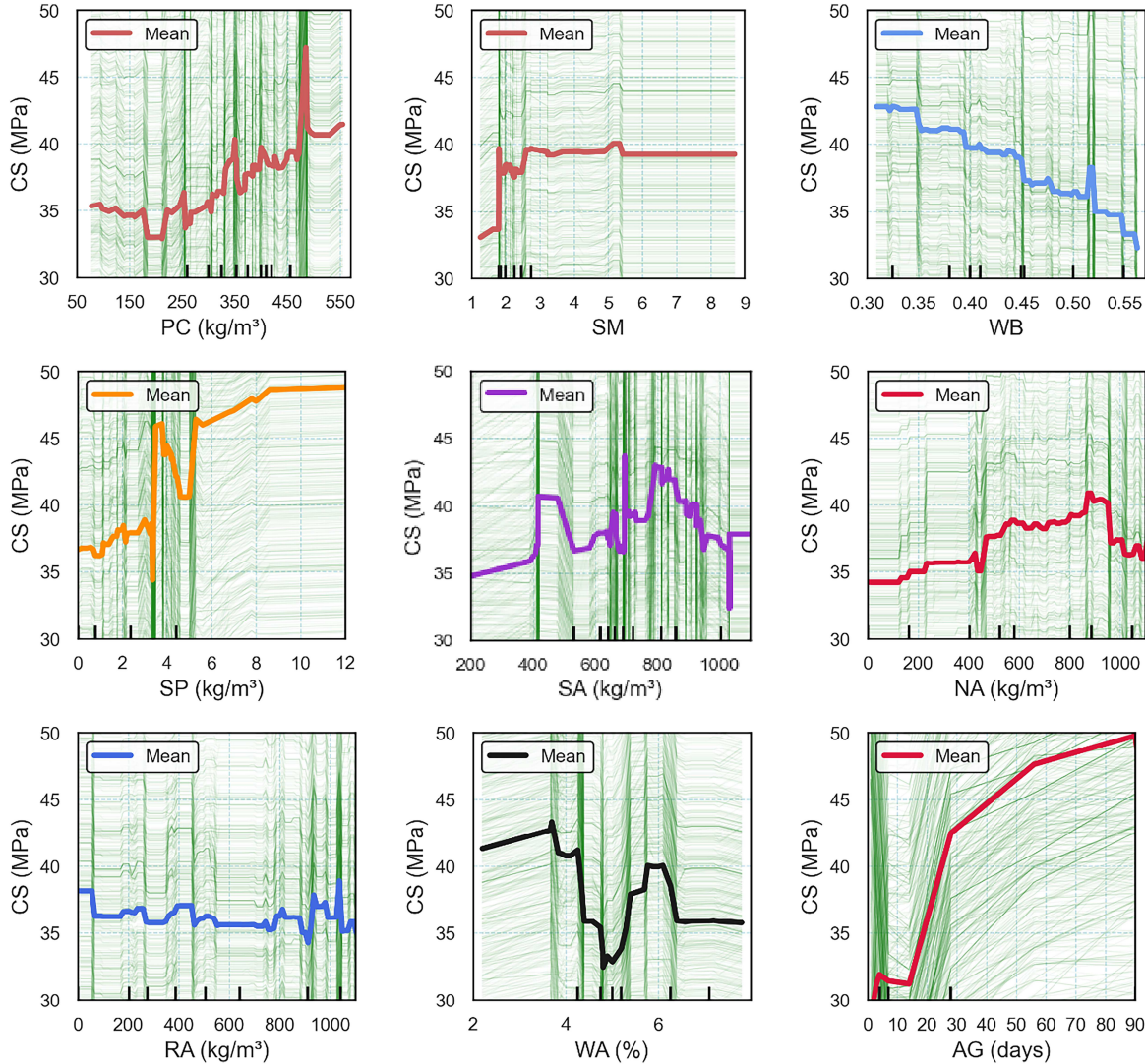


Figure 13: Partial dependence plots illustrating the impact of key features on the predicted CS

4.3.3 Recycled Aggregate Interactions

Fig. 14 presents iso-surface 3D plots illustrating the interaction effects between RA and various features on the predicted CS of RACs. These visualizations provide a deeper understanding of the combined influences of two variables simultaneously on the model output, beyond the marginal effects captured by PDPs. In Fig. 14a, the interaction between RA and PC is depicted. At low RA levels, increases in PC correlate with moderate gains in CS. However, as RA content rises, the beneficial effect of increasing PC diminishes, suggesting that a higher amount of PC cannot fully compensate for the detrimental effects of

excessive RA, likely due to inherent porosity and weaker interfacial transition zones associated with recycled materials [60,62]. Fig. 14b shows the combined influence of RA and SM. Across the range of SM values, CS remains relatively stable at low RA content but declines as RA content increases. This indicates that while SM may slightly enhance durability or mitigate some deficiencies, it offers limited improvement to CS when RA content is high. The interaction between RA and SP [Fig. 14c] reveals a pronounced beneficial effect. At lower RA contents, increases in SP lead to modest improvements in CS; however, at higher RA levels, greater SP content significantly enhances CS [51,63]. This pattern suggests that adequate superplasticizer dosages are crucial for maintaining workability and achieving dense packing in mixes with high RA content, thus partially offsetting the negative effects of RA. Fig. 14d illustrates the interaction between RA and SA. A moderate SA appears to support higher CS across all RA levels, while either very low or very high SA leads to reductions in strength. In Fig. 14e, the combined effects of RA and WA are explored [56,62,63]. CS is generally higher when WA is low, regardless of RA content, emphasizing the detrimental role of aggregates with high water absorption [55,56]. At elevated RA contents, increased WA exacerbates strength loss, highlighting the sensitivity of RAC to the quality of the aggregate phase. Finally, Fig. 14f depicts the interaction between RA and NA. As expected, higher NA contents consistently lead to greater CS, and this positive effect is more pronounced at lower RA levels.

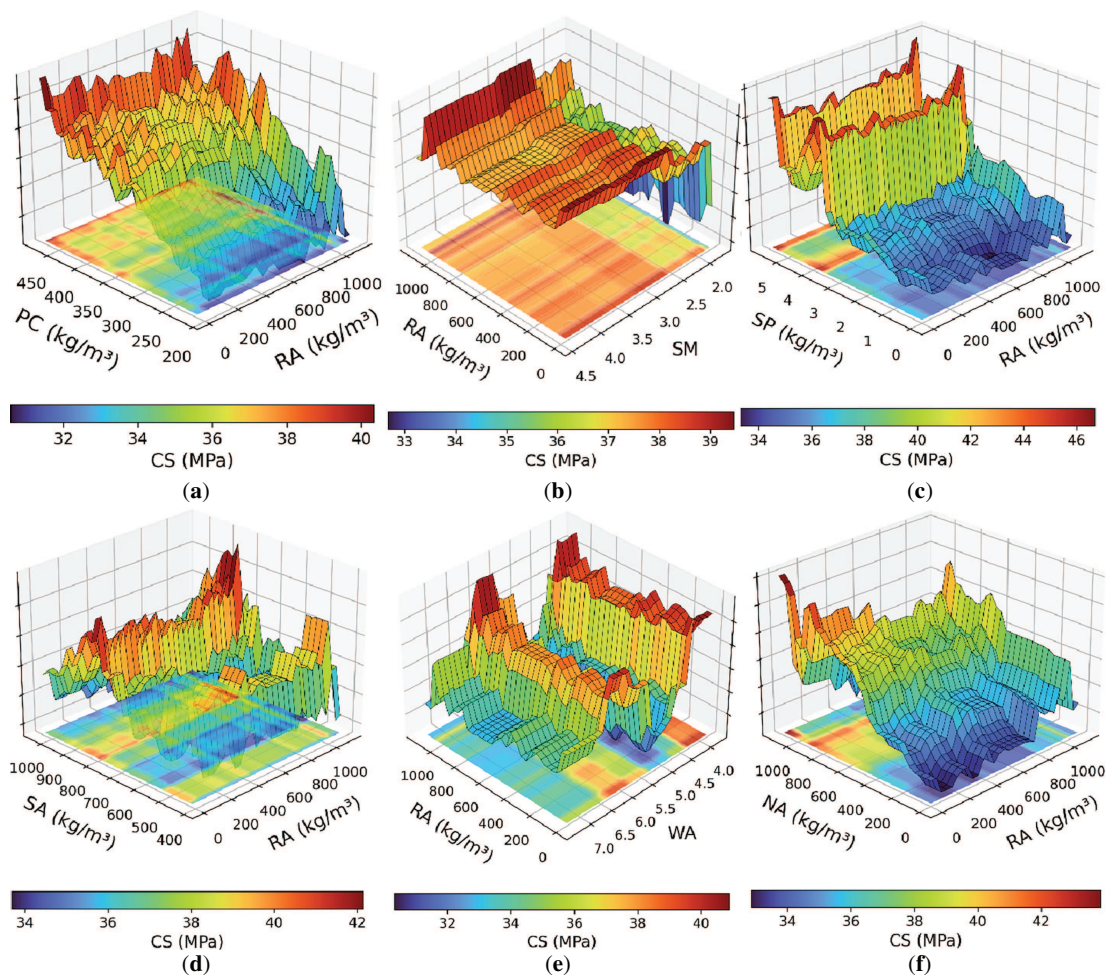


Figure 14: Influence of RA- (a) PC, (b) SM, (c) SP, (d) SA, (e) WA, and (f) NA interactions

5 Conclusion and Future Work

This investigation established a robust predictive framework for the CS of RAC using a comprehensive dataset of 1243 mixtures incorporating various SCMs. The hybrid machine learning approach, integrating engineering knowledge with advanced statistical techniques, yielded several key insights:

- (1) Among all algorithms, XGBoost achieved the best predictive accuracy ($R^2 = 0.947$, $MAE = 0.598$, $RMSE = 1.193$) with superior computational efficiency, outperforming Extra Trees, LightGBM, and all conventional regressors. SHAP analysis revealed AG as the dominant predictor of CS (mean absolute SHAP ≈ 7.25), followed by WA (≈ 3.2) and WB (≈ 2.92). Pruning low-impact features (AM, RM, FA, SF, BF) retained $\sim 80\%$ of total importance while preserving accuracy to enhance model interpretability without significant loss of predictive performance.
- (2) PDPs confirmed AG as the strongest positive driver of CS, with rapid early gains. Higher WB and WA reduced CS by increasing porosity, while SP and PC enhanced strength beyond thresholds ($\sim 4 \text{ kg/m}^3$ SP, $\sim 400 \text{ kg/m}^3$ PC). Optimal SA ($\sim 800 \text{ kg/m}^3$) maximized strength; excessive RA slightly lowered CS, whereas NA improved it.

Despite the strong predictive performance of the developed model, certain limitations remain. The low representation of certain SCMs (e.g., SF and BF) and broad variability in AG and RA absorption introduce uncertainty in isolated effect estimation. Future work should expand data coverage to balance SCM representation and explore symbolic regression or hybrid models for closed-form predictive equations. Field-scale validation and long-term durability testing are further recommended to confirm the model's robustness and practical applicability.

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Availability of Data and Materials: The data that support the findings of this study are available on request from the corresponding author, Yassir M. Abbas. The data are not publicly available due to their inclusion in an ongoing collaborative project containing pending intellectual property evaluations that restrict immediate open access.

Ethics Approval: Not applicable.

Conflicts of Interest: The authors declare no conflicts of interest to report regarding the present study.

Nomenclature

ML	Machine Learning
ANN	Artificial Neural Network
KNN	K-Nearest Neighbors

GPR	Gaussian Process Regression
RF	Random Forest
AdaBoost	Adaptive Boosting
GBoost	Gradient Boosting
XGBoost	Extreme Gradient Boosting
CatBoos	Categorical Boosting
LGBoost	Light Gradient Boosting
SVM	Support Vector Machine
RBFNN	Radial Basis Function Neural Network
SVR	Support Vector Machine
DT	Decision Tree
RT	Random Tree
BP	Backpropagation
GBDT	Gradient Boosting Decision Tree
BPNN	Backpropagation Neural Network
MLP	MultiLayer Perceptron
SSA	Sparrow Search Algorithm
BO-TPE	Bayesian Optimization with a Tree-structured Parzen Estimator
GPR	Gaussian Process Regression
CART	Classification and Regression Tree
PDP	Partial Dependence Plot
RMSE	Root Mean Squared Error
MSE	Mean Squared Error
MAE	Mean Absolute Error
RAC	Recycled Aggregate Concrete
RA	Recycled coarse aggregate
RR	Recycled aggregate percentage ratio
PC	Portland cement content
SF	Silica fume content
FA	Fly ash content
BF	Blast furnace slag
SP	Superplasticizer
NA	Natural coarse aggregate content
WA	RA water absorption
AG	Age of curing
W/B	Water-to-binder ratio
W/C	Water-to-cements ratio
W	Water content
CS	Compressive strength
CT	Cement type
MPSRA	Maximum particle size of recycled aggregate
MPSNA	Maximum particle size of natural aggregate
ADNA	Apparent density of natural aggregate
ADRA	Apparent density of recycled aggregate
FMRA	Fineness modulus of recycled aggregate
SGC	Strength grade of cement
ACR	Aggregate-to-cement ratio
NSRA	Nominal size of recycled aggregate
SP/C	Superplasticizer-to-cement ratio

FA/C Fly ash-to-cement ratio
SCM Supplementary cementitious materials

Appendix A

Table A1: Overview of the collected RAC's CS data

Ref.	*No.	PC [kg/m ³]	FA [kg/m ³]	GGBFS [kg/m ³]	SF [kg/m ³]	WB [-]	SA [kg/m ³]	NA [kg/m ³]	RA [kg/m ³]	WA [%]	AG [Day]	CS [MPa]
[64]	60	175.5– 390.0	0.0– 136.5	0.0– 214.5	0.0– 39.0	0.5	640.0– 678.0	0.0– 1107.0	0.0– 1078.0	4.26	1–90	4.76– 67.16
[65]	36	78.0– 433.0	0.0– 127.0	0.0– 78.0	0.0	0.3– 0.5	532.0– 770.0	0.0– 990.0	0.0– 1115.0	5.2	7– 90	15.0– 52.7
[66]	8	360.0	0.0	0.0	0.0	0.5	650.0	0.0– 1190.0	0.0– 1190.0	5.3	28– 90	30.3– 38.9
[67]	12	386.4	0.0	0.0	33.6	0.3– 0.4	883.0– 938.0	0.0– 750.0	0.0– 682.0	5.4	28	50.4– 78.1
[68]	20	300.0– 400.0	0.0– 100.0	0.0	0.0– 100.0	0.38– 0.48	667.0	0.0– 919.0	0.0– 919.0	3.7	7– 28	29.1– 72.1
[69]	6	450.0	0.0	0.0	0.0	0.4	725.0	0.0– 1085.0	0.0– 1085.0	7.8	28	38.25– 51.43
[70]	4	414.37	73.31	0.0	0.0	0.3	631.0	574.5– 1149.0	0.0– 574.5	6.58	28	27.3– 48.7
[71]	81	325.0– 425.0	0.0	0.0	0.0	0.35– 0.45	905.0– 1105.0	355.0– 1082.0	0.0– 541.0	7.1	7– 90	23.2– 51.3
[72]	5	380.0	0.0	0.0	0.0	0.42	687.0	1037.0– 1303.0	65.15– 266.0	–	28	18.5– 27.6
[73]	16	364.0	0.0	0.0	0.0	0.5	892.0	0.0– 909.0	0.0– 821.0	3.84	7– 28	24.7– 37.9
[3]	36	300.0– 450.0	0.0	0.0	0.0	0.4– 0.5	614.0– 763.0	0.0– 1366.0	0.0– 1150.0	6.4	28	29.3– 52.8
[74]	12	386.4	0.0	0.0	33.6	0.28– 0.37	883.0– 938.0	0.0– 750.0	0.0– 682.0	5.4	28	7.88– 72.45
[75]	12	363.0– 396.0	0.0	0.0	0.0	0.36– 0.37	619.0– 712.0	0.0– 1051.0	0.0– 1093.0	4.81	28	24.8– 52.78
[76]	20	375.0– 468.0	0.0	0.0	0.0	0.38– 0.62	651.0	0.0– 952.0	0.0– 797.0	4.35	14– 56	25.46– 52.21
[77]	60	192.5– 332.5	0.0	0.0– 140.0	0.0– 35.0	0.28– 0.47	1031.0	0.0– 844.0	0.0– 814.0	4.8	7– 90	13.7– 45.5
[78]	20	386.4– 420.0	0.0	0.0	0.0– 33.6	0.4	1032.4– 1032.5	0.0– 526.2	0.0– 478.2	5.4	28– 91	21.9– 56.7
[79]	120	266.5– 410.0	0.0– 143.5	0.0	0.0	0.41– 0.55	479.0– 642.0	0.0– 1048.0	0.0– 1017.0	4.26	1–90	4.8– 76.2

(Continued)

Table A1 (continued)

Ref.	*No.	PC [kg/m ³]	FA [kg/m ³]	GGBFS [kg/m ³]	SF [kg/m ³]	WB [-]	SA [kg/m ³]	NA [kg/m ³]	RA [kg/m ³]	WA [%]	AG [Day]	CS [MPa]
[80]	30	340.0– 425.0	0.0	0.0	0.0	0.51– 0.63	640.0	0.0– 1265.0	0.0– 1172.0	6.71	3– 90	10.23– 32.62
[81]	26	420.0	0.0	0.0	0.0	0.4	892.3– 1032.5	0.0– 526.2	0.0– 478.2	3.67	7– 28	25.05– 52.79
[82]	120	260.0– 410.0	0.0– 140.0	0.0	0.0	0.45– 0.55	598.0– 708.0	0.0– 1108.0	0.0– 1075.0	4.26	1–90	4.8– 72.3
[13]	24	245.0– 400.0	0.0	0.0	0.0	0.4– 0.65	690.0– 950.0	225.0– 1125.0	0.0– 740.0	3.9– 6.0	28	22.34– 54.05
[83]	48	212.0– 530.0	0.0– 318.0	0.0	0.0	0.31	389.0	0.0– 1240.0	0.0– 1240.0	4.5	28– 90	22.23– 59.65
[12]	30	380.0	0.0	0.0	0.0	0.36– 0.46	927.0	0.0– 1086.6	0.0– 1010.2	4.9	1–28	56.62– 108.51
[11]	33	258.0– 495.0	0.0– 101.0	0.0	0.0	0.32– 0.62	614.0– 691.0	0.0– 1060.0	0.0– 911.0	–	7–91	15.0– 55.0
[14]	24	353.4– 448.6	117.8– 149.5	0.0	0.0	0.3– 0.65	203.7– 814.8	404.3	387.1	–	28	17.1– 41.73
[84]	24	213.0– 426.0	107.0	0.0– 213.0	0.0	0.36	772.0	624.0	267.0	4.75	3– 90	17.3– 55.61
[85]	4	493.0	145.0	0.0	0.0	0.3	323.0– 646.0	0.0– 787.0	0.0– 737.0	7.2	28	63.6– 65.52
[10]	18	550.0	55.0	0.0	0.0– 55.0	0.28– 0.29	633.0– 690.0	0.0– 889.0	0.0– 847.0	3.9	7–91	76.6– 103.3
[86]	9	350.0	0.0	0.0	0.0	0.43– 0.44	859.0	0.0– 1027.0	0.0– 943.0	6.1	7– 56	58.9– 74.3
[9]	22	350.0	0.0	0.0	0.0	0.39– 0.55	792.9– 837.3	0.0– 1008.6	0.0– 984.6	4.57	7– 28	35.4– 67.6
[87]	12	329.0– 466.0	148.0– 247.0	0.0	0.0	0.31– 0.32	695.0– 698.0	0.0– 787.0	0.0– 770.0	2.2	7–91	24.8– 89.1
[88]	45	221.9– 554.7	0.0– 332.8	0.0	0.0	0.3– 0.6	742.1– 814.8	0.0– 808.6	0.0– 741.0	7.32	28	23.0– 53.5
[89]	32	300.0– 485.0	0.0	0.0	0.0	0.34– 0.68	685.0– 706.0	0.0– 1143.0	0.0– 1089.0	5.77	28– 90	27.7– 88.3
[90]	20	455.0	80.0	0.0	0.0	0.48	412.0– 814.0	0.0– 808.0	0.0– 778.0	7.32	7–14	16.5– 39.9
[8]	29	353.1	111.6	0.0	0.0	0.28– 0.48	416.2– 832.6	0.0– 866.8	0.0– 805.9	–	28	27.4– 56.3
[91]	21	412.5– 500.7	72.8– 88.3	0.0	0.0	0.32– 0.6	814.8	0.0– 808.6	0.0– 774.2	–	28	26.44– 48.08
[92]	12	184.5– 410.0	0.0– 225.5	0.0	0.0	0.55	530.0– 642.0	0.0– 1048.0	0.0– 1017.0	6.26	28	26.6– 48.6

(Continued)

Table A1 (continued)

Ref.	*No.	PC [kg/m ³]	FA [kg/m ³]	GGBFS [kg/m ³]	SF [kg/m ³]	WB [-]	SA [kg/m ³]	NA [kg/m ³]	RA [kg/m ³]	WA [%]	AG [Day]	CS [MPa]
[93]	128	400.0– 487.5	0.0– 25.0	0.0	0.0	0.32– 0.55	582.0– 729.0	0.0– 1140.0	0.0– 1107.0	4.26	1–90	10.2– 85.2
[49]	4	265.0	80.0	40.0	20.0	–	789.0	0.0– 943.0	0.0– 943.0	5.7	28	34.8– 41.2
Total	1243	78.0– 554.7	0.0– 332.8	0.0– 214.5	0.0– 100.0	0.28– 0.68	203.7– 1105.0	0.0– 1366.0	0.0– 1240.0	2.2– 7.8	1–91	4.76– 108.51

Note: *No.: Number of mixes.

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