

Evaluation of Iron Stone and Gravel Based Modified Concrete Using Random Forest Algorithms

DOI: 10.36108/laujoces/6202.71.0182

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Abstract

The rising demand for sustainable and high-performance concrete has increased interest in alternative aggregates such as ironstone, while conventional empirical approaches remain inadequate for accurate prediction of mechanical behaviour. Accordingly, this study evaluates the predictive efficiency of Random Forest models for ironstone-based concrete. The investigation commenced with physicochemical characterization of ironstone using X-ray fluorescence spectroscopy and energy-dispersive spectroscopy. Subsequently, the mechanical properties of ironstone, gravel, and granite aggregates were determined through Aggregate Crushing Value and Aggregate Impact Value tests. Fresh concrete behaviour was assessed using slump and compaction factor tests, followed by evaluation of hardened concrete properties, including compressive strength, splitting tensile strength, flexural strength, and density. Thereafter, predictive models were developed using Random Forest algorithms, and their performance was assessed using standard statistical indicators. The results revealed that ironstone particles were heterogeneous, angular to sub-angular, and porous, with iron oxide, silicon oxide, and aluminium oxide as the dominant constituents. Aggregate Crushing Value and Aggregate Impact Value ranged from 30.23–36.73% and 27.02–31.48%, respectively, while slump and compaction factor varied between 25–47 mm and 0.71–0.87. Compressive strength and tensile strength, ranged from 6–20 N/mm² and 1.4–3.1 N/mm. Overall, moderate ironstone replacement levels achieved satisfactory performance; therefore, a replacement range of 25–50% is recommended for balanced structural applications.

Keywords: Ironstone, Sustainable concrete, Mechanical properties; Machine learning modelling, Gene Expression Programming and Random Forest.

Introduction

The persistent incidence of structural distress and building collapse in developing economies, particularly Nigeria, has intensified concern over the quality and reliability of construction materials, especially coarse aggregates that largely govern concrete performance (Ajayi *et al.*, 2024). Conventional aggregates such as granite and river gravel remain dominant; however, escalating costs, environmental degradation from quarrying, and supply limitations have increased interest in locally available alternatives. Consequently, materials such as ironstone, which occur abundantly within Nigerian sedimentary formations, are increasingly considered for concrete production due to their accessibility and economic advantages. This shift aligns with global sustainability objectives that promote resource efficiency and reduced ecological impact in construction practices (Atadoga, 2021; Tijani, 2023).

Ironstone is a ferruginous sedimentary rock whose mineralogical composition, texture, and mechanical behaviour vary considerably due to differences in iron oxide content and weathering processes. Recent studies report that ironstone aggregates are typically angular, rough-textured, and porous, features that may improve mechanical interlocking with cement paste but also introduce variability in strength performance if not adequately characterized (Bamidele, 2022; Ahmed *et al.*, 2025). In Nigeria, substantial deposits exist within the Benue Trough and related sedimentary basins, where ironstone has been widely used in rural and peri-urban construction. Nevertheless, its application has largely been based on availability rather than scientific validation, raising safety and standardization concerns (Onyenweife *et al.*, 2020; Atadoga, 2021).

Concrete remains the most widely utilized construction material worldwide because of its versatility and load-bearing capacity, with aggregates accounting for the largest proportion of its volume. The type, grading, surface morphology, and mechanical integrity of aggregates significantly influence density, stiffness, strength development, and durability performance (Surahyo *et al.*, 2019). Furthermore, the environmental burden associated with conventional aggregate extraction, including carbon emissions and ecosystem degradation, has intensified the search for sustainable alternatives. Thus, integrating locally sourced aggregates such as ironstone into concrete production presents an opportunity to achieve both structural efficiency and environmental sustainability when supported by proper material characterization (Vijerathne *et al.*, 2024).

Nigeria's rapid urbanization and growing demand for high-rise and infrastructure projects have increased the need for high-performance concrete capable of meeting modern structural requirements. Traditional empirical mix design methods and conventional statistical models often fail to capture the nonlinear interactions between heterogeneous materials such as ironstone and cementitious systems (Kühne *et al.*, 2019). Consequently, machine learning approaches, particularly Random Forest, have gained relevance due to their capacity to model complex relationships and provide reliable predictions of concrete strength properties. (Zhang *et al.*, 2019). Despite increasing use of ironstone aggregates, a major problem persists due to the absence of comprehensive laboratory validation and predictive assessment of their mechanical performance in concrete. In many Nigerian regions, ironstone is used extensively without standardized testing, even as incidents of building failure continue to be reported (Sahani *et al.*, 2025). Additionally, engineers often lack reliable predictive tools to estimate concrete strength prior to construction, resulting in unsafe assumptions and inefficient material use. The limited application of data-driven modeling for locally sourced aggregates further constrains informed decision-making. Thus, the absence of validated machine learning models for ironstone- and gravel-based concrete represents a critical knowledge and practice gap.

The evaluation of ironstone and gravel-based modified concrete is significant for engineering practice, economic development, and environmental sustainability. Technically, it provides reliable data for material selection and structural design while improving prediction accuracy through machine learning models such as Random Forest. Economically, it promotes the use of locally available aggregates, reducing construction costs and dependence on imported or distant materials. Furthermore, it supports sustainable construction by minimizing environmental degradation associated with conventional aggregate extraction and aligning with global low-carbon development goals.

Methodology

Study Area

The study was conducted in Nigeria using locally sourced construction materials to reflect realistic field conditions and enhance the applicability of the findings. Ironstone was obtained from Otukpo in Otukpo Local Government Area of Benue State, a region characterized by extensive ferruginous sedimentary deposits. Gravel and granite were sourced from certified aggregate suppliers in Ibadan, Oyo State, a major hub for crushed stone production. These locations were selected to represent commonly used aggregate sources in Nigerian construction practice and to enable comparative assessment of ironstone- and gravel-based concrete under similar climatic and environmental conditions.

Sample Collection and Preservation

Ordinary Portland Cement used in this study was Lafarge CEM II/A-L 42.5N, manufactured in Nigeria and conforming to BS EN 197-1. Fine aggregate consisted of clean river sand obtained from Lagos State, while potable water satisfying ASTM C1602 (2019) requirements was used for mixing and curing. After collection, all aggregates were washed to remove impurities, air-dried, and stored in labeled, moisture-free

containers. River sand was oven-dried at 105 ± 5 °C using a Memmert UN110 drying oven (Germany) to maintain a consistent water–cement ratio, while coarse aggregates were preserved in sealed containers to prevent contamination.

Sample Preparation

Coarse aggregates comprising ironstone, gravel, and granite were crushed where necessary and sieved to obtain particles passing a 12.5 mm sieve and retained on a 10 mm sieve to ensure uniform grading. Sieving was carried out using a mechanical sieve shaker (Endecotts EFL2000, United Kingdom). Fine aggregate was sieved through a 4.75 mm sieve in accordance with ASTM C33. All prepared samples were allowed to equilibrate to laboratory temperature prior to testing to ensure consistency in subsequent experimental procedures.

Physicochemical and Mechanical Characterization

Chemical composition of ironstone was determined using X-ray Fluorescence spectroscopy with a PANalytical AxiosmAX spectrometer (Netherlands), following ASTM C114-18. Mineralogical analysis was conducted using an X-ray Diffraction system (Bruker D8 Advance, Germany) in accordance with ASTM C1365-18. Microstructural characteristics were examined using a Scanning Electron Microscope equipped with Energy Dispersive Spectroscopy (JEOL JSM-7600F, Japan). Aggregate mechanical properties were evaluated through Aggregate Impact Value and Aggregate Crushing Value tests using a standard impact testing machine and a 2000 kN compression testing machine (Controls Automax Pro, Italy), ensuring compliance with relevant international standards.

Concrete Mix Design and Production

Concrete was produced using a nominal mix proportion of 1:2:4 (cement: fine aggregate: coarse aggregate) by weight, with a constant water–cement ratio of 0.50. Mix design followed ACI 211.1 and BS EN 206-1 guidelines, adopting the absolute volume method. Gravel was partially replaced with ironstone at 25%, 50%, and 75%, while a granite-only mix served as the control. Batching was performed by weight, and mixing was carried out using a laboratory tilting drum mixer (Matest E093, Italy). All mixing, casting, and sampling procedures conformed to BS EN 12390 provisions.

Fresh Concrete Testing

Fresh concrete properties were evaluated immediately after mixing to assess workability and compactability. Slump tests were conducted using a standard slump cone in accordance with ASTM C143. Compaction characteristics were determined using a compacting factor apparatus (ELE International, United Kingdom) following BS 1881: Part 103. The compaction factor was calculated using Equation 1:

$$CF = \frac{W_1}{W_2} \quad (1)$$

Where; W_1 is the weight of partially compacted concrete and W_2 is the weight of fully compacted concrete.

Hardened Concrete Testing

Hardened concrete properties were evaluated after curing in water. Compressive strength tests were performed on 150 mm cube specimens using a 2000 kN compression testing machine (Controls Automax Pro, Italy) in accordance with ASTM C39. Splitting tensile strength was determined on 150×300 mm cylindrical specimens using ASTM C496. Plate 1 and shows the experimental procedure of the hardened concrete properties test.

Machine Learning Modelling Using Random Forest

Predictive modelling of concrete mechanical properties was conducted exclusively using the Random Forest algorithm due to its robustness in handling nonlinear relationships and heterogeneous datasets typical of construction materials. Random Forest modelling was implemented using IBM SPSS Modeler

version 18.2 (USA). Input variables included mix proportion, percentage replacement of gravel with ironstone, and curing age, while output variables comprised compressive and splitting tensile strengths. The algorithm constructed multiple decision trees using bootstrapped samples of the dataset, with final predictions obtained through ensemble averaging, thereby reducing overfitting and improving generalization accuracy. Predictor importance rankings and decision rules were extracted to identify the most influential parameters affecting concrete strength.



Plates 1: Compressive strength test



Plates 2: Tensile strength test

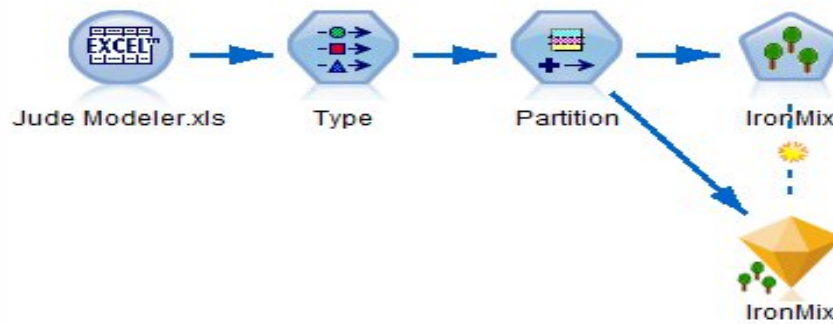


Figure 1: Model Generation in SPSS Modeler.

Results and Discussion

Physicochemical and Mechanical Characterization

The study examined the physicochemical and mechanical properties of the aggregates used in the concrete mixes. The physical characteristics of ironstone, including particle shape, size, texture, and porosity, were assessed, while its chemical composition, focusing on major oxides such as iron, silicon, and aluminium, was analyzed. The mechanical strength of ironstone, gravel, and granite was determined through standard crushing and impact tests to evaluate their suitability as coarse aggregates and their influence on concrete performance.

Physical Composition of Ironstone

The SEM micrograph of the ironstone obtained at a magnification of 1000× and an accelerating voltage of 15 kV reveals a heterogeneous and irregular surface morphology consisting of densely packed particles with varying sizes as shown Figure 1. The grains are predominantly angular to sub-angular, with visible micro-voids distributed within a relatively compact matrix. This textural configuration indicates good particle interlocking potential, which is favorable for compressive strength development, while the observed porosity may influence abrasion resistance and long-term durability, as reported for ferruginous aggregates by Zhang *et al.* (2018). Additionally, EDX analysis shows that oxygen is the most dominant element with a peak intensity of 645 counts, followed by carbon at 352 counts, confirming the dominance of oxidized iron phases and silicate minerals. Other detected elements include magnesium at 138 counts, sodium at 128 counts, calcium at 135 counts, aluminum at 112 counts, iron at 102 counts, phosphorus at 170 and 142 counts, titanium at 55 counts, manganese at 46 counts, and nitrogen at 102 counts as illustrated in Figure 2. The presence of calcium- and phosphorus-rich phases suggests carbonate and phosphate minerals capable of enhancing cementitious bonding.

Chemical Composition of Ironstone

The mechanical performance, durability, and chemical reactivity of ironstone are strongly governed by its oxide composition, particularly iron, silicon, and aluminum oxides. In this study, X-ray fluorescence analysis was employed to determine the major and minor oxide constituents of

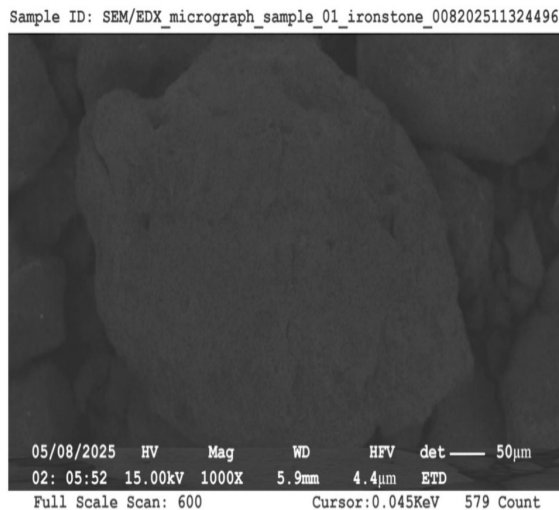


Figure 1: SEM Analysis of Ironstone.

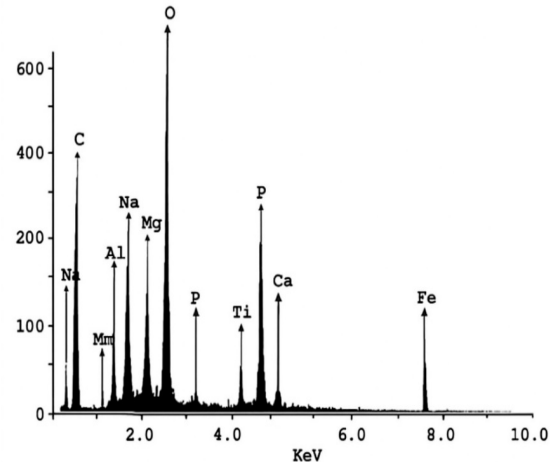


Figure 2: EDX Analysis of Ironstone.

the ironstone sample, as summarized in Table 1. Iron oxide is the dominant constituent, with Fe_2O_3 accounting for 58.42 percent, confirming the ferruginous nature of the material. This level of iron enrichment indicates good binding potential and suitability for construction-related applications. Similar Fe_2O_3 contents exceeding 55 percent have been reported for hematitic ironstones in southwestern Nigeria, supporting the classification of the material (Atadoga, 2021).

Silicon oxide constitutes 18.76 percent of the composition, indicating a substantial silicate phase within the matrix. This proportion contributes to improved hardness and abrasion resistance, although it may limit pozzolanic reactivity when blended with cementitious materials. Cheng *et al.* (2020) reported comparable silica contents between 15 and 20 percent in ironstones exhibiting good mechanical stability but moderate chemical reactivity, which aligns with the present findings. Aluminum oxide is present at 9.85 percent, reflecting aluminosilicate minerals that enhance thermal stability and influence workability. Similar Al_2O_3 levels have been associated with improved resistance to thermal loading in ironstone aggregates (Adediran *et al.*, 2023).

Minor oxides such as CaO at 2.14 percent and MgO at 1.62 percent indicate limited calcareous content but may still support secondary binding reactions. Other oxides, including TiO₂ at 2.13 percent, MnO at 0.71 percent, K₂O at 0.89 percent, and Na₂O at 0.54 percent, reflect geochemical maturity and contribute to chemical stability. The low loss on ignition value of 4.22 percent indicates minimal volatile content, consistent with structurally stable ironstones suitable for engineering applications (Kalinina *et al.*, 2023).

Table 1: Chemical Composition of Ironstone Sample using XRF.

S/N	Basic Oxides	Formulae	Percentage Composition (%)
1	Iron Oxide	Fe ₂ O ₃	58.42
2	Silicon Oxide	SiO ₂	18.76
3	Aluminum Oxide	Al ₂ O ₃	9.85
4	Calcium Oxide	CaO	2.14
5	Magnesium Oxide	MgO	1.62
6	Potassium Oxide	K ₂ O	0.89
7	Sodium Oxide	Na ₂ O	0.54
8	Phosphorus Oxide	P ₂ O ₅	0.47
9	Titanium Oxide	TiO ₂	2.13
10	Manganese Oxide	MnO	0.71
11	Zinc Oxide	ZnO	0.03
12	Copper Oxide	CuO	0.02
13	Sulphur Oxide	SO ₃	0.12
14	Chromium Oxide	Cr ₂ O ₃	0.07
15	Tin (IV) Oxide	SnO ₂	0.01
16	Loss on Ignition	LOI	4.22

Mechanical Strength of Aggregates

The mechanical strength of coarse aggregates is a key determinant of their suitability for concrete production, particularly for structural elements subjected to high static and dynamic loads. Aggregate crushing value and aggregate impact value tests were conducted in accordance with BS 812-110:1990 to evaluate the resistance of the aggregates to compressive and impact stresses. These parameters provide a reliable indication of aggregate durability and structural integrity in service conditions.

Aggregate Crushing Value (ACV)

The aggregate crushing values for granite, gravel, and ironstone, presented in Table 4.2, were obtained from triplicate tests to ensure consistency. Granite recorded an average ACV of 30.23 percent, indicating high resistance to crushing and confirming its suitability for heavy-duty concrete applications. This value complies with the BS 812 limit of 45 percent and agrees with findings by Almadani *et al.* (2022), who reported ACV values between 28 and 32 percent for high-quality granite aggregates.

Gravel exhibited an average ACV of 34.58 percent, reflecting moderate resistance to compressive loads. The higher value compared to granite is attributed to its sedimentary origin and relatively smoother particle surfaces. Similar ACV ranges have been reported for natural gravel aggregates by Telloli *et al.* (2021), supporting its suitability for general concrete works. Ironstone recorded the highest ACV of 36.73 percent, though still within the permissible standard. This indicates lower crushing resistance, likely due to its ferruginous composition and inherent micro-porosity. Musonda (2023) similarly observed that ironstone aggregates with ACV values above 35 percent produce concrete with moderate but acceptable strength.

Table 2: Aggregate Crushing Values of Granite, Gravel, and Ironstone

Sample	WA(kg)	WAPS(kg)	CV (%)	ACV (%)	BS 812-110:1990 (Remarks)
Granite	2.85	1.01	35.26	30.23	<45%
	2.84	0.92	32.44		
	2.8	0.64	23.05		

Gravel	2.86	1.03	36.01	34.58	<45%
	2.83	0.97	34.28		
	2.81	0.94	33.45		
Ironstone	2.9	1.05	36.21	36.73	<45%
	2.88	1.08	37.5		
	2.85	1.04	36.49		

Weight of Aggregate (WA) (kg), Weight of Aggregate Passing through Sieve (WAPS) (kg), Crushing value (CV) (%) and Average crushing value (ACV) (%).

Aggregate Impact Value (AIV)

The aggregate impact values shown in Table 4.3 indicate that granite has an average AIV of 27.7 percent, demonstrating high toughness and suitability for pavements and dynamic loading conditions. This aligns with observations by Kalaimani and Srinivasan (2024).

Gravel recorded an AIV of 31.48 percent, indicating adequate toughness but reduced impact resistance compared to granite, consistent with findings by Onwasigwe and Onodagu (2024). Ironstone exhibited the lowest AIV of 27.02 percent, suggesting superior impact resistance. This behavior is consistent with reports by Dash *et al.* (2022), who associated ferruginous aggregates with enhanced resistance to impact-induced failure.

Table 3: Aggregate Impact Value of Granite, Gravel, and Ironstone

Sample	WA(kg)	WAPS(kg)	CV (%)	AIV (%)	BS 812-110:1990 (Remarks)
Granite	0.7	0.25	35.7	27.7	<45%
	0.75	0.15	20		
	0.78	0.2	27.4		
Gravel	0.76	0.26	34.21	31.48	<45%
	0.74	0.22	29.73		
	0.77	0.25	30.5		
Ironstone	0.8	0.22	27.5	27.02	<45%
	0.82	0.19	23.17		
	0.79	0.24	30.38		

Weight of Aggregate (WA) (kg), Weight of Aggregate Passing through Sieve (WAPS) (kg), Crushing value (CV) (%) and Average crushing value (AIV) (%)

Fresh Concrete Properties

Slump Test

Concrete workability governs the ease of mixing, placement, and compaction of fresh concrete without segregation or bleeding. The slump results presented in Figure 3 demonstrate the influence of aggregate type and proportion on workability. The control mix containing 100 percent granite recorded a slump of 25 mm, indicating relatively low workability. In contrast, the mix with 100 percent gravel achieved a slump of 41 mm, reflecting improved flowability associated with the rounded and smooth surface texture of gravel. When gravel was partially replaced with 25 percent ironstone, the slump reduced to 36 mm, indicating increased internal friction due to the angular and rough texture of ironstone particles.

Notably, the mix containing equal proportions of gravel and ironstone produced the highest slump of 47 mm, suggesting improved particle packing and more effective paste lubrication. However, increasing the ironstone content to 75 percent resulted in a slump of 29 mm, confirming that excessive ironstone reduces workability by increasing resistance to flow and water demand. This trend is consistent with findings by Baciú and Kiss (2025), who reported reduced workability with angular aggregates, and Kumar *et al.* (2023), who observed that limited replacement with angular particles can enhance cohesion without severely impairing flow.

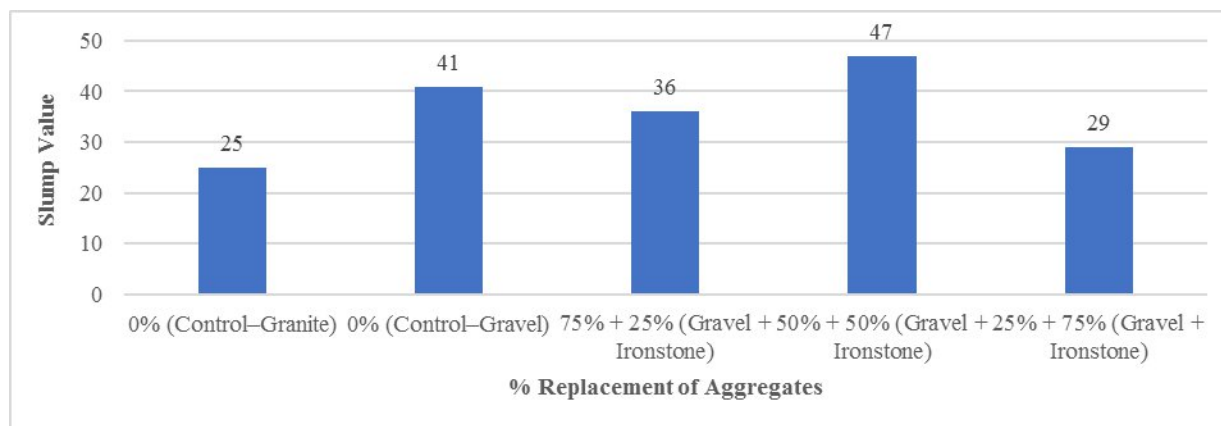


Figure 3: Slump Values for Different Granite, Gravel, and Ironstone Mixes.

Compaction Factor

The compaction factor results shown in Figure 4 further illustrate the effect of aggregate composition on fresh concrete workability. The control mix with 100 percent granite recorded a compaction factor of 0.84, indicating moderate compactability. A higher value of 0.89 was obtained for the 100 percent gravel mix, reflecting improved flow and reduced internal friction due to the smooth particle surface of gravel. When 25 percent ironstone was introduced into the gravel mix, the compaction factor decreased to 0.82, suggesting a slight reduction in ease of compaction caused by the denser and more angular ironstone particles. However, the mix containing equal proportions of gravel and ironstone recorded an increased compaction factor of 0.87, indicating improved particle arrangement and reduced void content. Further increase in ironstone content to 75 percent led to a significant reduction in compaction factor to 0.71, reflecting poor compactability and higher resistance to consolidation. These observations align with the findings of Mahdi *et al.* (2024), and Ji *et al.* (2021), who reported that excessive inclusion of angular and dense aggregates adversely affects compaction efficiency.

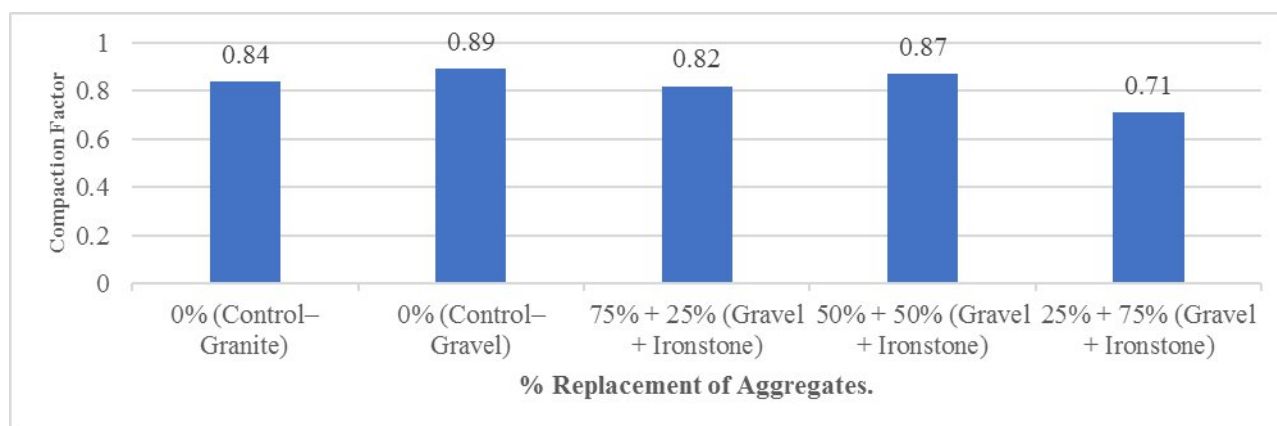


Figure 4: Compaction Factor for Different Granite, Gravel, and Ironstone Mixes.

Mechanical Strength Evaluation

The mechanical properties of the concrete were evaluated through compressive strength, tensile strength, flexural strength, and density tests to assess its structural performance and suitability.

Compressive Strength Test

The development of compressive strength is influenced by curing age, aggregate characteristics, hydration progression, and the quality of the interfacial transition zone. As shown in Figure 5, noticeable variations were observed among mixes incorporating granite, gravel, and ironstone aggregates. At 7 days, the granite control achieved a compressive strength of 8.49 N/mm², while the gravel control recorded 8.20 N/mm², indicating comparable early-age hydration. The mix containing 75 percent gravel and 25 percent ironstone attained 7.57 N/mm², reflecting a slight reduction attributed to the dense and irregular ironstone surface. Conversely, the 50 percent gravel and 50 percent ironstone mix achieved 8.46 N/mm², comparable to granite, whereas increasing ironstone to 75 percent reduced strength significantly to 6.10 N/mm².

At 14 days, strength gains were evident across all mixes due to continued hydration. Granite and gravel controls achieved 13.55 N/mm² and 13.10 N/mm², respectively. The highest strength of 13.99 N/mm² was recorded for the 75 percent gravel and 25 percent ironstone mix, followed closely by 13.94 N/mm² for the 50–50 blend, indicating improved packing and bonding at moderate ironstone contents. At 21 and 28 days, similar trends persisted, with granite consistently exhibiting the highest strength and mixes with higher ironstone content showing reduced performance. At 28 days, strengths ranged from 19.67 N/mm² for granite to 10.64 N/mm² for the 75 percent ironstone mix. By 56 days, continued hydration further enhanced strength; however, excessive ironstone content remained detrimental, confirming observations by Mahdi *et al.* (2024), Rabahi-Touloum and Brara (2021), and Beyene *et al.* (2023).

Tensile Strength Test

The development of tensile strength in the concrete mixes reflects the progress of cement hydration and the effectiveness of the interfacial transition zone. As shown in Figure 6, tensile strength increased progressively with curing age across all aggregate combinations. At 7 days, the granite control achieved 1.60 N/mm², while the gravel control recorded 1.52 N/mm². The 75 percent gravel–25 percent ironstone blend exhibited 1.62 N/mm², surpassing both controls, suggesting that the combination of smoother gravel and angular ironstone enhances stress transfer within the matrix. In contrast, the 50 percent gravel–50 percent ironstone mix recorded 1.39 N/mm², and the 25 percent gravel–75 percent ironstone sample achieved 1.54 N/mm², indicating that excessive ironstone substitution may initially reduce tensile performance due to weaker matrix cohesion. These trends correspond with Tamayo *et al.* (2022), who reported that moderate inclusion of ferruginous aggregates improves early-age tensile strength, whereas excessive amounts reduce interfacial bonding efficiency. With further curing, tensile strength gains continued, reflecting ongoing hydration and microstructural refinement. At 28 days, granite and gravel controls reached 3.01 N/mm² and 2.92 N/mm² respectively, while the 75 percent gravel–25 percent ironstone blend recorded 2.91 N/mm²,

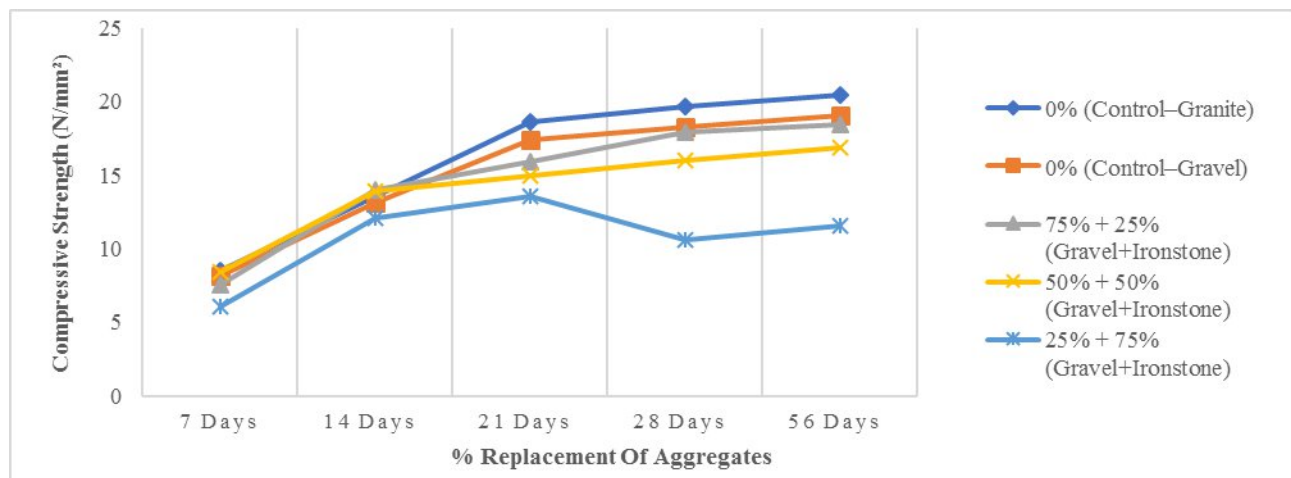


Figure 5: Concrete Compressive Strength at Different Curing Ages.

demonstrating performance comparable to traditional aggregates. The 50–50 blend and the 25–75 ironstone mix recorded 2.53 N/mm² and 2.37 N/mm² respectively, confirming that higher ironstone content negatively affects tensile capacity. By 56 days, the trend persisted, with the granite control achieving 3.13 N/mm², gravel 2.96 N/mm², and the 75 percent gravel–25 percent ironstone mix 3.02 N/mm². These observations suggest that limited ironstone incorporation can sustain or slightly enhance tensile durability over time, consistent with Feng *et al.* (2020), who highlighted the role of moderate angular aggregates in improving long-term tensile resistance.

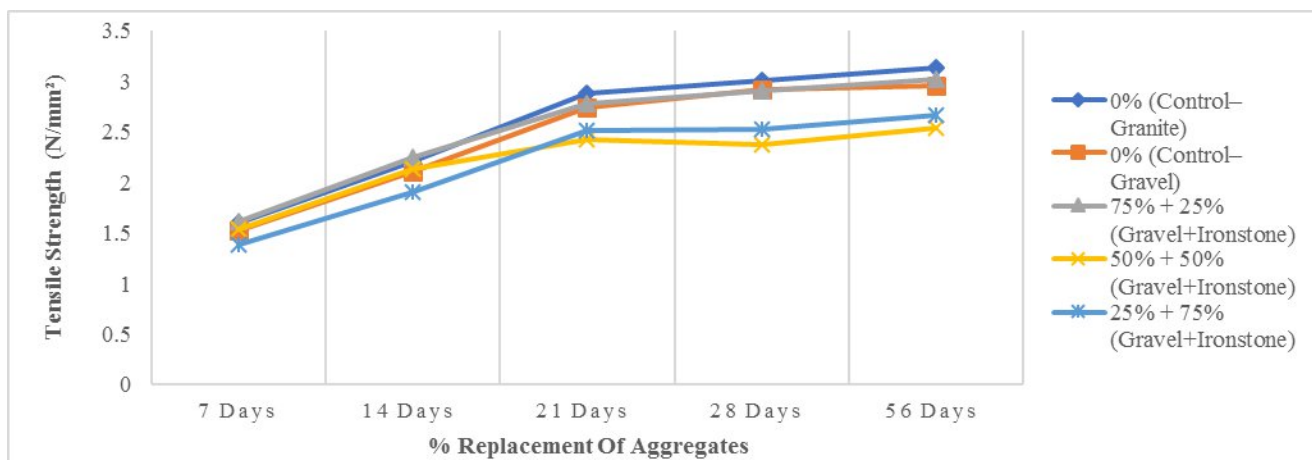


Figure 6: Concrete Tensile Strength at Different Curing Ages.

Predictive Model Development Using Random Forest

The Random Forest model analysis highlights the relative significance of each predictor in forecasting compressive strength of ironstone-based concrete. As shown in Figure 7, Gravel Mix emerged as the most influential variable, with an importance value of 2.5, reflecting the dominant role of aggregate composition and gradation on predictive accuracy. Early-age curing at 7 days followed closely, with an importance of 1.8, emphasizing the sensitivity of initial hydration and interfacial bonding to early strength development. Subsequent curing ages—14, 21, 28, and 56 days—exhibited progressively lower importance, indicating diminishing contribution as hydration stabilized. This trend aligns with the findings of Hilloulin and Umunnakwe (2024), who reported that Random Forest prioritizes mix-related variables over extended curing parameters once matrix densification is largely achieved. The high weighting of Gravel Mix and early-age curing underscores the critical influence of aggregate type, particle interlock, and hydration kinetics on load transfer and microstructural integrity, while later curing ages reflect a plateau effect in compressive development, consistent with Abdellatief *et al.* (2025).

The model's rule-based classification further illustrates its predictive precision for ironstone mixes. Table 4 presents top decision rules indicating how specific combinations of Gravel Mix and curing durations interact to produce distinct strength outcomes. For example, the rule assigning category 0.0 when Gravel Mix equals 0.0 and 7 Days $\leq$ 1743.0 demonstrates that absence of gravel and low early-age curing correlates with reduced strength. All rules achieved perfect rule and forest accuracy of 1.000, highlighting coherent interactions between predictors and compressive performance, consistent with Al-Shamasneh *et al.* (2025). The confusion matrix in Table 5 reveals classification accuracy across strength classes, with early and mid-range classes (0.0 and 25.0 MPa) achieving high precision of 0.80 and 1.00, whereas higher strength categories showed lower precision, reflecting limitations in extreme strength prediction. Overall, the model confirms that aggregate composition and early curing are the primary determinants of compressive strength, while later-age parameters have limited incremental influence.

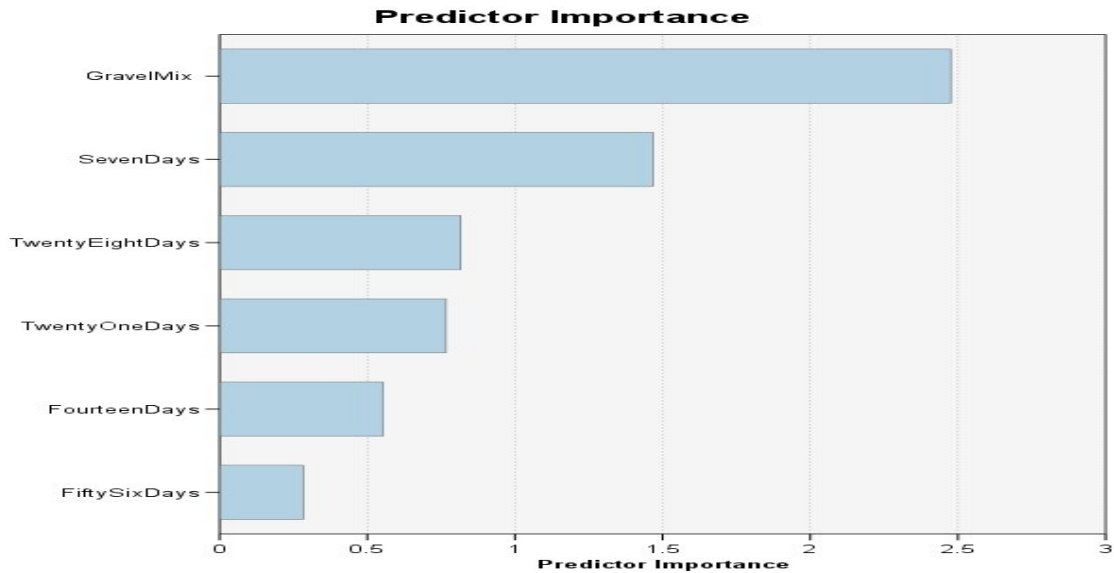


Figure 7: Predictor Importance Analysis using Random Forest.

Table 4: Top Decision Rules of the Random Forest Model for Ironstone Mix

Decision Rule	Most Frequent Category	Rule Accuracy	Forest Accuracy	Interestingness Index
(Gravel Mix = {0.0}) and (7 Days <= 1743.0)	0.0	1.000	1.000	1.000
(28 Days > 2.91) and (14 Days <= 13.1) and (56 Days > 2.96)	0.0	1.000	1.000	1.000
(Gravel Mix = {75.0}) and (56 Days > 2.96)	25.0	1.000	1.000	1.000
(14 Days <= 2.58) and (14 Days <= 1861.0) and (21 Days > 2.74)	0.0	1.000	1.000	1.000
(Gravel Mix = {75.0})	25.0	1.000	1.000	1.000

Table 5: Confusion Matrix of the Random Forest Model for Ironstone Mix

Observed	Predicted				Proportion Correct
	0.0	25.0	50.0	75.0	
0.0	4	0	0	1	0.80
25.0	0	2	0	0	1.00
50.0	0	0	2	1	0.67
75.0	3	0	1	1	0.20
Proportion Correct	0.57	1.00	0.67	0.33	0.60

Conclusion

The study demonstrated that the ironstone sample is ferruginous, containing high iron oxide 58.42 percent and silicon oxide 18.76 percent, with low trace oxides, and exhibits adequate mechanical properties with a crushing value of 36.73 percent and impact value of 27.02 percent, suitable as a durable coarse aggregate. Concrete workability was highest with equal proportions of gravel and ironstone, showing a slump of 47 mm and compaction factor of 0.87, while 75 percent ironstone reduced flow; moderate inclusion of 25 percent maintained practical placement. Compressive and tensile strengths were highest in granite controls at 56 days, reaching 20.47 MPa and 3.13 MPa, and lowest in mixes with 75 percent ironstone at 11.59 MPa and 2.67 MPa, whereas 75 percent gravel and 25 percent ironstone achieved satisfactory performance. Gravel proportion and early-age curing strongly influenced strength. Partial ironstone replacement up to 25 percent is recommended for optimal workability and strength.

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