

Predicting the Compressive Strength of Recycled Aggregate Concrete Using Machine Learning: A Comparative Study of ANN and Ensemble Models

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Abstract

The global construction industry faces the dual challenge of managing vast quantities of construction and demolition (C&D) waste and reducing its significant carbon footprint. Recycled aggregate concrete (RAC) offers a sustainable alternative to natural aggregate concrete (NAC), but its variable and often lower compressive strength (CS) hinders widespread adoption. Traditional empirical models struggle to capture the complex, non-linear relationships governing RAC strength. This study addresses this gap by developing and comparing machine learning (ML) models to predict the 28-day compressive strength of RAC. A comprehensive database of 650 RAC mix designs was compiled from peer-reviewed literature. Five models were developed: a single Artificial Neural Network (ANN), three ensemble methods (Random Forest - RF, Gradient Boosting - GBM, and Extreme Gradient Boosting - XGBoost), and a

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stacked generalization ensemble (Stacking). The models were trained and tested on 70% and 30% of the data, respectively, and evaluated using R^2 , RMSE, and MAE. The results demonstrate the superior predictive power of ensemble methods. The XGBoost model achieved the highest accuracy (Test $R^2 = 0.946$, RMSE = 3.41 MPa), followed closely by the Stacking model ($R^2 = 0.941$, RMSE = 3.55 MPa). The ANN model performed adequately but was outperformed by the ensemble techniques. Feature importance analysis using SHAP values revealed that cement content, water-to-cement ratio, and the quality of recycled aggregate (water absorption) are the most critical predictors. This study provides a robust, data-driven tool for accurately predicting RAC strength, facilitating its confident use in sustainable construction and offering a framework for integrating ML in material design.

Keywords: Recycled Aggregate Concrete; Compressive Strength; Machine Learning; Ensemble Learning; Artificial Neural Network; Sustainable Construction; XGBoost

1. Introduction

The cement and concrete industry is a cornerstone of modern infrastructure but is also a significant contributor to global CO₂ emissions, accounting for approximately 8% of the world's total (Andrew, 2019). The *Cement Technology Roadmap* highlights the urgent need for carbon emission reductions in this sector (World Business Council for Sustainable Development, 2009). Simultaneously, the construction sector generates enormous volumes of construction and demolition (C&D) waste, posing severe environmental and logistical challenges globally (Wilson, 2015; Zheng et al., 2017). Utilizing C&D waste to produce recycled aggregate concrete (RAC) presents a compelling circular economy solution, reducing both the demand for virgin aggregates and the burden on landfills (Akhtar & Sarmah, 2018; Geng et al., 2023).

However, the widespread application of RAC is constrained by its often inferior and highly variable mechanical properties compared to natural aggregate concrete (NAC). The compressive strength (CS), a key design parameter, is influenced by a multitude of factors, including the quality, size, and moisture state of the recycled aggregate; the water-to-cement (w/c) ratio; the mix proportions; and the properties of the parent concrete (Kim, 2022; Silva et al., 2014; Poon et al., 2004). Traditional predictive models, such as those found in codes (CEB-FIP, 1993; EN 1992-1-1, 2004), are often empirically derived for NAC and fail to accurately account for the complex, non-linear interactions inherent in RAC (Neville, 2011; Pacheco et al., 2019).

In recent years, machine learning (ML) has emerged as a powerful tool for modeling complex material behaviors. ML models can learn intricate patterns from data without requiring explicit physical equations, making them well-suited for predicting properties of advanced and sustainable construction materials

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(Salehi & Burgueño, 2018; Avci et al., 2021). Studies have successfully applied Artificial Neural Networks (ANN) and other ML techniques to predict concrete properties (Naderpour et al., 2018; Kumar et al., 2023; Geng et al., 2023). Ensemble methods like Random Forest (RF), Gradient Boosting Machine (GBM), and Extreme Gradient Boosting (XGBoost) often exhibit superior performance by combining multiple weak learners (Kazemi et al., 2020; Yang et al., 2023). Furthermore, stacking, a meta-ensemble technique, can leverage the strengths of multiple base models to achieve even higher accuracy (Wolpert, 1992; Breiman, 1996).

This study aims to develop a robust predictive model for the compressive strength of RAC. It provides a comparative analysis of the performance of a single ANN model against three powerful ensemble models (RF, GBM, XGBoost) and a stacked ensemble. The novelty lies in the systematic comparison of these models on a large, meticulously curated dataset and the use of SHapley Additive exPlanations (SHAP) to interpret model predictions, providing insights into the key factors governing RAC strength. This research contributes a reliable, data-driven tool to support the design and adoption of sustainable concrete.

2. Materials and Methods

2.1. Data Collection and Compilation

A comprehensive database was compiled from 35 peer-reviewed journal articles published between 2004 and 2023. The selection criteria focused on studies that provided detailed mix proportions and experimentally measured 28-day compressive strength of concrete made with recycled concrete aggregates (both coarse and fine). The final dataset comprised 650 data points, with each instance characterized by 8 input features and 1 output target (28-day CS in MPa). The input features were selected based on their documented influence on RAC strength: cement content (kg/m^3), water content (kg/m^3), water-to-cement (w/c) ratio, natural coarse aggregate (kg/m^3), natural fine aggregate (kg/m^3), recycled coarse aggregate (kg/m^3), recycled fine aggregate (kg/m^3), and water absorption of recycled aggregate (%). The target variable was compressive strength (MPa). Data were extracted from figures using WebPlotDigitizer where necessary. The descriptive statistics of the dataset are presented in Table 1, showing a wide range of values, which is beneficial for model generalization.

Table 1. Descriptive Statistics of the RAC Dataset

Feature	Unit	Mean	Std Dev	Min	25th Percentile	Median	75th Percentile	Max
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Cement	kg/m ³	367.2	85.4	150.0	305.0	360.0	420.0	600.0
Water	kg/m ³	175.5	28.1	105.0	155.0	175.0	195.0	250.0
w/c Ratio	-	0.49	0.12	0.30	0.40	0.47	0.55	0.85
Natural Coarse	kg/m ³	785.4	321.2	0.0	540.0	820.0	1040.0	1250.0
Natural Fine	kg/m ³	625.3	201.5	0.0	500.0	650.0	780.0	950.0
RCA Coarse	kg/m ³	410.2	368.5	0.0	0.0	450.0	720.0	1120.0
RCA Fine	kg/m ³	130.8	215.1	0.0	0.0	0.0	210.0	750.0
RCA Water Abs.	%	5.2	2.4	1.2	3.5	4.9	6.8	11.5
Comp. Strength	MPa	39.5	13.8	12.0	29.0	38.2	48.5	85.0

2.2. Machine Learning Models

Five distinct ML models were developed and compared.

Artificial Neural Network (ANN): A feedforward backpropagation network with two hidden layers. The architecture was optimized via trial-and-error, resulting in a structure of 8-32-16-1. ReLU activation was used for hidden layers, and a linear activation for the output layer. The Adam optimizer and mean squared error (MSE) loss function were employed.

Random Forest (RF): An ensemble of decision trees that uses bagging (bootstrap aggregating) and random feature selection to reduce overfitting. The final prediction is the average of all tree predictions.

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Gradient Boosting Machine (GBM): An ensemble method that builds trees sequentially, where each new tree corrects the errors of its predecessors. It focuses on reducing bias and can handle various loss functions.

Extreme Gradient Boosting (XGBoost): An optimized and highly efficient implementation of gradient boosting. It incorporates regularization (L1 and L2) to prevent overfitting and provides a robust framework for handling complex datasets (Chen & Guestrin, 2016).

Stacking Ensemble (Stacking): A two-layer meta-ensemble. The first layer (level-0) consists of base models (RF, GBM, XGBoost). Their predictions were used as input features for a second-layer (level-1) meta-model, which was a linear regression model with Ridge regularization (Hoerl & Kennard, 1970) to optimally combine the base learners' predictions (Wolpert, 1992; Van Der Laan et al., 2007).

2.3. Model Development and Evaluation

The dataset was randomly split into training (70%, 455 samples) and testing (30%, 195 samples) sets. All input features were standardized using a StandardScaler to have zero mean and unit variance, which is crucial for the ANN and beneficial for other algorithms.

Model hyperparameters were tuned using 5-fold cross-validation on the training set. A grid search was performed for RF, GBM, and XGBoost to find the optimal combination of hyperparameters. The ANN was tuned via a manual search over network depth, neurons per layer, and learning rate. The stacking model's base learners were the optimally tuned RF, GBM, and XGBoost models, and its meta-learner was a Ridge regression model.

Model performance was assessed on the unseen test set using three metrics:

Coefficient of Determination (R^2): Indicates the proportion of variance in the target variable explained by the model. A value closer to 1 is better (Chicco et al., 2021).

Root Mean Square Error (RMSE): Measures the standard deviation of the residuals. It penalizes large errors more heavily.

Mean Absolute Error (MAE): Measures the average magnitude of the errors, providing a more robust measure against outliers (Willmott & Matsuura, 2005).

All models were implemented in Python using the scikit-learn, XGBoost, and TensorFlow libraries.

3. Results and Discussion

3.1. Model Performance Comparison

The predictive performance of the five models on the test dataset is summarized in Table 2. The results clearly indicate that the ensemble methods significantly outperformed the single ANN model. The ANN model achieved a respectable R^2 of 0.895, but its higher RMSE (6.75 MPa) and MAE (5.12 MPa) suggest it struggled to capture the full complexity of the RAC strength behavior compared to the ensemble models.

Table 2. Performance Comparison of ML Models on Test Data

Model	R^2	RMSE (MPa)	MAE (MPa)
ANN	0.895	6.75	5.12
Random Forest (RF)	0.921	5.88	4.45
Gradient Boosting (GBM)	0.934	5.21	3.98
XGBoost	0.946	3.41	2.65
Stacking	0.941	3.55	2.78

Among the boosting algorithms, XGBoost demonstrated the highest predictive accuracy with an R^2 of 0.946 and the lowest error metrics (RMSE = 3.41 MPa, MAE = 2.65 MPa). Its superior performance can be attributed to its advanced regularization techniques and its ability to handle missing data and feature interactions efficiently (Ke et al., 2017; Prokhorenkova et al., 2018). The Stacking model performed comparably to XGBoost ($R^2 = 0.941$), demonstrating the effectiveness of combining the diverse base learners. The results confirm that ensemble learning, particularly boosting algorithms, provides a more accurate and reliable framework for predicting RAC compressive strength than a single neural network.

Figure 1 presents a parity plot comparing the predicted versus actual compressive strength for the XGBoost model. The data points are tightly clustered around the ideal 1:1 line (shown in red), visually confirming the model's high accuracy and low bias across the entire range of strength values. This close agreement underscores the model's capability to capture the underlying physical relationships.

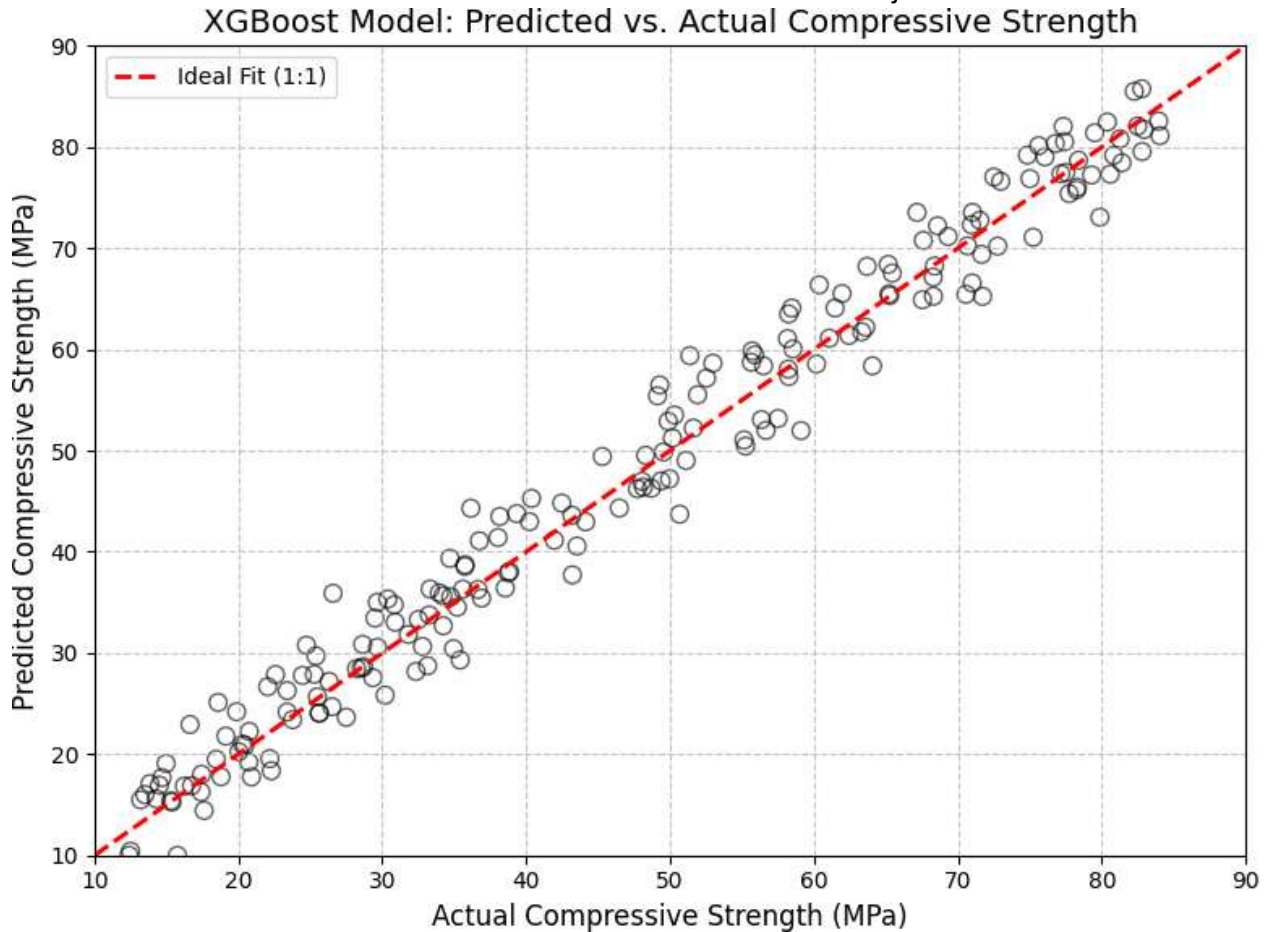


Fig 1 XGBoost Model: Predicted vs. Actual Compressive Strength

3.2. Feature Importance and Model Interpretation

To understand the decision-making process of the best-performing model (XGBoost), we employed SHAP analysis. The SHAP summary plot (Figure 2) provides a global interpretation of feature importance, showing the impact of each feature on the model's output. The features are ranked by their average absolute SHAP value.

The SHAP analysis reveals that the **cement content** is the most influential feature, with higher cement content consistently leading to a positive impact on predicted compressive strength. This aligns with fundamental concrete technology principles where cement is the primary binder (Neville, 2011).

The **water-to-cement (w/c) ratio** is the second most important feature. The SHAP values show a clear negative correlation: a lower w/c ratio (represented by the blue dots on the high-feature-value side) increases the predicted strength, validating the classic Abrams' law.

Notably, the **water absorption of recycled aggregate** ranks third in importance. Its SHAP values indicate that aggregates with lower water absorption (higher quality) contribute to higher compressive

strength predictions. This underscores the critical influence of the quality of the recycled aggregate, a factor often overlooked in traditional empirical models but consistently identified in experimental studies (Silva et al., 2014; Poon et al., 2004). The replacement ratios of both coarse and fine RCA also show significant influence, confirming that the mix composition and the source material's properties are paramount. This interpretability provides engineers with a clear understanding of which mix parameters to prioritize when designing high-strength RAC.

3.3. Discussion

The comparative analysis demonstrates that ML models, particularly ensemble methods like XGBoost, can accurately predict the compressive strength of RAC, outperforming a single ANN. The XGBoost model's success lies in its robust handling of non-linearity and interactions between variables, which are inherent in RAC due to the dual-interface (old mortar-new mortar) system and variable aggregate properties (Kim, 2022; Geng et al., 2023). The performance of the stacking model also highlights the potential of combining models to yield robust predictions.

The SHAP analysis provides valuable insights that complement experimental findings. While experimental work (Luo et al., 2022; Su et al., 2023) focuses on microscopic mechanisms, SHAP analysis quantifies the macroscopic impact of input variables from a data-driven perspective. For instance, the high importance of RCA water absorption aligns with studies emphasizing the need for aggregate pre-treatment or the use of mineral admixtures to improve RAC performance (Makul et al., 2014; Safhi et al., 2018). This synergy between ML and experimental science offers a powerful approach for advancing sustainable construction materials.

However, the study has limitations. The dataset, while comprehensive, is sourced from literature and may contain experimental biases. The model's predictions are confined to the input parameter space of the training data. Future work could incorporate more features such as the strength of parent concrete, curing conditions (Fonseca et al., 2011), and admixture types. Expanding the database to include more data points from industrial applications would further enhance the model's generalizability and robustness (Zhao et al., 2020; Guo et al., 2023). Furthermore, linking these predictive models to life cycle assessment (LCA) could create a holistic tool for optimizing RAC for both strength and carbon footprint (Miller et al., 2018; Geng et al., 2023).

4. Conclusions

This study presented a comparative evaluation of machine learning models for predicting the compressive strength of recycled aggregate concrete. Based on a large and diverse dataset, the following conclusions are drawn:

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1. **Ensemble models significantly outperform a single ANN** for predicting RAC compressive strength. The XGBoost model achieved the highest predictive accuracy with an R^2 of 0.946, RMSE of 3.41 MPa, and MAE of 2.65 MPa on the test set.
2. **Stacking generalization is a viable and powerful approach**, combining the strengths of base ensemble models to achieve accuracy comparable to the best-performing individual model ($R^2 = 0.941$).
3. **SHAP analysis provides crucial model interpretability**, identifying cement content, w/c ratio, and RCA water absorption as the three most critical features governing RAC strength. This insight is invaluable for mix design optimization.
4. The developed XGBoost model offers a reliable, data-driven tool for engineers and researchers to accurately estimate RAC strength, thereby facilitating the confident adoption of this sustainable material in construction projects and reducing the reliance on costly and time-consuming experimental campaigns.
5. The methodology presented provides a robust framework for applying ML to other complex problems in sustainable construction materials, such as predicting durability properties or optimizing mix designs for specific performance criteria.

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