Article

Recycled Aggregate Concrete Incorporating GGBS and Polypropylene Fibers using RSM and Machine Learning Techniques

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**Abstract:** In this study, response surface methodology (RSM) and machine learning models were used to predict the mechanical properties of recycled aggregate concrete (RAC) containing ground-granulated blast furnace slag (GGBS) and polypropylene fibers (PPFs). The percentage of GGBS varied between 0% and 50%, the percentage of Recycled Aggregate (RA) varied between 0% and 100%, and the percentage of PPF varied between 0% and 1%. The parameters investigated were the concrete's compressive strength (CS) and split tensile strength (STS) at curing periods of 7, 28, and 56 days. The RSM model was highly accurate (R² ≥ 0.92) in predicting the mechanical properties and was statistically significant (p-value < 0.0001). Machine learning models, including distributed random forest (DRF), gradient boosting machine (GBM), and stacked ensemble, effectively captured the variability of the data, with GBM demonstrating superior accuracy (R² > 0.95) for training, testing, and validation. Parity plots indicated that both RSM and machine learning models had no prediction bias. However, the Gradient boosting model (GBM) was superior due to its higher accuracy and efficiency in handling complex datasets. The use of GGBS and PPF significantly enhanced the mechanical properties and workability of the concrete.

**Keywords:** recycled aggregates; ground granulated blast furnace slag; polypropylene fiber; workability; compressive strength; ANOVA.

1. Introduction

Concrete is a fundamental construction material widely used globally due to its adaptability, durability, and cost-effectiveness. Despite its numerous benefits, concrete production poses significant environmental challenges, including resource depletion and the emission of greenhouse gases. Addressing these challenges is crucial for sustainable development in the construction industry. Integrating recycled materials and industrial byproducts into concrete mixtures is a promising approach for mitigating these environmental impacts [1]. Conventional concrete production involves extracting and processing raw materials such as limestone, clay, and sand, leading to substantial environmental degradation.

Additionally, cement manufacturing, a key component of concrete, is a significant source of carbon dioxide emissions, contributing significantly to global greenhouse gas levels. As the demand for concrete materials rises, finding sustainable alternatives has become imperative. Research has demonstrated that recycled aggregate concrete (RAC) can achieve compressive strength (CS) and carbonation behavior similar to traditional concrete mixes, indicating that recycled aggregate (RA) does not compromise structural integrity [1]. This finding is crucial because it supports using recycled materials in construction without sacrificing performance. Studies have shown that incorporating industrial byproducts such as silica fume and waste coconut shell aggregate can enhance the sustainability of concrete [2]. These materials reduce the need for virgin raw materials and promote effective waste management and recycling, aligning with the principles of the circular economy [3].

The emphasis on substituting conventional fuels and raw materials with alternative aggregates is vital for fostering a circular economy and sustainable waste management practices. This approach reduces the environmental footprint of concrete production and enhances resource efficiency while minimizing waste generation in the construction sector. The importance of using recycled coarse aggregate in concrete production is highlighted by studies focusing on the environmental benefits of incorporating materials from crushed demolition or earthquake waste concrete [4]. These practices align with sustainable construction principles by conserving natural resources and reducing construction waste. Incorporating sustainable supplementary materials into concrete mixtures is essential for improving the environmental performance of concrete [5]. Developing recycled aggregate concrete is a significant step toward reducing the environmental consequences of concrete manufacturing. With the growing emphasis on climate change mitigation and carbon footprint reduction, the construction industry is increasingly adopting sustainable practices, including using recycled materials in concrete mixes [6].

Using RA from construction and demolition waste is a significant step toward sustainability and environmental protection. By reducing landfill waste and preserving natural resources, this method offers an eco-friendly alternative to using natural aggregates. Extensive research has explored various aspects of RA in concrete production and their effects on concrete properties [7]. Different types of RA including those from construction and demolition waste, roof tiles, rubber, plastics, and glass, have been studied. Adjusting the proportions of these aggregates to align with the specific properties of each residue is crucial, as highlighted in recent studies [8].

Research indicates that RA can significantly improve self-compacting concrete's mechanical properties and structural performance [7]. A recent study highlighted the benefits of using electric arc furnace slag aggregate and cupola slag powder in high-performance self-compacting concrete. These materials enhance the density of the concrete and contribute to its self-compacting thixotropy, effectively preventing segregation [9]. Additionally, using recycled aggregates derived from electric arc furnace slag concrete has been investigated to create environmentally friendly concrete mixes, demonstrating innovative and sustainable possibilities [10].

Recycled aggregate concrete made from demolition and construction waste is gaining popularity as a sustainable option for addressing the environmental consequences of construction and minimizing the use of natural aggregate resources [6]. Using recycled concrete aggregates instead of natural aggregates makes it possible to address environmental concerns without compromising the structural integrity of concrete structures [11]. Recent studies have explored the use of RA in rendering mortars and bituminous pavement construction, highlighting the wide range of applications for recycled materials in construction [12,13]. In sustainable construction practices, researchers have explored using recycled materials as alternatives to traditional aggregates to reduce waste and promote the principles of a circular economy [14]. The importance of using RAs to reduce the environmental impact of construction activities and improve resource efficiency has been emphasized in related research [15].

Research has demonstrated that incorporating GGBS into concrete mixes positively impacts various concrete properties, such as strength and durability. Studies have examined the effects of GGBS on both fresh and hardened states of concrete, mainly when used alongside other supplementary materials such as metakaolin [16]. These studies have consistently shown that GGBS positively affects concrete properties, enhancing overall performance and sustainability in structural applications [17].

In addition to its performance benefits, GGBS has been extensively studied for its potential to create environmentally friendly concrete solutions. Using GGBS as an additional cementitious material aligns with sustainable construction principles, helping to mitigate the environmental impact of concrete manufacturing [18]. Researchers are increasingly exploring industrial waste and byproducts, such as GGBS, in concrete mixes to promote better waste management practices globally [18]. This approach supports a more environmentally friendly future for the construction industry by emphasizing the importance of materials such as GGBS.

Fibers are needed after the addition of GGBS to control microcracks, enhance toughness, and improve the concrete's overall durability and tensile strength. This combination ensures a balanced improvement in the mechanical properties and long-term performance.

Polypropylene fiber (PPF), a synthetic fiber, is widely recognized for its ability to enhance the strength and durability of concrete structures. Polypropylene (P.P.) is valued for its durability, affordability, and capacity to improve concrete resistance to shrinkage cracking [19]. Studies have shown that incorporating PPFs in concrete mixes can improve the toughness index, improving structural integrity and durability. Research has also explored the combination of PPFs with other materials, such as date palm fibers, to assess their impact on self-compacting concrete [20]. The findings indicate that adding PPFs can effectively reduce concrete plastic shrinkage, addressing cracking and durability issues [20]. Due to their excellent mechanical properties, corrosion resistance, and cost-effectiveness, PPFs are a popular choice for reinforcing concrete structures because they significantly enhance concrete performance and longevity [21]. Overall, PPFs play a crucial role in enhancing concrete structures' strength, durability, and performance. Research has shown that adding PPFs to concrete mixes yields numerous benefits, including increased resistance to cracking, improved flexure and CS, and enhanced durability. As a valuable reinforcement material for various concrete applications, PPFs offer cost-effectiveness and versatility, providing sustainable solutions to improve performance and longevity.

1.1. Research Objectives

The primary objectives of this research are as follows:

1. To evaluate the workability of M30 grade concrete mixes containing varying proportions of RA, GGBS, and PPF.
2. To measure the compressive strength (CS) and split tensile strength (STS) of the concrete mixtures at 7, 28, and 56 days.
3. To perform an analysis of variance (ANOVA) using the design of experiments (DoE) approach to identify the significance of each factor (RA, GGBS, and PPF) on the concrete properties.
4. To utilize machine learning modelling for comparing the Response Surface Methodology (RSM) and ensemble ML methods (distributed random forest, stacked ensemble, gradient boosting). Assess their predictive accuracy using metrics like R2, Mean squared Error (MSE), Root Mean Squared Error (RMSE), Mean Relative Error (MRE) and Mean Absolute Percentage Error (MAPE).

Figure 1 shows the process of the optimization methods, including the Design of Experiments (DoE) and machine learning methods, which were than applied. DoE uses Response Surface Methodology (RSM) with Central Composite Design (CCD) to evaluate the effects of input parameters like Polypropylene Fiber (PPF), Ground Granulated Blast Furnace Slag (GGBS), and Recycled Aggregates (RAs). Concurrently, ensemble learning methods with regressors such as distributed random forest, stacked ensemble and gradient boosting machine predict output parameters like compressive and split tensile strength. Model performance is evaluated using R-squared (R²), Mean Squared Error (MSE), Root Mean Squared Error (RMSE), Mean Relative Error (MRE), and Mean Absolute Percentage Error (MAPE). This integrated approach ensures accurate prediction and optimization of input parameters, effectively meeting the research objectives.

A diagram of a process flow

Description automatically generated

Figure 1. Research methodology.

2. Materials and Experimental Methods

2.1. Materials

In the material selection for this study, the grade 43 OPC cement had a specific gravity (S.G.) of 3.15. The sand exhibited an S.G. of 2.63 and a water absorption rate of 1.26%. The coarse aggregate (20 mm) had an S.G. of 2.675 and a water absorption of 0.946%. Recycled aggregate (20 mm) demonstrated an S.G. of 2.32 with a higher water absorption rate of 4.99%. The GGBS had an S.G. of 2.82 and a moisture content of 0.23% (within the 1% limit). Additionally, the PPFs used in this study were 12 mm in length and had an S.G. of 0.91. To enhance workability, the superplasticizer Sika Plast was used at 0.6% by weight of cement.

Figure 2 illustrates the materials used in this study, including RA, GGBS and PPF. Additionally, Figure 3 presents the gradation of fine and coarse aggregates (natural and RA), highlighting their distribution and size characteristics. Table 1 details the chemical properties of the GGBS and cement, while Table 2 outlines the properties of the PPF.

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| --- | --- | --- |
|  |  |  |
| **(a)** | **(b)** | **(c)** |

**Figure 2.** Materials used in this study: **(a)** RA; **(b)** GGBS; **(c)** PPF.

|  |  |
| --- | --- |
|  |  |
| **(a)** | **(b)** |

**Figure 3.** Gradation of **(a)** fine aggregates; **(b)** coarse aggregates.

**Table 1.** Chemical properties of GGBS and OPC.

|  |  |  |
| --- | --- | --- |
| **Chemical Composition** | **GGBS** | **Ordinary Portland Cement (OPC)** |
| Silicon Dioxide (SiO2) | 32% | 22% |
| Calcium Oxide (CaO) | 45% | 63% |
| Aluminum Oxide (Al2O3) | 10% | 5% |
| Magnesium Oxide (MgO) | 8% | 2% |
| Sulfate (SO3) | 1.5% | 3% |
| Iron Oxide (Fe2O3) | 1% | 3% |
| Loss on Ignition (LOI) | 2% | 1% |

*2.2. RSM Modeling*

The design of the experiment (DOE) and response surface methodology (RSM) are utilized to optimize and analyze the relationships between various input factors and the resulting responses. RSM is a group of statistical techniques used to investigate and model functional relationships between input variables and a response of interest [22], as shown in equation 1. An RSM polynomial model is given by:

, (1)

Where is the input variable, is the output variable, is a vector of unknown constant coefficients referred to as parameters, and is a random experimental error assumed to have a zero mean [23].

**Table 2.** PPF properties.

|  |  |
| --- | --- |
| **Property** | **Value** |
| Material | Polypropylene |
| Specific Gravity | 0.91 |
| Tensile Strength | 500 MPa |
| Elastic Modulus | 10 GPa |
| Melting Point | 165°C |
| Diameter | 30 micrometers |
| Length | 12 mm |

Specifically, central composite design (CCD), a fundamental element of RSM, was employed to efficiently fit a second-order (quadratic) model without requiring a complete three-level factorial experiment. The factors considered in this study included GGBS (ground granulated blast furnace slag), ranging from 0% to 50; RA (recycled aggregate), ranging from 0% to 100; PPF (polypropylene fiber), ranging from 0% to 1; and curing time, ranging from 7 to 56 days. The responses measured were CS (24.47 MPa to 59.83 MPa) and STS (0.63 MPa to 7.81 MPa). Table 3 shows the input variables and corresponding responses, and Table 4 shows the various mix designs [24].

**Table 3.** Specification of the input variables and corresponding response.

|  |  |  |  |
| --- | --- | --- | --- |
| **Designation** | **Data** | **Unit** | **Data band** |
| Factor 1 | GGBS | % | 0 ≤ x ≤ 50 |
| Factor 2 | RA | % | 0 ≤ x ≤ 100 |
| Factor 3 | PPF | % | 0 ≤ x ≤ 1 |
| Factor 4 | Curing Time | Days | 7 ≤ x ≤ 56 |
| Response 1 | Compressive Strength | MPa | 24.47 ≤ y ≤ 59.83 |
| Response 2 | Split Tensile Strength | MPa | 0.63 ≤ y ≤ 7.81 |

**3. Experimental Setup**

3.1. Casting and Curing

The casting and curing procedure involved cleaning and oiling the molds, dry mixing the weighed quantities of cement and fine and coarse aggregates until a uniform color was obtained, and then adding the coarse aggregates for further dry mixing. The measured water was added to two equal parts, with the superplasticizer mixed into the second part before being added. The concrete mixture was then thoroughly mixed in a concrete mixer. The mixture was poured into molds in layers, each compacted with a tamping rod, and the surface was leveled with a trowel. Cubic specimens (150 mm × 150 mm × 150 mm) were cast for CS testing. Cylindrical specimens (150 mm diameter × 300 mm height) were cast for STS. Following molding, the specimens were submerged in a curing tank with clean water until testing at 7, 28, and 56 days, ensuring proper hydration and strength development. Figure 4 shows the experimental setup.



**Figure 4.** Experimental Setup.

3.2. Workability

The workability of the concrete mixtures was measured using the slump test. This standard outlines the method for measuring the consistency of fresh concrete, which is crucial for assessing the ease with which concrete can be mixed, placed, and finished.

3.3. Compressive Strength (CS)

The CS test indicates the concrete's load-bearing capacity. The CS of the concrete was determined using cube specimens and tested using a compression testing machine (CTM). These specimens were prepared and tested at 7, 28, and 56 days, following the guidelines specified in IS 516 (Part 1/Section 1): 2021 [25].

3.4. Split Tensile Strength (STS)

The STS test is essential for understanding the tensile properties of concrete, which are critical for its performance under various loading conditions. This test was measured using cylindrical specimens using a CTM.

4. Results and Discussions

This section presents a detailed analysis of the experimental findings, focusing on the impact of varying GGBS, RA and PPF proportions on concrete properties such as workability, compressive strength, and split tensile strength. The effectiveness of the RSM and advanced machine learning models namely distributed random forest (DRF), gradient boosting machine (GBM), and stacked ensemble in predicting these properties is also discussed, highlighting the performance of different models and the implications of the results for sustainable concrete mix design.

4.1. Experimental Analysis

4.1.1. Workability

Other mixes exhibited significant changes compared to the reference mix M1 (120 mm workability). The maximum decrease in workability was observed in M25 (100% RA, 50% GGBS, 0.75% PPF) at 69 mm (-42.50%), while the minimum decrease was seen in M5 (0% RA, 50% GGBS, 1% PPF) at 109 mm (-9.17%). Concrete mixtures, including increasing amounts of RA and PPF, typically demonstrate decreased workability due to heightened friction and diminished aggregate quality [26]. The decrease in workability can be ascribed to the increased friction caused by the RA and PPF in the mixture, which affects the ease of placing and compacting during construction. Nevertheless, the inclusion of GGBS in these mixtures can partially mitigate these impacts by improving the cohesion of the mixture and filling empty spaces. However, the overall ease of working with the mixture still needs to be higher than standard concrete mixes. Utilizing GGBS in the concrete mixture enhances its overall performance by reducing the adverse effects of high RA content and PPF levels on workability [27].

**Table 4.** Various mix designs.

|  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- |
| **Mix** | **Cement (kg/m3)** | **Fine aggregate (kg/m3)** | **Coarse aggregate (kg/m3)** | **GGBS (kg/m3)** | **RA (kg/m3)** | **P.P. Fiber (kg/m3)** | **Water (kg/m3)** |
| M1 | 407.00 | 658.02 | 1159.35 | 0 | 0 | 0 | 175 |
| M2 | 356.13 | 653.79 | 1151.89 | 50.88 | 0 | 2.28 | 175 |
| M3 | 305.25 | 649.56 | 1144.45 | 101.75 | 0 | 4.55 | 175 |
| M4 | 254.38 | 645.34 | 1137.00 | 152.63 | 0 | 6.83 | 175 |
| M5 | 203.50 | 641.11 | 1129.56 | 203.50 | 0 | 9.10 | 175 |
| M6 | 407.00 | 655.61 | 866.32 | 0 | 250.45 | 2.28 | 175 |
| M7 | 356.13 | 651.38 | 918.12 | 50.88 | 248.84 | 4.55 | 175 |
| M8 | 305.25 | 647.16 | 798.14 | 101.75 | 247.22 | 6.83 | 175 |
| M9 | 254.38 | 642.93 | 792.93 | 152.63 | 245.61 | 9.10 | 175 |
| M10 | 203.50 | 650.74 | 802.56 | 203.50 | 248.59 | 0 | 175 |
| M11 | 407.00 | 653.20 | 575.43 | 0 | 499.07 | 4.55 | 175 |
| M12 | 356.13 | 648.98 | 571.71 | 50.88 | 495.84 | 6.83 | 175 |
| M13 | 305.25 | 644.75 | 567.99 | 101.75 | 492.61 | 9.10 | 175 |
| M14 | 254.38 | 652.56 | 574.86 | 152.63 | 498.57 | 13.00 | 175 |
| M15 | 203.50 | 626.67 | 552.06 | 203.50 | 478.80 | 2.28 | 175 |
| M16 | 407.00 | 650.79 | 286.66 | 0 | 198.89 | 6.83 | 175 |
| M17 | 356.13 | 646.57 | 284.79 | 50.88 | 197.60 | 9.10 | 175 |
| M18 | 305.25 | 654.38 | 288.23 | 101.75 | 199.99 | 0 | 175 |
| M19 | 254.38 | 650.15 | 286.37 | 152.63 | 198.69 | 2.28 | 175 |
| M20 | 203.50 | 645.92 | 284.51 | 203.50 | 197.40 | 4.55 | 175 |
| M21 | 407.00 | 648.39 | 0 | 0 | 990.78 | 9.10 | 175 |
| M22 | 356.13 | 656.19 | 0 | 50.88 | 1002.70 | 0.00 | 175 |
| M23 | 305.25 | 651.97 | 0 | 101.75 | 996.25 | 2.28 | 175 |
| M24 | 254.38 | 647.74 | 0 | 152.63 | 989.79 | 4.55 | 175 |
| M25 | 203.50 | 643.52 | 0 | 203.50 | 983.33 | 6.83 | 175 |

4.1.2. Compressive Strength (CS)

This section evaluates the compressive strength of concrete mixtures at various curing periods, focusing on the impact of GGBS, RA and PPF. The analysis provides insights into optimizing mix designs for enhanced load-bearing capacity.



**Figure 5.** CS analysis.

The CS results at 7, 28, and 56 days are shown in Figure 5. The inclusion of GGBS significantly enhanced the concrete's early and later-age CS. At seven days, mix M5 (0% RA, 50% GGBS, 1% PPF) showed a 30.34% increase, and mix M9 (25% RA, 37.5% GGBS, 1% PPF) achieved a 36.23% increase. A high RA content without sufficient GGBS or PPF reduced the strength, as seen in mix M18 (75% RA, 25% GGBS, 0% PPF), with a 2.36% decrease. At 28 days, mix M5 had a 30.18% increase, and mix M9 had a 34.67% increase. At 56 days, the benefits of GGBS and PPF were more pronounced, with those of mix M5 showing a 31.12% increase and those of mix M9 showing a 36.37% increase. Research has shown that a high RA content alone can lead to a reduction in long-term strength, as evidenced by mix M18, which exhibited a 1.27% decrease in strength [28]. However, studies have demonstrated that the negative impact of RA on concrete strength can be mitigated through strategic mix design. For instance, in mixes such as M25, which contained 100% RA, 50% GGBS, and 0.75% PPF, the negative effects of RA were counteracted, resulting in a remarkable 16.81% increase in strength.

4.1.3. Split Tensile Strength (STS)

This section evaluates the STS of concrete mixtures at various curing periods, focusing on the impact of GGBS, RA and PPF.

The STS results at 7, 28, and 56 days are shown in Figure 6. At seven days, higher amounts of GGBS significantly improved the STS: the STS of mix M5 (0% RA, 50% GGBS, 1% PPF) increased by 240.58% (2.35 MPa), and that of mix M9 (25% RA, 37.5% GGBS, 1% PPF) increased by 330.43% (2.97 MPa) compared to that of M1 (0.69 MPa). A high RA content reduced the STS: mix M16 (75% RA, 0% GGBS, 0.75% PPF), showing a 120.29% increase (1.52 MPa). At 28 days, the tensile strength of M5 increased by 107.69% (4.32 MPa), and that of M9 increased by 132.69% (4.84 MPa) compared to that of M1 (2.08 MPa), while that of M16 increased by 39.42% (2.90 MPa). At 56 days, mix M5 showed a 130.71% increase (5.86 MPa), and mix M9 had the most significant increase, at 188.98% (7.34 MPa), compared to M1 (2.54 MPa). Mix M16 increased the impact of RA by 44.09% (3.66 MPa), but mix M25 (100% RA, 50% GGBS, 0.75% PPF) mitigated the impact of RA by 144.88% (6.22 MPa).



**Figure 6.** STS analysis.

Incorporating GGBS and PPF in concrete mixtures containing high levels of RA significantly enhances both early and long-term tensile strength. GGBS contributes to the strength of concrete through its pozzolanic reaction, which improves the material's overall performance [29].

4.2. RSM Modeling

The summarized results of the variance analysis for the 7, 28, and 56 days compressive and split tensile strengths of the concrete using the response surface model are presented in Table 5. The analysis provides the R², adjusted R², and predicted R² values at the 5% significance level. An R² ≥ 0.92 was achieved for all three responses, indicating a robust model fit. The adjusted R² values were very close to the R² values, demonstrating that nonsignificant variables do not overly influence the models and that only key variables contribute to the overall physical interpretation of the response. Additionally, the predicted R² values were also in close agreement with the adjusted R² values, indicating good predictive ability of the models. The p values, all less than 0.0001, further confirm that the models are statistically significant. The final equation in terms of Coded Factors for CS and STS are shown as equations 2 and 3, respectively.

**Table 5.** Overview of the precision of the RSM.

|  |  |  |
| --- | --- | --- |
| **Response** | **Compressive Strength** | **Split Tensile Strength** |
| Type | Quadratic | Quadratic |
| R² | 0.9314 | 0.9436 |
| Adjusted R² | 0.9264 | 0.9385 |
| Predicted R² | 0.8306 | 0.8985 |
| P value | <0.0001 | <0.0001 |
| Standard Deviation | 3.52 | 0.5153 |
| Mean | 41.51 | 3.94 |
| C.V. % | 8.48 | 13.07 |

4.2.1. Final Equations in Terms of Coded Factors

Compressive Strength (2)

Split Tensile Strength (3)

In equation 2 and 3:

* A, B, C, and D represent the coded values of the GGBS, RA PPF, and curing days.
* The interactions are represented by the product of the corresponding factors (e.g., .B. represents the interaction between factors and ).

4.2.2. 3D Response Surface Maps and Actual vs. Predicted Graphs

This study used 3D response surface maps and actual vs. predicted graphs to show how different components in concrete mixes interact and affect their mechanical properties. These graphical tools helped visualize the impact of factors such as GGBS, RA and polypropylene fiber (PPF) on CS and STS. The response surface maps illustrated how varying levels of these factors influenced concrete performance, helping to identify the best combinations.

Figure 7 illustrates the response surfaces and the actual vs. predicted plot for the CS of recycled aggregate concrete. Plots 7(a-c) depict the impact of various factors on CS. In plot 7(a), increasing the percentage of GGBS significantly enhanced CS, particularly at lower levels of RA. A higher RA content generally decreases CS, indicating that its damaging effect can be mitigated by increasing the GGBS content [30–32]. Plot 7(b) shows that while polypropylene fiber (PPF) alone does not significantly enhance CS, its combination with higher GGBS levels leads to improved strength, emphasizing the crucial role of GGBS. Plot 7(c) demonstrates that increasing the RA content decreases the CS, but the addition of PPF can partly mitigate this reduction, although not as effectively as GGBS. Finally, plot 7(d) shows the actual vs. predicted CS values, with points closely following the 45-degree line, indicating high model accuracy. Adding polypropylene fiber (PPF) to concrete has a less pronounced effect on CS than on GGBS [33]. However, PPF can help offset the strength reduction caused by a higher RA content [34].

Figure 8 illustrates the response surfaces and the actual vs. predicted plot for the STS of concrete. Plots 8(a-c) depict the impacts of various factors on the STS. In plot 8(a), increasing the GGBS content significantly increased the STS, especially at lower levels of RA. However, as the RA content increases, the STS decreases, indicating that a higher RA content negatively impacts the strength unless adequately compensated by GGBS [30–32]. Plot 8(b) shows that incorporating PPF in concrete improved the splitting tensile strength. Plot 8(c) demonstrates that increasing the RA content results in a noticeable decrease in the STS, but the presence of PPF helps to mitigate this reduction to some extent. Finally, plot 8(d) shows the actual vs. predicted STS values, with points closely following the 45-degree line, indicating high model accuracy. Overall, these plots emphasize the importance of optimizing the balance between RA, GGBS and PPF to achieve the desired STS in concrete.

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**Figure 7.** **(a-c)** Response surfaces illustrating the impact of factors on CS; **(d)** the actual vs. predicted plot.

4.2.3. Confirmation Experiment

The confirmation experiment was conducted with a mixture comprising 25% GGBS, 50% RA 0.5% PPF, and a curing period of 48.5 days. The response data included three runs, yielding CS values of 47.3 MPa, 47.4 MPa, and 47.4 MPa and STS values of 5.2 MPa, 5.2 MPa, and 5.3 MPa. The analysis of these results, with a two-sided 95% confidence level, provided the predicted means and medians. The CS had a predicted mean and median of 49.8 MPa, with observed values showing a standard deviation of 2.3 and a mean of 47.4 MPa, fitting within the 95% prediction interval of 47.1 to 52.5 MPa. The STS had a predicted mean and median of 5.8 MPa, with an observed standard deviation of 0.4 and a data mean of 5.2 MPa, fitting within the 95% prediction interval of 5.3 to 6.3 MPa. These confirmation results validate the model's predictions with the observed experimental values.

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**Figure 8.** **(a-c)** Response surfaces illustrating the impact of factors on the STS; **(d)** the actual vs. predicted plot.

The variance analysis results for the compressive and tensile strengths of concrete at 7, 28, and 56 days, using the response surface model (RSM), show an excellent match with the model. The R² values for all responses were ≥ 0.92, indicating high prediction accuracy. The adjusted R² values closely correspond to the R² values, indicating that the models are not significantly affected by factors that do not have a significant impact. Furthermore, the forecasted R² values are in good agreement with the adjusted R² values, thereby verifying the predictive dependability of the models. The models' statistical significance is validated by the p values, all of which are less than 0.0001. Table 5 displays the accuracy of the RSM model. The R² values for CS and STS were 0.9314 and 0.9436, respectively. The adjusted R² values are 0.9264 and 0.9385, while the projected R² values are 0.8306 and 0.8985, respectively. The standard deviation, mean, and coefficient of variation (C.V. %) data indicate the models' resilience and precision. The ultimate equations, expressed in terms of encoded variables, emphasize the impact of elements such as GGBS, RA and PPF and the duration of curing on both CS and STS. 3D response surface maps and actual vs. expected graphs illustrate the influence of various parameters, highlighting the significance of optimizing the equilibrium between them to achieve the desired concrete qualities.

5. Machine Learning Models

The selection of the three machine learning models Distributed Random Forest (DRF), Gradient Boosting Machine (GBM), and Stacked Ensemble was driven by their complementary strengths and their proven ability to handle complex data patterns effectively. DRF was chosen for its robustness in handling large, high-dimensional datasets with both categorical and continuous variables. As an ensemble method, it builds multiple decision trees, reducing variance and improving prediction accuracy while maintaining interpretability, which is crucial for understanding feature importance. GBM was selected for its capacity to model non-linear relationships and its iterative approach to improving predictive accuracy by correcting errors in each successive tree. Its flexibility in optimizing loss functions and the ability to handle various types of data made it particularly suitable for this study. The decision to combine DRF and GBM into a Stacked Ensemble was based on the desire to leverage the strengths of both models. Ensemble methods, especially stacking, have been shown to improve performance by combining predictions from different models, thus reducing both bias and variance. The Stacked Ensemble uses the predictions from DRF and GBM as inputs for a meta-model, allowing it to capture the unique patterns each base model identifies and provide a more stable, generalized prediction. This combination of models, each excelling in different aspects of predictive modeling was chosen to ensure high accuracy, generalization, and robustness. The ensemble approach is particularly effective when dealing with complex datasets, where no single model is sufficient to capture all underlying patterns, making it a justified and optimal choice for this study.

5.1. Distributed Random Forest

The Random Forest (RF) algorithm is a robust ensemble learning model known for its ability to handle large and high-dimensional datasets while minimizing overfitting. It works by constructing multiple decision trees, each trained on a random subset of the data with random feature selection, and then aggregates their predictions to produce a final result. This ensemble approach reduces the model's variance and enhances its generalizability, making it less prone to overfitting compared to a single decision tree [35]. The Distributed Random Forest (DRF) extends this concept by distributing the training of individual trees across multiple machines, which significantly improves its scalability and performance when dealing with large datasets. DRF’s parallel nature allows it to efficiently process large volumes of data while maintaining high accuracy. This makes it particularly suited for high-dimensional feature spaces and datasets with complex structures, as it can learn from diverse data patterns without sacrificing computational efficiency. In addition to its flexibility and scalability, DRF is also able to assess the importance of features, providing insights into the key variables driving the model’s predictions [36].

Its ability to handle missing data, categorical variables, and outliers further solidifies its suitability for complex real-world applications. The use of ensemble learning in DRF ensures a robust performance across different data types and applications, making it a reliable choice for large-scale machine learning tasks [38].

5.2. Gradient Boosting Machine

Gradient Boosting Machine (GBM) is a powerful ensemble technique that builds decision trees in a sequential manner, where each subsequent tree corrects the errors made by its predecessor. Unlike Random Forest, which trains trees independently and aggregates their results, GBM builds trees in a stepwise fashion, with each new tree focusing on the residual errors of the previous trees. This iterative approach allows GBM to capture complex, non-linear relationships within the data and improve the model's predictive accuracy over time [39]. GBM is particularly effective in handling sparse, high-dimensional data and can be fine-tuned using various hyperparameters such as learning rate, tree depth, and the number of trees, which further enhance its performance. One of the key advantages of GBM is its ability to focus on hard-to-predict cases by giving them more weight in the model training process. This property enables GBM to achieve high accuracy and handle diverse data distributions [40]. Additionally, the gradient descent optimization employed in GBM allows it to minimize a chosen loss function, typically the mean squared error (MSE) for regression tasks or logarithmic loss for classification tasks. This flexibility in loss functions allows GBM to be adapted to different problem domains and has made it a go-to algorithm in many real-world applications. Due to its powerful predictive capabilities, GBM has been widely adopted in fields such as finance, healthcare, and marketing, where high-performance models are critical [41]. For more information, this book is referred to readers [42].

5.3. Stacked Ensemble Learning

Stacking, also referred to as Super Learning [43] or Stacked Regression [44], is an algorithm that utilizes a second-level meta-learner to determine the optimal combination of base learners. Stacking, in contrast to bagging and boosting, focuses on creating a diverse and powerful group of learners. Even though stacking was first introduced in 1992, its theoretical guarantees were only established after the publication of the 2007 paper titled Super Learner. Polikar (2009) described this method in detailing [45].

The process began by training the DRF and GBM models separately on the training dataset with optimized hyperparameters obtained through grid search. Once both models were trained, they were used to generate predictions on the same training set, which were then used as input features for the ensemble meta-model. The meta-model, typically a logistic regression or another simple model, was trained to learn the optimal weights for combining these base predictions. This meta-model aims to minimize the overall prediction error by leveraging the strengths of both base models. The stacking process allows the ensemble to capture complementary patterns that each model excels at individually. The final output is a weighted combination of the DRF and GBM predictions, where the meta-model decides the best way to aggregate them. By combining diverse models, the Stacked Ensemble enhances predictive accuracy, reduces overfitting, and improves generalization to unseen data, thus providing a more robust solution than any single base model.

6. Model Development

6.1. Data preprocessing

The first step in the modeling process was data preprocessing, a critical phase to ensure data quality and compatibility with machine learning algorithms. The dataset, *FinalData.csv*, was loaded and inspected for missing values and inconsistencies. To address missing values, numerical columns were imputed with their median values, as the median is robust to outliers and ensures minimal distortion of the data distribution. Categorical columns were imputed using their mode, representing the most frequent value in the column. Additionally, column names were stripped of leading and trailing whitespaces to avoid errors during processing. Following these steps, the preprocessed data was converted into an H2OFrame, a format optimized for use with H2O’s machine learning tools. This conversion allowed seamless integration with the selected algorithms. The target variable, "Strength (output)", was defined explicitly, and all remaining columns were designated as predictors. Finally, the data was split into training (80%) and testing (20%) sets to enable robust model development and evaluation.

6.2. Model Training and Hyperparameter Optimization

To develop predictive models, Distributed Random Forest (DRF), Gradient Boosting Machine (GBM), and a Stacked Ensemble were employed. Each model underwent extensive hyperparameter tuning to identify configurations that minimized prediction error.

For the DRF model, a grid search was performed over hyperparameters such as the number of trees (ntrees), maximum tree depth (max\_depth), minimum rows per leaf node (min\_rows), and sampling rate (sample\_rate). These hyperparameters control the size and complexity of the random forest, ensuring an optimal balance between bias and variance. Similarly, GBM model optimization involved exploring combinations of the number of trees, tree depth, learning rate (learn\_rate), and sampling rate.

GBM’s learning rate was particularly significant, as it determines the step size in gradient descent and directly influences convergence speed and model performance. Both models used 3-fold cross-validation to validate hyperparameter configurations, ensuring robust performance on unseen data. Cross-validated predictions were retained for integration into the ensemble model.

A Stacked Ensemble model was constructed as a meta-learner, combining the predictions of the best-performing DRF and GBM models. The ensemble leveraged the diversity of these models, capturing complementary patterns in the data and mitigating individual model weaknesses. By integrating the strengths of multiple learners, the ensemble aimed to deliver superior accuracy and generalization.

7. Evaluation Matrices

The performance of these models is evaluated using several metrics, including the mean squared error (MSE), R-squared (R²), root mean squared error (RMSE), mean relative error (MRE), and mean absolute percentage error (MAPE). These metrics comprehensively assess model accuracy and robustness in predicting the target variables as shown in equation 4-8.

* **Mean Squared Error**

, (4)

Represents the average of the squared differences between the observed actual outcomes and the outcomes predicted by the model .

* **R-squared**

, (5)

Indicates the proportion of the variance in the dependent variable that is predictable from the independent variables. Here, is the mean of the actual observed values.

* **Root Mean Squared Error**

, (6)

* **Mean Relative Error**

, (7)

* **Mean Absolute Percentage Error**

, (8)

Represents the average of the absolute percentage errors between the observed actual outcomes and the outcomes predicted by the model, expressed as a percentage.

7.1. Compressive Strength (CS)

The compressive strength of recycled aggregate concrete (RAC) with GGBS and PPF was predicted using Random Forest, GBM, and Stacked Ensemble models. GBM demonstrated the highest accuracy with an R² value of 0.9784 for training and 0.9618 for testing.

Figure 9 illustrate the comparison between measured and predicted compressive strength using three different machine learning models: Random Forest, Gradient Boosting, and Stacked Ensemble.

In the Distributed Random Forest model, the training phase (Figure 9a) displays a high correlation between measured and predicted compressive strengths, with an R2 value of 0.9667, indicating effective learning from the training data. However, in the testing phase (Figure 9b), while the correlation remains strong with an R2 value of 0.9253, there is a noticeable drop in predictive accuracy, suggesting that the model might not generalize as well to unseen data.

|  |  |
| --- | --- |
|  |  |
| **(a)** | **(b)** |
|  |  |
| **(c)** | **(d)** |
|  |  |
| **(e)** | **(f)** |

**Figure 9.** Measured vs. predicted compressive strength using **(a-b)** Random Forest; **(c-d)** Gradient Boosting; **(e-f)** Stacked Ensemble Models.

For the Gradient Boosting Machine, the training phase (Figure 9c) shows a high correlation with an R2 value of 0.9784, indicating robust learning capabilities. The testing phase (Figure 9d) maintains this strong performance, achieving an R2 value of 0.9618, demonstrating the model's ability to generalize well from the training data to new, unseen data. This consistency highlights the effectiveness of the Gradient Boosting approach.

The Stacked Ensemble Learning model also exhibits a high correlation during the training phase (Figure 9e), with an R2 value of 0.9781, indicating that it can effectively combine the strengths of various base learners. In the testing phase (Figure 9f), the model continues to perform well, maintaining a strong correlation with an R2 value of 0.9513. This consistency in performance across both phases underscores the reliability and robustness of the Stacked Ensemble Learning model.

Based on the analysis, the Gradient Boosting Machine appears to be the best model among the three. It demonstrates the highest R2 values in both training (0.9784) and testing (0.9618) phases, indicating robust learning and excellent generalization capabilities.

7.2. Split Tensile Strength (STS)

The split tensile strength of RAC incorporating GGBS and PPF was analyzed using Random Forest, GBM, and Stacked Ensemble models. GBM showed superior predictive performance with an R² value of 0.9773 for training and 0.97 for testing.

Figure 10 illustrates the comparison between measured and predicted split tensile strength using three different machine learning models: Random Forest, Gradient Boosting, and Stacked Ensemble.

In the Distributed Random Forest model, the training phase (Figure 10a) displays a high correlation between measured and predicted split tensile strengths, with an R2 value of 0.9708, indicating effective learning from the training data. However, in the testing phase (Figure 10b), while the correlation remains strong with an R2 value of 0.957, there is a noticeable drop in predictive accuracy, suggesting that the model might not generalize as well to unseen data. For the Gradient Boosting Machine, the training phase (Figure 10c) shows a high correlation with an R2 value of 0.9773, indicating robust learning capabilities. The testing phase (Figure 10d) maintains this strong performance, achieving an R2 value of 0.97, demonstrating the model's ability to generalize well from the training data to new, unseen data. This consistency highlights the effectiveness of the Gradient Boosting approach.

The Stacked Ensemble Learning model also exhibits a high correlation during the training phase (Figure 10e), with an R2 value of 0.9787, indicating that it can effectively combine the strengths of various base learners. In the testing phase (Figure 10f), the model continues to perform well, maintaining a strong correlation with an R2 value of 0.9697. This consistency in performance across both phases underscores the reliability and robustness of the Stacked Ensemble Learning model. Based on the analysis of the split tensile strength predictions, theGradient Boosting Machine emerges as the best model. It demonstrates the highest R2 values in both the training phase (0.9773) and the testing phase (0.97), indicating robust learning and excellent generalization capabilities. This consistent performance makes the Gradient Boosting Machine the most reliable model for predicting split tensile strength.

7.3. Statistical Matrix

Table 6(a) presents the statistical metrics for evaluating the performance of different approaches in predicting compressive and split tensile strengths for both training and testing datasets. For the compressive strength, the Distributed Random Forest model shows a Mean Squared Error (MSE) of 3.1685 and a Mean Absolute Percentage Error (MAPE) of 3.8395 with an R2 value of 0.9667 during training, but its performance drops significantly in the testing phase with an MSE of 9.7958, MAPE of 6.7467, and an R2 value of 0.9235. The Gradient Boosting Machine performs better, with lower errors and higher R2 values in both phases. During training, it achieves an MSE of 1.5114, MAPE of 2.4368, and R2 value of 0.9784. Its testing performance remains strong, with an MSE of 3.5313, MAPE of 4.1955, and R2 value of 0.9618.

|  |  |
| --- | --- |
|  |  |
| (a) | (b) |
|  |  |
| (c) | (d) |
|  |  |
| (e) | (f) |

**Figure 10.** Measured vs. predicted split tensile strength using **(a-b)** Random Forest; **(c-d)** Gradient Boosting; **(e-f)** Stacked Ensemble Models.

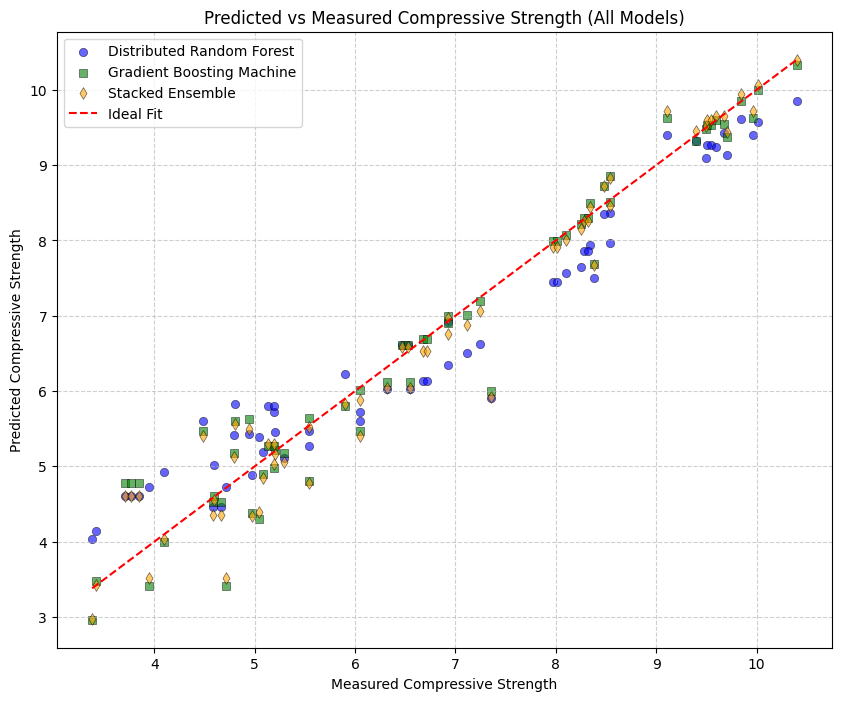
**Table 6.** Statistical matrix for compressive and split tensile strength.

|  |  |  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- |
| **(a)** | **Training data set**  **(Compressive Strength)** | | | | | **Testing data set**  **(Compressive Strength)** | | | | |
| Approaches | **MSE** | **MAPE** | **R²** | **MAE** | **RMSE** | **MSE** | **MAPE** | **R²** | **MAE** | **RMSE** |
| Distributed Random Forest | 3.16852 | 3.83952 | 0.96669267 | 1.52842 | 1.78003 | 9.79575 | 6.74668 | 0.92349 | 2.44281 | 3.12981 |
| Gradient Boosting Machine | 1.51136 | 2.43681 | 0.97844337 | 0.99559 | 1.22937 | 3.53128 | 4.19553 | 0.96180 | 1.57714 | 1.87917 |
| Stacked Ensemble Learning | 1.56286 | 2.46652 | 0.97809981 | 1.01089 | 1.25014 | 3.38536 | 4.10225 | 0.96134 | 1.56486 | 1.83993 |
| **(b)** | **Training data set**  **(Split Tensile Strength)** | | | | | **Testing data set**  **(Split Tensile Strength)** | | | | |
| Approaches | **MSE** | **MAPE** | **R²** | **MAE** | **RMSE** | **MSE** | **MAPE** | **R²** | **MAE** | **RMSE** |
| Distributed Random Forest | 0.11894 | 6.99099 | 0.97080521 | 0.25272 | 0.34488 | 0.26794 | 17.0712 | 0.95702 | 0.39958 | 0.51762 |
| Gradient Boosting Machine | 0.06258 | 4.94785 | 0.97725820 | 0.19538 | 0.25017 | 0.11336 | 9.32642 | 0.97004 | 0.24598 | 0.33669 |
| Stacked Ensemble Learning | 0.05807 | 3.85231 | 0.97873320 | 0.15810 | 0.24099 | 0.13068 | 10.7962 | 0.96971 | 0.24044 | 0.36149 |

The Stacked Ensemble Learning model also shows strong performance, similar to Gradient Boosting. In the training phase, it records an MSE of 1.5629, MAPE of 2.4665, and R2 value of 0.9781. In the testing phase, it maintains an MSE of 3.3854, MAPE of 4.1023, and R2 value of 0.9613. Overall, the Gradient Boosting Machine demonstrates the best balance of low error rates and high R2 values across both training and testing datasets, making it the most effective approach among the models compared for predicting compressive strength.

Table 6(b) provides a comprehensive comparison of the statistical metrics for predicting split tensile strength using three different machine learning approaches: Distributed Random Forest, Gradient Boosting Machine, and Stacked Ensemble Learning, for both training and testing datasets. The Distributed Random Forest model shows an MSE of 0.1189, MAPE of 6.9910, and R2 value of 0.9708 during training. However, its performance decreases during testing with an MSE of 0.2679, MAPE of 17.0712, and R2 value of 0.9570. The Gradient Boosting Machine demonstrates better performance, with an MSE of 0.0626, MAPE of 4.9479, and R2 value of 0.9773 in the training phase. It maintains strong performance during testing, with an MSE of 0.1134, MAPE of 9.3264, and R2 value of 0.9700, indicating robust generalization capabilities. The Stacked Ensemble Learning model also performs well, achieving an MSE of 0.0581, MAPE of 3.8523, and R2 value of 0.9787 during training. In testing, it records an MSE of 0.1307, MAPE of 10.7963, and R2 value of 0.9697, showing consistent and reliable performance.

Overall, the Gradient Boosting Machine emerges as the best model for predicting split tensile strength, balancing low error rates and high R2 values across both training and testing datasets, demonstrating superior generalization and predictive accuracy compared to the other models.

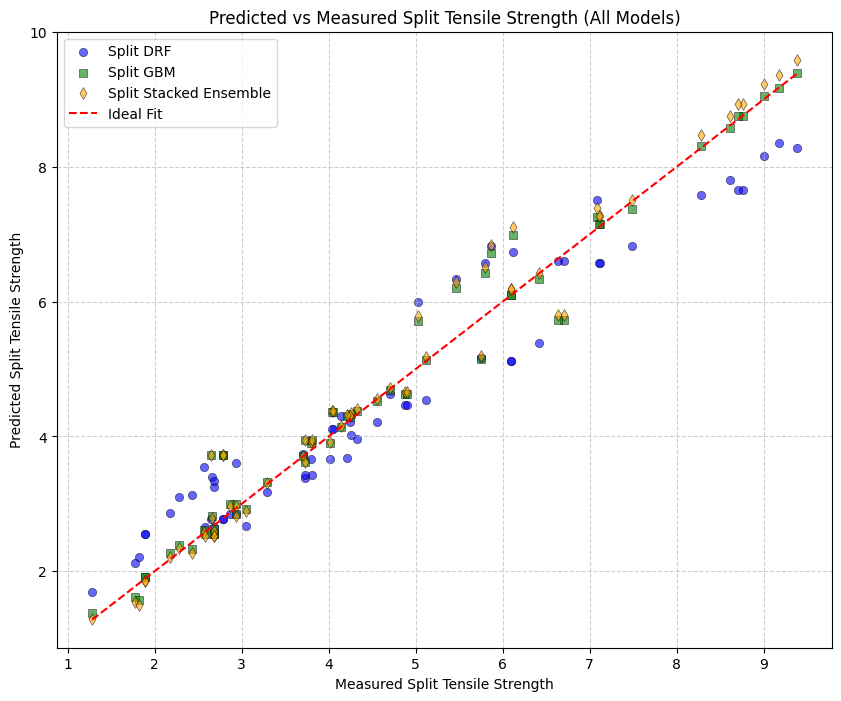


**Figure 11.** Scatter plot of predicted and measured compressive strengths.

The scatter plot for compressive strength is shown in Figure 11, for three models: Distributed Random Forest, Gradient Boosting Machine, and Stacked Ensemble Learning. Among these, the Gradient Boosting Machine demonstrates the best predictive accuracy, with its predictions closely aligning with the measured values, indicating robust performance. The Stacked Ensemble Learning model also shows strong performance, but the Gradient Boosting Machine consistently exhibits superior reliability and precision. In contrast, the Distributed Random Forest model displays greater variability and less precision. Overall, the Gradient Boosting Machine stands out as the most effective method for predicting compressive strength.

The scatter plot for split tensile strengths is shown in Figure 12, for three models: Distributed Random Forest, Gradient Boosting Machine, and Stacked Ensemble Learning. Among these, the Gradient Boosting Machine demonstrates the best predictive accuracy, with its predictions closely aligning with the measured values, indicating robust performance. The Stacked Ensemble Learning model also shows strong performance, but the Gradient Boosting Machine consistently exhibits superior reliability and precision. In contrast, the Distributed Random Forest model displays greater variability and less precision. Overall, the Gradient Boosting Machine stands out as the most effective method for predicting split tensile strength.

In this research on recycled aggregate concrete incorporating GGBS and polypropylene fibers, a similar group of performance metrics was employed to evaluate the efficacy of different modeling approaches. The results obtained from this study demonstrate superior predictive capabilities in both compressive strength and splitting tensile strength compared to the models analyzed in the study on concrete with ceramic waste and nylon fiber [46] as shown in Table 7. This indicates that the integration of recycled aggregate concrete with GGBS and polypropylene fibers, alongside advanced predictive modeling techniques such as Response Surface Methodology (RSM) and machine learning, provides enhanced accuracy and reliability in performance prediction.



**Figure 12.** Scatter plot of predicted and measured split tensile strengths.

**Table 7.** Different model with statistical index.

|  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- |
| **Model/Kernel** | **R2 (CS)** | **MAE (CS)** | **MSE (CS)** | **RMSE (CS)** | **R2 (STS)** | **MAE (STS)** | **MSE (STS)** | **RMSE (STS)** |
| GBM | 0.947 | 1.035 | 1.617 | 1.272 | 0.923 | 0.23 | 0.07 | 0.265 |
| Dist. RF | 0.923 | 2.443 | 9.796 | 3.13 | 0.957 | 0.4 | 0.268 | 0.518 |
| GBM [46] | 0.962 | 1.577 | 3.531 | 1.879 | 0.97 | 0.246 | 0.113 | 0.337 |
| Stacked Ens. | 0.961 | 1.565 | 3.385 | 1.84 | 0.97 | 0.24 | 0.131 | 0.361 |

7.4. Comparison of RSM and Machine Learning

The machine learning models, particularly GBM, demonstrated higher R² values (0.9618 for CS and 0.97 for STS) compared to RSM (0.9314 for CS and 0.9436 for STS), indicating better predictive accuracy. Machine learning models showed superior performance in both training and testing phases, with lower error rates and higher consistency. GBM, for instance, maintained strong performance with R² values of 0.9618 and 0.97 for CS and STS respectively, in both phases. Machine learning models are more complex but offer robust predictions by capturing nonlinear relationships in the data. RSM, while simpler and effective in identifying key interactions, may not capture complex patterns as effectively as machine learning models.

8. Practical Implications

The practical implications of this study are significant for the construction industry, particularly in the context of promoting sustainable building materials and practices. The developed machine learning models can be used to predict the mechanical properties of recycled aggregate concrete (RAC), which plays a key role in reducing the environmental impact of traditional concrete production. By utilizing these models, engineers and construction professionals can better assess the performance of RAC with different proportions of recycled aggregates, ground-granulated blast furnace slag (GGBS), and polypropylene fibers (PPF), ultimately leading to optimized mix designs that offer a balance between sustainability and mechanical strength. These models can aid in the design of more eco-friendly concrete mixtures by reducing the reliance on virgin materials and minimizing waste, which aligns with global efforts to reduce CO2 emissions and conserve resources.

Additionally, the models provide a reliable tool for simulating various concrete mixes, allowing for faster and more cost-effective decision-making during the design phase, without the need for extensive physical testing. The insights gained from these models can also help in improving the durability and longevity of RAC in real-world applications, such as in the construction of roads, buildings, and infrastructure. Overall, the findings of this study offer a practical approach to enhancing the performance of sustainable concrete while reducing the environmental footprint of the construction industry.

9. Conclusion

* The study suggests that the optimal mix proportions for achieving high compressive strength (CS) and split tensile strength (STS) in RAC include 25% GGBS, 50% recycled aggregates (RA), and 0.5% PPF. This combination demonstrated significant improvements in mechanical properties.
* The experimental results indicated that the inclusion of GGBS and PPF significantly enhances the compressive strength of RAC. At 56 days, mixes with 50% GGBS and 1% PPF showed up to a 36.37% increase in CS compared to control mixes. However, high RA content without adequate GGBS and PPF reduced the strength.
* Incorporating GGBS and PPF improved the split tensile strength of concrete. Mixes with 50% GGBS and 1% PPF showed the highest increase in STS, with an enhancement of up to 188.98% at 56 days. The presence of PPF mitigated the reduction in STS caused by high RA content.
* The RSM analysis yielded high R² values of 0.9314 for CS and 0.9436 for STS, with p-values less than 0.0001, demonstrating the model's robustness and accuracy. The quadratic models developed using RSM provided a clear understanding of the interaction effects between GGBS, RA, PPF, and curing time, facilitating the optimization of concrete mix designs.
* Among the machine learning models evaluated, the Gradient Boosting Machine (GBM) emerged as the most effective for predicting both CS and STS. The GBM model achieved high R² values of 0.9618 for CS and 0.97 for STS, indicating robust predictive accuracy and reliability. The Stacked Ensemble Learning model also performed well, closely following the GBM in terms of predictive accuracy.
* Overall, this study demonstrates that recycled aggregate concrete incorporating GGBS and PPF can achieve superior mechanical properties and durability while supporting environmental sustainability. The integration of RSM and advanced machine learning techniques provides a robust framework for optimizing concrete mix designs and predicting their performance. The findings highlight the potential of these innovative materials and methods to enhance the sustainability and efficiency of modern construction practices.

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