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Predicting Compressive Strength of M20 Concrete with Partial Replacement of Coarse Aggregates by Nueva Ecija Sourced Recycled Portland Cement Concrete Pavement using XGBoost Algorithm

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Abstract. This research delves into the potential impact of replacing the coarse aggregates in M20 concrete with recycled concrete. The study aims to explore the possibility of recycling waste material from road construction to address sustainability challenges in the construction industry, especially in developing countries like the Philippines. The research adopts an experimental design involving preparing and testing recycled concrete aggregates, alongside sample preparation and testing. The study also employs the XGBoost machine learning algorithm to help predict the compressive strength of concrete. The XGBoost algorithm was trained using fine-tuned hyperparameters, and the model's evaluation was done using R-squared and Root Mean Squared Error. The research findings indicate a positive correlation between RCA content and compressive strength, with the average compressive strength of concrete mixtures increasing over time. The XGBoost outperforms the Multi Linear Regression model in predicting compressive strength, and incorporating RCA within the optimal range can enhance the strength properties of concrete. The study concludes that the XGBoost model with fine-tuned hyperparameters is reliable for predicting compressive strength, contributing to sustainable concrete production and reliable strength outcomes.

Keywords: M20 Concrete; Machine Learning; Materials; Recycled Concrete Aggregate; XGboost;

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1. Introduction

Road reconstruction and weak road network expansion in the Philippines contribute to limited mobility, poor road safety, and insufficient connectivity (ADB, 2017). These projects also generate construction waste, which, if not disposed of properly, can harm public health and ecosystems (Yeheyis et al., 2013). Quarrying for urban expansion leads to soil instability, altered river flow, and increased flood and landslide risks (Esguerra et al., 2008), causing damage to underwater fauna and landfill issues in Cebu (Montenegro, 2016). The construction sector globally accounts for about 30% of resource extraction and 25% of solid waste (Benachio et al., 2020). Sustainable measures in construction are crucial to mitigate these environmental effects (Hawken et al., 1999; Mehta, 2001).

The construction industry faces challenges in meeting sustainability goals, including high construction waste, resource consumption, and budget constraints (Azis et al., 2012). Reutilizing waste material, such as concrete aggregates from road reconstruction, is a recognized sustainability measure (Azis et al., 2012). Determining recyclability through research can promote cost-efficient and ecological practices.

High construction costs and waste disposal negatively impact sustainability goals, particularly in developing countries like the Philippines (PSO, 2022). Inflation has tripled the retail price index for construction materials in the National Capital Region, posing a threat to the allocation of budgets for waste disposal and other sustainability efforts (PSO, 2022).

Considering the high cost and environmental impact of improper waste disposal and the mechanical durability properties of recycled concrete aggregates, strategies should be identified to facilitate waste management and assess the feasibility of reutilizing waste materials. Based on the foregoing, this study has the following primary objective: to predict the effects of partially replacing the coarse aggregates with recycled concrete on the compressive strength of concrete. Such a prediction will help determine if such waste material from roads may be reutilized for other purposes. The primary objective of this study branches out into three secondary objectives, namely:

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- To test the effect of Recycled Coarse Aggregate on the compressive strength of concrete.
- To develop a prediction model for the performance of M20 concrete with coarse aggregates partially replaced with Nueva Ecija Sourced Recycled Portland Cement Concrete Pavement using Extreme Gradient Boosting (XGBoost) machine learning algorithm.

2. Methodology

This study utilized an experimental research design. It is a framework of techniques, methods, and processes chosen to conduct scientific studies using two sets of variables (one dependent, the other independent). In other words, it is a design focused on determining the causal relationship between two identified variables to derive causal validity or inferences (Mitchell, 2015).

The independent variables of this study are (1) the Percentage of RCA replacement of coarse aggregate and (2) the Age of the Sample. Meanwhile, the dependent variable is Compressive Strength. The causal inferences will be drawn out from these two sets of variables by following through an experiment.

2.1. Preparation and Test for RCA

Demolished PCCP was sourced, collected, crushed, and sized. The crushed PCCP underwent sieve analysis, washing, and drying. After that was used as Recycled Concrete Aggregate (RCA).

2.2. Preparation of Samples

Concrete proportions of M20, 1 Part cement, 1.5 parts fine aggregates, and three parts coarse aggregates (1:1.5:3) were prepared to reach a design strength of 20 MPa. The coarse aggregate part of which was partially replaced/replaced with an incremental percentage of RCA. After that, a total of 180 – 150 x 150 x 150 mm cubical samples of the design mix were prepared as follows:

Table 1 Sample Proportion

Coarse Aggregate	Design Mix (%)								
	1	2	3	4	5	6	7	8	9
NCA	100	87.5	75	62.5	50	37.5	25	12.5	0
RCA	0	12.5	25	37.5	50	62.5	75	87.5	100

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Sample 1 (0 RCA) served as the control sample of the experiment. The samples were cured in curing tanks and taken out for one day before undergoing the compressive test.

2.3. Testing of Samples

A total of 185 samples of each mix went through compressive strength testing using a Universal Testing Machine at the Civil Engineering Laboratory of the Nueva Ecija University of Science and Technology on it's the 7th, 14th, 21st, and 28th day; Results were recorded and tabulated for data analysis.

Figure 1 Compressive Strength Testing using a Universal Testing Machine.

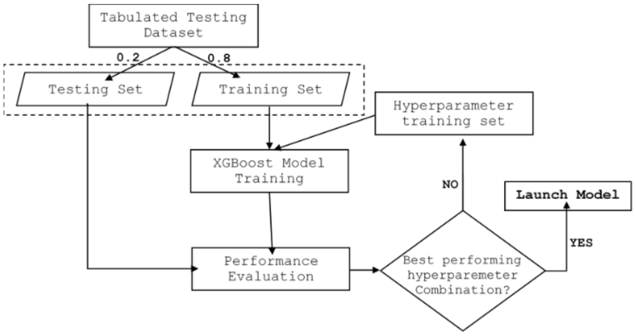

Figure 2 XGBoost Model Flow Chart.

2.4. XGBoost algorithm

For prediction modeling, XGBoost (Figure 2) was employed. XGBoost is a highly efficient and accurate machine learning algorithm that combines weak predictive models, such as decision trees, to create a powerful ensemble model. It utilizes gradient-based optimization and regularization techniques to iteratively improve the model's performance and handle various data challenges, making it a popular choice for predictive analytics tasks (Simplilearn, 2023).

2.4.1. Data Processing

The tabulated experimental result was analyzed and tested for correlation. Pearson correlation coefficients were computed to determine the relationship between the variables.

After that, the experimental result was split into 0.8 training and 0.2 testing subsets to avoid data snooping bias.

2.4.2. Training

XGBoost training started with determining the best-performing hyperparameters (max_depth, learning rate, n_estimators, gamma, and subsample). Table 2 shows the ranges of hyperparameters used in the fine-

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tuning of the model. Using the training set, the best-performing hyperparameter was determined using the generated model prediction's Root Mean Squared Error (RMSE). The XGBoost predictive model of compressive strength of M20 concrete with partial replacement of coarse aggregates by Nueva Ecija sourced recycled portland cement concrete pavement was then trained and generated using the best-performing hyperparameter. F weight score was also calculated to determine how RCA and AGE influence compressive strength. Model Loss was also computed to check for overfitting.

Table 2 XGBoost hyperparameter training set

XGBoost hyperparameter	Range	Increment
max_depth	1-15	1
learning_rate	0.1 – 0.5	0.05
n_estimators	200-1000	1
gamma	0.01-0.05	0.01
subsample	0.1-1.5	0.1

2.5. Model Evaluation

The XGboost prediction model was then assessed by comparing its performance with the Multi Linear Regression model. R-squared (R^2) and Root Mean Squared Error (RMSE) was used in the evaluation.

3. Results and Discussion

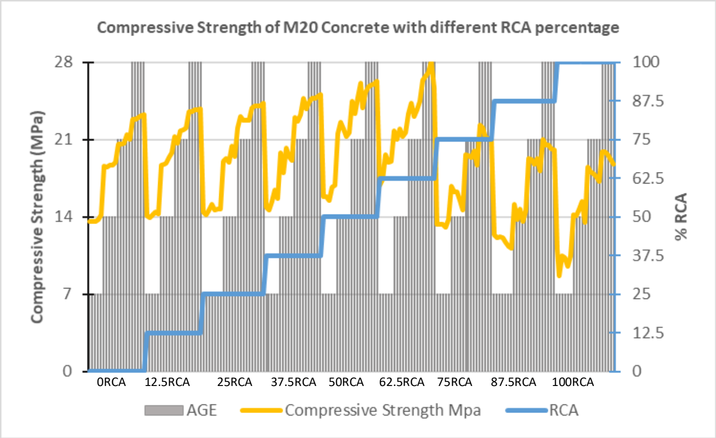

Figure 3 Compressive Strength Result of the concrete samples

3.1. Effect of Recycled Coarse Aggregate on the compressive strength of concrete.

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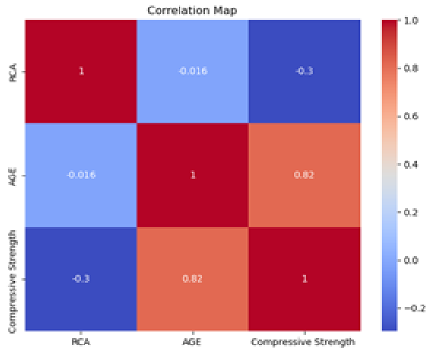

Figure 4 Pearson Correlation Coefficients between Compressive Strength, AGE, and RCA Replacement in Total Sample (N = 185)

	RCA	Compressive Strength
RCA	1.000	0.947
Compressive Strength	0.947	1.000

Figure 5 Pearson Correlation Coefficients between Compressive Strength, and RCA Replacement (0–62.5RCA) in 28th day. Sample (N = 30)

As shown in Figure 3, the average compressive strength of all mixtures consistently increased from day 7 to day 28, similar to Etxeberria et al.'s (2007) findings on recycled coarse aggregate. Correlation analysis (Figure 4) shows a moderate negative correlation (–0.296) between RCA content and compressive strength, but within the range of 0RCA to 62.5RCA, there is a positive correlation (0.947) (Figure 5), specifically in the 28th-day result. Age of the concrete exhibits a strong positive correlation (0.816) with compressive strength. The 28th-day compressive strength is crucial for assessing concrete quality and durability. Mixtures from 0RCA to 75RCA surpass the desired M20 strength (20MPa), with the 62.5RCA mixture reaching the highest compressive strength (26.188MPa). RCA's adhered mortar's rough texture and absorption capacity enhances bonding, leading to improved strength properties compared to natural coarse aggregates (NCA).

3.2. XGBoost Model predicting the compressive strength of Concrete with Recycled coarse aggregate.

Table 3 Best XGBoost hyperparameter after fine-tuning

XGBoost hyperparameter	Value
max_depth	3
learning_rate	0.5
n_estimators	138
gamma	0.04
subsample	0.1

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As a result of fine-tuning, the best hyperparameter (shown in Table 3) was then used to train and generate the final prediction model.

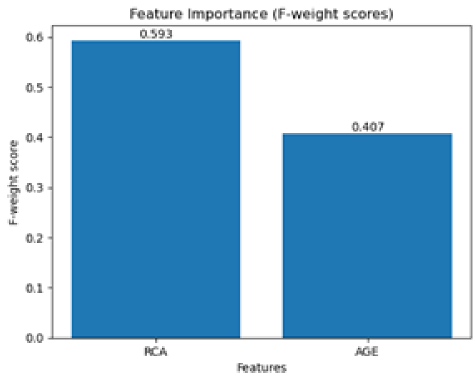

Figure 6 Feature Importance

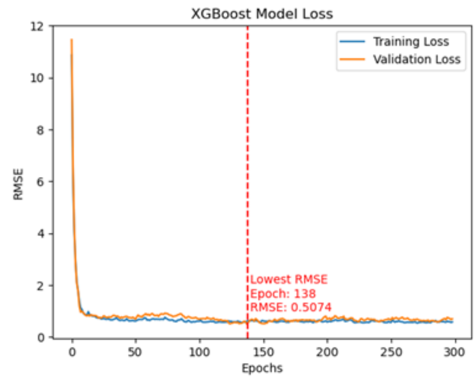

Figure 7 XGBoost Model Loss

F-weight scores (Figure 6) indicate that the RCA feature has a stronger influence on predicting compressive strength (score: 0.593) compared to the AGE feature (score: 0.407), despite the AGE feature having a higher correlation.

After identifying the best hyperparameters, the optimal prediction model was obtained and evaluated using training and testing sets. The model achieved an R^2 score of 0.981 on the training set (Figure 8), explaining 98.1% of the variance, with an RMSE of 0.5862. On the testing set (Figure 9), the model achieved an R^2 score of 0.9769, explaining 97.7% of the variance, with an RMSE of 0.7061. The loss diagram (Figure 7) analysis indicated the absence of overfitting, as the model remained stable and performed consistently on seen and unseen data. Overall, the fine-tuned XGBoost model demonstrated improved accuracy, generalization, and explanatory power in predicting compressive strength, making it reliable for real-world applications.

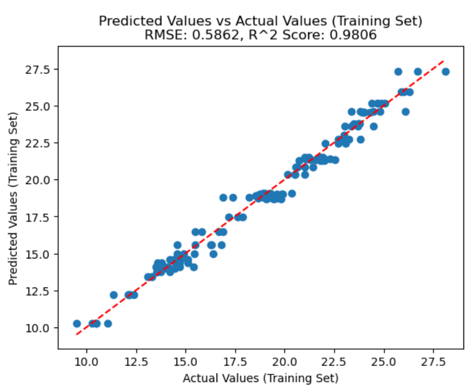

Figure 8. XGBoost's Predicted Values vs Actual Value (Training Set)

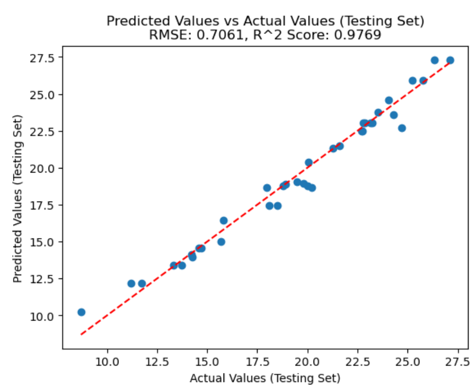

Figure 9. XGBoost's Predicted Values vs Actual Value (Testing Set)

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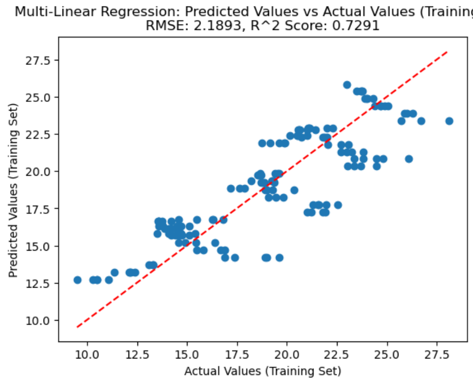

Figure 10. MLRE Predicted Values vs Actual Value (Training Set)

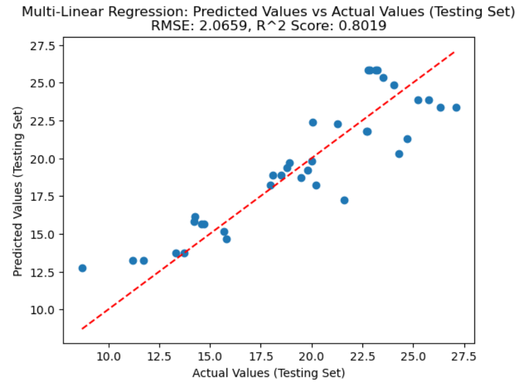

Figure 11. MLRE Predicted Values vs Actual Value (Testing Set)

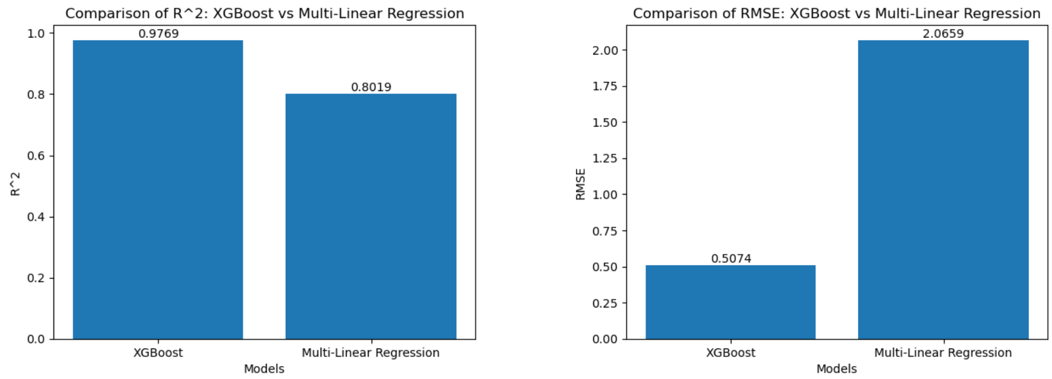

Figure 12 RMSE comparison between XGBoost and Multi Linear Regression Model

The MLRE and XGBoost models were assessed by comparing their R^2 and RMSE values on the testing set. In terms of performance, the MLRE model exhibited an R2 of 0.8019 and an RMSE of 2.0659 (refer to Figure 11), while the XGBoost model yielded an R^2 of 0.9769 and an RMSE of 0.7061 (refer to Figure 9). Analyzing the data depicted in Figure 12, it can be inferred that the XGBoost model outperforms the MLRE model in terms of predictive accuracy. This conclusion stems from the consistently higher R^2 values and lower RMSE values observed with the XGBoost model, indicating its superior capability in predicting the target variable. Overall, these findings suggest that the XGBoost model serves as a more dependable predictor compared to the MLRE model.

4. Conclusions

This research has yielded valuable insights into the factors that significantly impact the compressive strength of M20 concrete. The study conclusively establishes that the content of recycled coarse aggregate (RCA) and the age of the concrete are the primary variables affecting compressive strength.

Incorporating RCA within the optimal range has been shown to substantially enhance the strength properties of concrete. Additionally, the fine-tuned hyperparameters of the XGBoost model have proven to be a highly reliable and precise method for predicting compressive strength, surpassing the performance of the MLR model. These findings are crucial in optimizing M20 concrete mixtures, selecting appropriate modeling techniques, and realizing a sustainable approach to concrete production, ensuring dependable strength outcomes while considering the recycling effect.

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