

Development of Regression Models for Predicting the Strength Properties of Normal and Pozzolanic Concrete

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ABSTRACT: Concrete strength prediction is important for improving mix design, quality control, and the effective utilization of supplementary cementitious materials. This study developed regression models for predicting the strength properties of normal and pozzolanic concrete incorporating rice husk ash (RHA) as a partial replacement for cement. Concrete was produced using a 1:2:4 mix proportion and a constant water-to-binder ratio of 0.58, with 10% of the cement replaced by RHA in the pozzolanic concrete. A total of 60 cubes ($150 \times 150 \times 150$ mm) were cast and cured for 28 and 56 days, while 30 cylinders (150×300 mm) were cured for 56 days. Specimens were tested for compressive and split tensile strength in accordance with British Standards. The RHA contained 80.70% SiO_2 , confirming its pozzolanic suitability. Regression analysis using SPSS produced strong predictive models with R^2 values of 0.996 and 0.998 for compressive strength and 0.951 and 0.994 for split tensile strength of normal and pozzolanic concrete, respectively. Pozzolanic concrete achieved 3.33% higher compressive strength and 9.68% higher split tensile strength than normal concrete at 56 days. Differences between observed and predicted strength values ranged from 1.23% to 16.86%. Cement was the most statistically significant predictor in all models ($p = 0.000$). The study concluded that regression analysis provides useful predictive models for the strength properties of normal and pozzolanic concrete and can support concrete mix assessment, performance prediction, and optimization of sustainable concrete incorporating agricultural waste materials.

Keywords: Regression models, concrete strength, normal concrete, pozzolanic concrete, rice husk ash

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I. INTRODUCTION

Concrete is one of the most widely used construction materials because of its relatively high compressive strength, durability, availability of constituent materials, and adaptability to different structural applications (Surahyo et al., 2019). The performance of concrete is influenced by several factors, including the properties and proportions of cement, fine aggregate, coarse aggregate, water, curing conditions, and the use of supplementary cementitious materials (Yaseen et al., 2024). Among the mechanical properties of concrete, compressive strength is particularly important because it provides a primary indication of the load-bearing capacity and overall quality of concrete. Consequently, accurate prediction of concrete strength is essential for mix proportioning, quality control, structural design, and the efficient use of construction materials (Channa et al. 2026; Do et al. 2026; Mylvaganam & Yogarajah, (2023).

Conventional or normal concrete generally consists of cement, water, fine aggregate, and coarse aggregate (Surahyo et al., 2019). Although cement provides the binding action necessary for strength development, its extensive production is associated with considerable consumption of energy and natural resources as well as substantial carbon dioxide emissions (Ahmed, 2024). The growing demand for sustainable construction has therefore encouraged the investigation of alternative cementitious materials capable of partially replacing ordinary Portland cement without compromising the required engineering properties of concrete (Singh et al., 2025). Pozzolanic materials, including rice husk ash (RHA), fly ash, silica fume, and other industrial or agricultural residues, have received considerable attention because of their potential to improve

sustainability while utilizing locally available waste materials (Amran et al., 2021).

Rice husk ash is a promising pozzolanic material because rice husk contains a substantial quantity of silica, and controlled combustion can produce an ash with reactive amorphous silica (Amran et al., 2021). When incorporated into concrete, the silica in RHA can react with calcium hydroxide released during cement hydration to form additional calcium silicate hydrate (C-S-H), which is one of the principal products responsible for the strength and durability of cement-based materials (Vijaya et al., 2025). However, the incorporation of pozzolanic materials can alter the fresh and hardened properties of concrete depending on their replacement level, chemical composition, fineness, water demand, and interaction with other mix constituents. Therefore, establishing reliable relationships between mixture proportions and strength properties is necessary for the effective application of pozzolanic concrete (Moutassem & Chidiac, 2023). Amran et al., 2021).

Traditionally, concrete strength is determined experimentally by casting and curing specimens and subsequently testing them at specified ages, commonly 7, 14, 28, 56 and 90 days (Whwah et al., 2025; Ibrahim et al., 2025; Hassan et al., 2026). Although experimental testing provides reliable measurements, it can be time-consuming, labour-intensive, and costly when a large number of mix combinations are considered (Obam et al. 2024). Furthermore, conventional trial-and-error approaches may not adequately reveal the complex relationships between concrete constituents and strength development (Ziolkowski 2025). These limitations have created a need for mathematical and statistical approaches capable of predicting concrete strength from readily available mixture parameters. The use of statistical approaches to predict the **compressive strength** of concrete based on mixture proportions, on account of its industrial importance, has received significant attention (Kumar et al., 2025, Adsul et al., 2025; Altuncı, 2024; Moutassem & Chidiac, 2023; Young et al. 2019).

Regression analysis provides an effective statistical technique for establishing quantitative relationships between a dependent variable and one or more independent variables (Lal et al. 2025; Nagwani et al., 2014). In concrete technology, regression models can be used to relate compressive strength to factors such as cement content, fine aggregate, coarse aggregate, water content, water-to-cement ratio, and pozzolanic material content (Mondal, 2026). A properly developed regression model can provide a relatively simple means of estimating concrete strength without conducting an extensive number of laboratory tests. The reliability of such a model can be assessed using statistical indicators such as the coefficient of

determination (R^2), adjusted R^2 , standard error of the estimate, significance level, and prediction error.

The prediction of strength becomes more important when comparing normal concrete with pozzolanic concrete because the introduction of a pozzolanic material changes the relationship between the constituent materials and the resulting strength. A regression model developed for normal concrete may therefore not adequately represent pozzolanic concrete unless the effect of the pozzolanic material is explicitly incorporated into the model. Developing separate or comparative regression models for normal and pozzolanic concrete can provide a better understanding of the contribution of individual mix constituents to strength development and can establish suitable predictive equations for each concrete type.

In addition to providing predictive capability, regression modelling can support concrete mix optimization by identifying the relative influence of constituent materials on strength. This is particularly useful where agricultural waste materials such as RHA are employed as partial replacements for cement. A reliable predictive model can reduce the number of experimental trials required during mix development, assist engineers in selecting appropriate mix proportions, and contribute to the production of concrete with desirable mechanical performance and reduced environmental impact. Against this background, this study focuses on the development of regression models for the prediction of strength properties of normal and pozzolanic concrete.

II. MATERIALS AND METHODS

2.1 Materials

- Cement: Bua 43-grade cement conforming to NIS 444-1:2018 (CEM II/A-L) was used. It was obtained from North Bank Market, Makurdi, Nigeria.
- Fine Aggregate: River sand obtained from River Benue, Makurdi, Nigeria, was used as the fine aggregate. It was sieved through a 4.75 mm sieve to remove pebbles and other oversized particles.
- Coarse Aggregate: Granite with a maximum size of 20 mm was used as the coarse aggregate. It was obtained from Court 5, North Bank, Makurdi, Nigeria, and conformed to the requirements for structural concrete specified in BS 8110 (1997).
- Water: Pipe-borne water obtained from the Civil Engineering Laboratory, Joseph Sarwuan Tarka University, Makurdi, Nigeria, was used for concrete production.
- Rice Husk Ash (RHA): Rice husk was subjected to controlled burning for 72 hours to produce ash. The resulting rice husk ash was subsequently sieved through a 75 μ m BS sieve to obtain a relatively fine and uniform material for use as a partial cement replacement.

2.2 Method

2.2.1 Concrete Production

The experiment comprised two concrete mixtures: normal concrete containing 0% rice husk ash (RHA), which served as the control, and pozzolanic concrete containing 10% RHA as a partial replacement for cement. The choice of the 10% RHA replacement level was based on previous literature and experimental investigations that reported its suitability for concrete production (Adedeji et al., 2026; Adefisoye et al., 2025; Alhassan et al., 2023;

Barua et al., 2018; Li et al., 2022; Patil, 2024). Both mixtures were produced using a 1:2:4 mix proportion and a constant water–cement ratio of 0.58. For each concrete mixture, 30 cubes measuring 150 × 150 × 150 mm and 15 cylinders measuring 150 × 300 mm were produced. Thus, a total of 60 cubes and 30 cylinders were produced and tested. The concrete mixtures and specimen allocation are presented in Table 1. The 60 cube specimens were equally divided between the two curing ages, with 30 cubes cured for 28 days and the remaining 30 cubes cured for 56 days before testing. Similarly, all 30 cylinder specimens were cured for 56 days before testing.

Table 1: Concrete Mix Proportions

Parameter	Normal Concrete (NC)	Pozzolanic Concrete (RHA10)
RHA replacement level (%)	0	10
Cement (%)	100	90
Cement (kg/m ³)	347.95	313.64
RHA (kg/m ³)	0.00	34.84
Sand (kg/m ³)	696.46	696.46
Gravel (kg/m ³)	1,392.92	1,392.92
Water (kg/m ³)	201.91	201.91
Mix proportion (cement:sand:gravel)	1:2:4	1:2:4
Water–cement ratio	0.58	0.58
Cube size (mm)	150 × 150 × 150	150 × 150 × 150
Number of cubes	30	30
Cubes cured for 28 days	15	15
Cubes cured for 56 days	15	15
Cylinder size (mm)	150 × 300	150 × 300
Number of cylinders	15	15
Total specimens	45	45

2.2.2 Experimental Method

(a) Chemical Composition: The chemical composition of the rice husk ash was determined using X-ray Fluorescence (XRF) spectrometry in accordance with ASTM D5185 and ASTM E2412 standards.

(b) Grading of aggregates: The sieve analysis was performed on river sand and granite in accordance with the method described in BS EN 933-1:(2012).

(c) Specific gravity test: The specific gravity test was carried out according to the method described in BS EN 1097-6 (2013). The specific gravity was calculated using equation (1):

$$G_s = \frac{M_2 - M_1}{(M_4 - M_1) - (M_3 - M_2)} \quad (1)$$

where,

G_s = specific gravity, M₁ = weight of empty flask, (g), M₂ = weight of empty flask + weight of the sample, (g), M₃ = weight of empty flask + weight of the sample + water, (g), M₄ = weight of empty flask + water, (g)

(d) Compressive strength test: this test was performed in accordance to BS EN 12390-3:(2019) the expression in equation (2) was used:

$$\sigma = \frac{F}{A} \quad (2)$$

Where ;

σ is the Compressive Strength (N/mm²), F = crushing load of cube (N), A = Area of cubes (mm²)

(e) Split tensile strength: This test was conducted in accordance with the provisions of BS EN 12390-6:(2023) and the expression in equation (3) was used:

$$T_s = \frac{2F}{\pi ld} \quad (3)$$

Where:

T_s is the splitting tensile strength (N/mm²), F is the maximum applied load (in Newtons) by the testing machine, l is the length of the specimen (mm), and d is the diameter of the specimen (mm).

2.3 Modeling the Prediction of Concrete Strength

Four regression model equations were developed to predict the 56-day strength properties of normal and pozzolanic concrete. Two model equations were developed for the 56-day compressive strength and split tensile strength of normal concrete using Equation (4), while two additional model equations were developed for the 56-day compressive strength and split tensile strength of pozzolanic concrete using Equation (5). The development of the regression equations was based on the experimental results obtained from the normal and pozzolanic concrete mixes. The 56-day compressive strength and split tensile strength results were subjected to regression analysis using the Statistical Package for the Social Sciences (SPSS) software. The analysis established

the relationship between the concrete constituent materials and the corresponding strength properties. From the regression output, the values of the regression constants, β_0 , β_1 , β_2 , β_3 , β_4 , and β_5 , were determined and substituted into the general regression equations to obtain the respective predictive models for normal and pozzolanic concrete.

$$Y = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \beta_3 X_3 + \beta_4 X_4 + \epsilon \quad (4)$$

$$Y = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \beta_3 X_3 + \beta_4 X_4 + \beta_5 X_5 + \epsilon \quad (5)$$

Y = Compressive strength or tensile strength of concrete at 28-day

X_1 = proportion of cement in the mix

β_i (i=0-5) coefficients of regression equation and they depend on concrete ingredients.

X_2 = proportion of fine aggregate in the mix

X_3 = proportion of coarse aggregate in the mix

X_4 = proportion of water/cement ratio in the mix

X_5 = proportion of RHA in the mix

ϵ = Error term

III. RESULT AND DISCUSSION

3.1 Chemical Composition of Rice Husk Ash

Table 2 shows the chemical composition of rice husk ash (RHA). The chemical analysis shows that the RHA is predominantly silica-rich, with SiO₂ (80.70%), followed by Fe₂O₃ (9.92%), CaO (8.65%), MgO (6.12%), and smaller quantities of K₂O (3.93%), Al₂O₃ (3.87%), Na₂O (2.96%) and CuO (1.32%). The Loss on Ignition (LOI) of 4.84% indicates a relatively moderate amount of unburnt or volatile material. The high silica content confirms the potential of the RHA as a pozzolanic material, since silica can react with calcium hydroxide during cement hydration to form additional calcium-silicate-hydrate (C-S-H).

Table 2: Chemical Composition of Rice Husk Ash (RHA)

Parameter	Chemical Formula	Percentage (%)
Silica	SiO ₂	80.70
Ferrous oxide	Fe ₂ O ₃	9.92
Calcium oxide	CaO	8.65
Magnesium oxide	MgO	6.12
Loss of Ignition (LOI)	-	4.84
Potassium oxide	K ₂ O	3.93
Aluminium oxide	Al ₂ O ₃	3.87
Sodium oxide	Na ₂ O	2.96
Copper oxide	CuO	1.32

The present 80.70% SiO₂ is closely comparable with the 80.02% reported for Nigerian RHA by a Nduka et al. (2022), demonstrating good agreement with

locally produced RHA. Alhadhrami et al. (2022) and Hossain et al. (2018) reported that RHA generally contains more than 70% silica, with values ranging from about 73.60% to 93.80% among different studies, supporting the high silica content obtained in this study. Similarly, Raheem et al. (2017), Jongpradist et al. (2018), Rambo et al. (2011) and Rama Subbarao et al. (2011) reported SiO₂ contents of 86.51%, 93.00%, 91.40% and 91.10%, respectively. The result also agrees with the findings Hamidu et al. (2025) showing that RHA is principally composed of silica with relatively smaller quantities of CaO, MgO, K₂O, Fe₂O₃ and Al₂O₃. In Korchunov et al. (2026), RHA contained 86.48% SiO₂, 3.36% CaO, 1.93% MgO and 0.64% Fe₂O₃, further confirming the dominance of silica in RHA. However, the present values of Fe₂O₃ (9.92%) and CaO (8.65%) are considerably higher than those reported in many previous studies. Such variations can result from rice variety, soil conditions, geographical origin, combustion temperature, burning duration and ash-processing methods.

3.2 Particle-Size Distribution

Figures 1 and 2 presented particle-size distribution for river sand and granite respectively. The particle-size distribution results showed that the sand had a coefficient of uniformity (Cu) of 2.61 and a coefficient of curvature (Cc) of 1.22. The Cu value indicates that the sand contains particles within a relatively narrow size range. Although the Cc value of 1.22 falls within the commonly accepted range of 1–3, the Cu value is below 6, which is generally used as the minimum criterion for well-graded sand. The sand can therefore be classified as poorly graded.

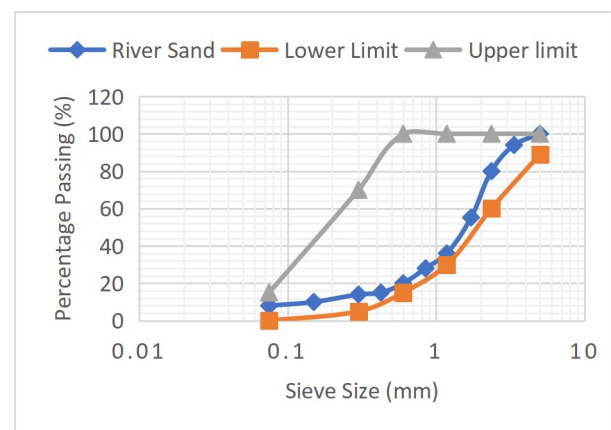


Fig. 1: Particle-Size Distribution for Sand

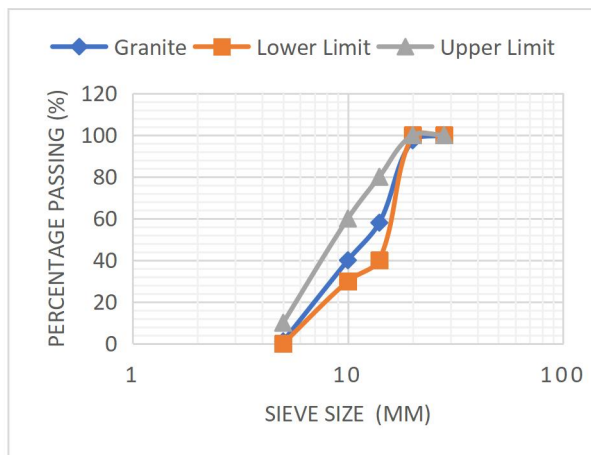


Fig. 2: Particle-Size Distribution for Granite

This observation is similar with the findings of Omopariola and Jimoh (2023), who reported C_u values ranging from 3.6 to 10 and C_c values from 0.53 to 2.56, with some of the investigated sands failing to meet specified grading requirements. The granite aggregate recorded a C_u of 1.29 and C_c of 0.82. The low C_u indicates a relatively uniform particle-size distribution, while the C_c value below 1–3 suggests that the aggregate does not possess the ideal distribution of intermediate-sized particles required for well-graded material. Poor aggregate grading may affect particle packing and increase the volume of voids within the concrete. This is important because aggregate packing influences the quantity of cement paste and water required to achieve adequate workability and compactness. The importance of aggregate physical characteristics is also demonstrated by previous research on Nigerian aggregates, which found considerable differences in gradation, specific gravity, absorption and bulk density among aggregate sources (Omopariola and Jimoh, 2023).

3.3 Specific Gravity Test

Table 3 shows the results of specific gravity tests. The average specific gravity values obtained for the materials were 2.54 for river sand, 2.17 for rice husk ash (RHA), and 2.68 for granite. The river sand recorded a specific gravity of 2.54, indicating that it is a normal-weight fine aggregate suitable for concrete production. This value is slightly lower than the 2.64 reported by Pathan et al. (2021) for river sand, but remains within the commonly reported range for natural aggregates used in concrete. The variation may be associated with differences in mineral composition, source, particle characteristics, and degree of weathering of the sand. Pathan et al. (2021) reported river-sand specific gravities within the range generally associated with normal-weight aggregates, supporting the suitability of the present material for concrete production. The specific gravity of RHA was 2.17, which was substantially lower than those of river sand and granite. This relatively low value is expected because RHA contains a high proportion of silica-rich, porous and lightweight particles. Fapohunda et al. (2017) reported RHA specific gravities ranging from approximately 2.05 to 2.53, which confirms that the value of 2.17 obtained in this study falls well within the range reported in the literature. In addition, Ali et al. (2017) reported an experimentally measured RHA density corresponding to a specific gravity of 2.17. Ogundiran et al. (2026) reported a specific gravity of approximately 2.06, further demonstrating that RHA generally has a lower specific gravity than conventional cementitious and aggregate materials. The lower specific gravity of RHA is important in concrete mix proportioning because replacement of cement with RHA on an equal-mass basis results in a greater volume of RHA, potentially influencing the density, packing, workability and pore structure of the concrete.

Table 3: Results of Specific Gravity Tests

Description	River sand		Rice Husk Ash		Granite	
Soil specimen	Test 1	Test 2	Test 1	Test 2	Test 1	Test 2
Mass of flask + sample + water (M_3) g	110.80	111.50	108.50	89.70	779.6	782.1
Mass of flask + sample (M_2) g	37.50	38.80	44.80	44.30	294.0	252.8
Mass of flask + water (M_4) g	104.50	104.30	82.60	80.50	649.0	649.0
Mass of flask (M_1) g	27.00	27.00	27.00	27.00	37.90	37.90
($M_2 - M_1$) g	10.50	11.80	17.80	17.30	206.1	214.9
($M_4 - M_1$) g	77.50	77.30	63.70	53.50	611.1	611.1
($M_3 - M_2$) g	73.30	72.70	55.60	45.40	535.6	529.3
$[(M_4 - M_1) - (M_3 - M_2)]$ g	4.20	4.60	8.10	8.10	75.50	81.80
$G_s = (M_2 - M_1) / [(M_4 - M_1) - (M_3 - M_2)]$	2.50	2.57	2.20	2.14	2.73	2.63
Average Specific Gravity	2.54		2.17		2.68	

The granite recorded the highest specific gravity of 2.68. This value indicates that the granite is a relatively dense normal-weight coarse aggregate and is suitable for concrete applications. The result agrees closely with previous findings. Sidi et al. (2021)

reported specific gravity values ranging from 2.63 to 2.71 and concluded that the materials were suitable as normal-weight construction aggregates. This difference is relevant to the production of pozzolanic concrete. Since RHA has a considerably lower

specific gravity than conventional mineral aggregates, its incorporation as a partial cement replacement can reduce the mass of binder required for an equivalent volume and may contribute to lower concrete density. Similarly, Fapohunda et al. (2017) identified the relatively low specific gravity of RHA as an important physical characteristic influencing its behaviour when used as a supplementary cementitious material.

3.4 Regression Model Equations

Values of the constants in the regression equations (equations 4 and 5) are shown in Table 4. The four regression model equations are shown in equations 6 to 9.

Normal Concrete Model for Compressive Strength

$$Y = -2013.033 - 5.607X_1 + 1860.980X_2 + 2056.806X_3 + 5971.162X_4 \quad (6)$$

Pozzolanic Concrete Model for Compressive Strength

$$Y = 26.584 + 11.962X_1 - 75.657X_2 - 4.878X_3 + 250.421X_4 - 2.852X_5 \quad (7)$$

Normal Concrete Model for Split Tensile Strength

$$Y = 23.735 - 18.700X_1 - 20.553X_2 - 20.562X_3 + 53.797X_4 \quad (8)$$

Pozzolanic Concrete Model for Split Tensile Strength

$$Y = 3.124 - 21.710X_1 + 0.719X_2 + 8.853X_3 + 0.669X_4 + 0.751X_5 \quad (9)$$

Table 4 presents the regression coefficients, p-values, R^2 , adjusted R^2 and standard errors obtained from SPSS for predicting the compressive and split tensile strengths of normal and pozzolanic concrete. For the normal concrete compressive-strength model, the R^2 of 0.996 and adjusted R^2 of 0.982 indicate that 99.6% of the variation in compressive strength is explained by cement, sand, gravel and water. The standard error of 0.780 N/mm² further indicates a relatively small prediction error. Cement was statistically significant ($p = 0.000$), whereas sand, gravel and water were not individually significant. The high overall R^2 indicates that the combined effect of the mixture variables is more important than the isolated effect of some individual variables. This agrees with This agrees with the Jee et al. (2004) water-cement ratio, cement content and cement-aggregate ratio as important variables for predicting compressive strength using multiple linear regression.

Table 4: Values of model constants (as obtained from SPSS Software Analysis)

Coefficient (Symbol)	Values	p-value
Normal Concrete Model for Compressive Strength		
Constant (β_0)	-2013.033	
Cement (X_1)	-5.607	0.000
Sand (X_2)	1860.980	0.256
Gravel (X_3)	2056.806	0.238
Water (X_4)	5971.162	0.225
R Square	0.996	-
Adjusted R Square	0.982	-
Standard Error of the Estimate	0.780	
Pozzolanic Concrete Model for Compressive Strength		
Constant (β_0)	26.584	
Cement (X_1)	11.962	0.000
Sand (X_2)	-75.657	0.165
Gravel (X_3)	-4.878	0.000
Water (X_4)	250.421	0.047
Rice Husk Ash (X_5)	-2.852	0.811
R Square	0.998	-
Adjusted R Square	0.993	-
Standard Error of the Estimate	0.428	
Normal Concrete Model for Split Tensile Strength		
Constant (β_0)	23.735	
Cement (X_1)	-18.700	0.000
Sand (X_2)	-20.553	0.417
Gravel (X_3)	-20.562	0.421
Water (X_4)	53.797	0.435
R Square	0.951	-

Adjusted R Square	0.805	-
Standard Error of the Estimate	0.016	
Pozzolanic Concrete Model for Split Tensile Strength		
Constant (β_0)	3.124	
Cement (X_1)	-21.710	0.000
Sand (X_2)	0.719	0.133
Gravel (X_3)	8.853	0.000
Water (X_4)	0.669	0.119
Rice Husk Ash (X_5)	0.715	0.060
R Square	0.994	-
Adjusted R Square	0.978	-
Standard Error of the Estimate	0.0032	

The result for pozzolanic concrete compressive strength was even stronger, with $R^2 = 0.998$, adjusted $R^2 = 0.993$ and a standard error of 0.428 N/mm². Cement, gravel and water were significant predictors, while sand and RHA were not significant at the 5% level. The very high R^2 demonstrates that the selected mixture variables provide an excellent explanation of compressive-strength variation. This finding is supported by Iftikhar et al. (2022) who developed prediction models using cement, RHA, water, aggregate and other mixture variables and obtained an R^2 of approximately 0.966 using gene-expression programming. Similarly, Li et al. (2023), a hybrid Artificial Neural Network model for RHA concrete achieved an R^2 of 0.9709, confirming the strong relationship between mixture parameters and compressive strength. The higher R^2 of 0.998 obtained in the present study therefore demonstrates particularly strong fitting of the experimental dataset. The normal concrete split tensile-strength model produced an R^2 of 0.951 and adjusted R^2 of 0.805, indicating that 95.1% of the variation in split tensile strength was explained by the selected variables. The standard error was only 0.016 N/mm², demonstrating close agreement between predicted and observed values. Cement was significant ($p = 0.000$), while sand, gravel and water were not individually

significant. The high explanatory power supports the use of mixture proportions as predictors of tensile performance. For the pozzolanic concrete split tensile-strength model, R^2 was 0.994, adjusted R^2 was 0.978, and the standard error was only 0.0032 N/mm². Cement and gravel were significant, while sand and water were not. RHA had a positive coefficient of 0.715 with a p-value of 0.060. Although this is slightly above the 0.05 significance level, its proximity to significance suggests a possible contribution of RHA to tensile-strength prediction. Previous experimental research supports the relevance of RHA to tensile performance. Hasan et al. (2022) reported measurable changes in splitting tensile strength at 7, 28 and 56 days, with some RHA mixtures achieving higher tensile strengths than the control concrete. Chrismaningwang et al. (2017) reported that incorporating RHA increased split tensile strength and improved other mechanical properties under certain curing conditions.

3.7 Observed and Predicted Strength for Normal and Pozzolanic Concrete

Figures 3-6 shows observed and predicted strength for normal and pozzolanic concrete. Table 5 shows that the regression models generally provided reasonable predictions of the strength properties of both normal and pozzolanic concrete at 56 days.

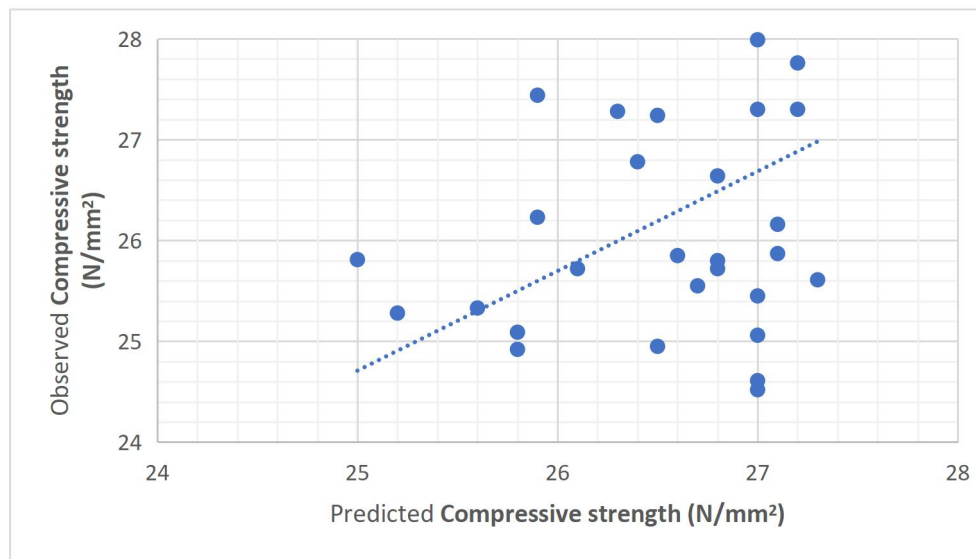


Figure 3: Observed and Predicted Compressive strength for Normal Concrete

For normal concrete compressive strength, the observed mean was 26.43 N/mm², compared with a predicted mean of 26.09 N/mm², with a difference of 0.34 N/mm² (1.23%). This indicates a close agreement between the experimental and predicted values and demonstrates good predictive performance. For pozzolanic concrete, the observed compressive strength was 27.31 N/mm², while the predicted value was 29.98 N/mm², with a difference of -2.67 N/mm² (-9.99%). Despite the model overpredicting the strength, the experimental result shows that pozzolanic concrete achieved approximately 3.33% higher compressive strength than normal concrete at 56 days. This agrees with Hasan et al (2022) that pozzolanic materials such as rice husk ash can produce greater later-age strength because of continued pozzolanic reaction and additional formation of calcium silicate hydrate (C-S-H).

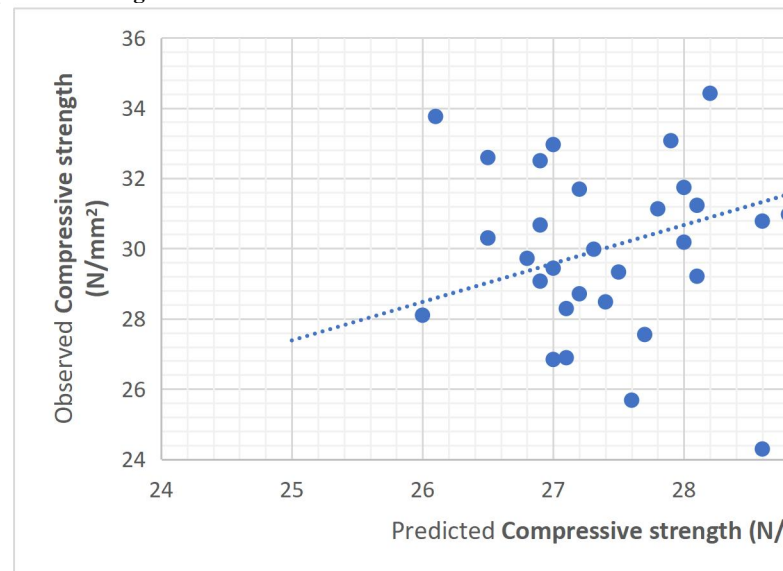


Figure 4: Observed and Predicted Compressive strength for Pozzolanic Concrete

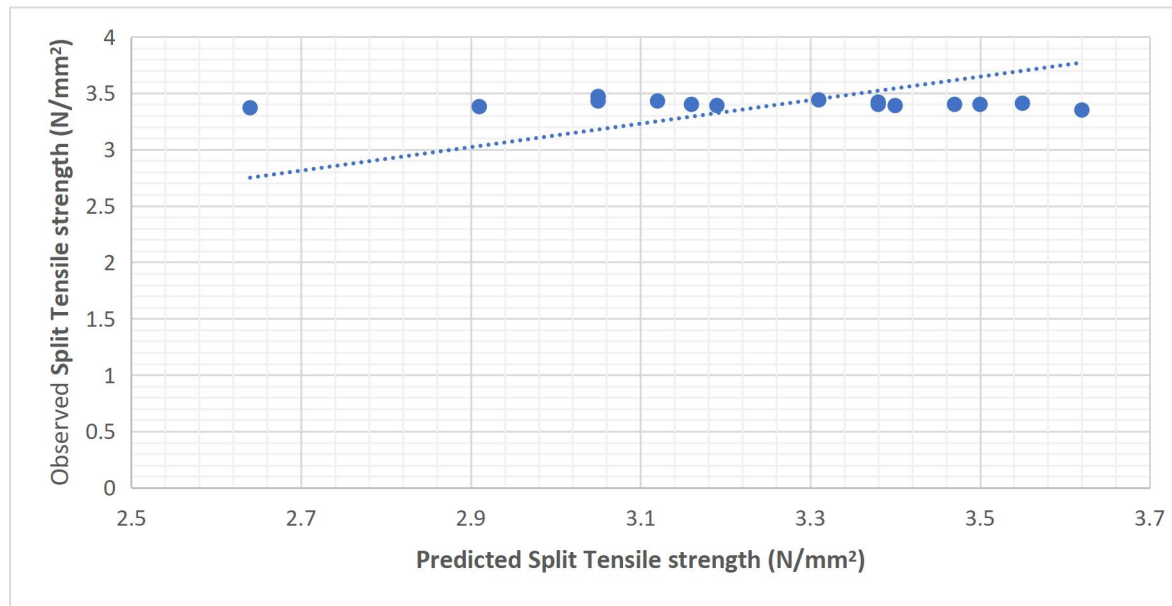


Figure 5: Observed and Predicted Split Tensile Strength for Normal Concrete

For split tensile strength, normal concrete recorded an observed mean of 3.41 N/mm², compared with a predicted value of 3.25 N/mm², with a difference of 0.16 N/mm² (4.69%). The pozzolanic concrete recorded 3.74 N/mm², while the predicted value was 3.11 N/mm², with a difference of 0.63 N/mm²

(16.86%). The experimental result was 9.68% higher than the normal concrete. Albadrani, (2025) reported improvements in splitting tensile strength of RHA concrete due to the filler effect, pore refinement and continued pozzolanic reaction.

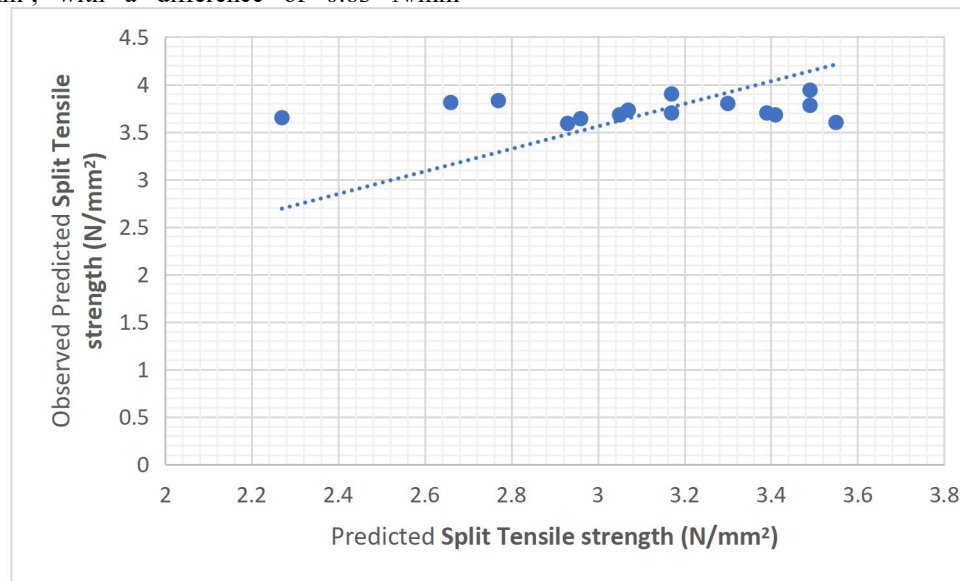


Figure 6: Observed and Predicted Split Tensile Strength for Pozzolanic Concrete

Table 5: Strength Properties for Normal and Pozzolanic Concrete

Property	Observed Mean	Predicted Mean	Mean Difference	Mean Difference (%)
Normal Compressive Strength at 56 days (N/mm ²)	26.43	26.09	+0.34	+1.23
Pozzolanic Compressive Strength at 56 days (N/mm ²)	27.31	29.98	-2.67	-9.99
Normal Split Tensile Strength at 56 days (N/mm ²)	3.41	3.25	+0.16	+4.69
Pozzolanic Split Tensile Strength at 56 days (N/mm ²)	3.74	3.11	+0.63	+16.86

IV. CONCLUSION

The study concludes that rice husk ash (RHA) containing 80.70% SiO₂ is suitable as a pozzolanic material for partial cement replacement in concrete. Pozzolanic concrete incorporating 10% RHA achieved a 56-day compressive strength of 27.31 N/mm², which was 3.33% higher than the 26.43 N/mm² recorded for normal concrete. Similarly, pozzolanic concrete attained a split tensile strength of 3.74 N/mm², representing a 9.68% increase over the 3.41 N/mm² obtained for normal concrete. Regression models demonstrated strong predictive capability, with R² values of 0.996 and 0.998 for compressive strength and 0.951 and 0.994 for split tensile strength of normal and pozzolanic concrete, respectively. Cement was the most statistically significant predictor in all models ($p = 0.000$). Regression modelling is therefore a reliable tool for predicting concrete strength and supporting sustainable concrete optimization.

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