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Performance Evaluation of RCA-Based Sustainable Concrete Using Artificial Neural Networks

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Abstract:
The usage of recycled coarse aggregate (RCA) in concrete is growing in order to satisfy consumer demand for environmentally friendly building materials. However, RCA can degrade the mechanical qualities of concrete because of the old mortar and increased porosity it contains. The strength and microstructure of the finished concrete were improved by the addition of silica fume as a mineral additive to address these problems. In order to evaluate fresh and hardened properties, including as workability using slump cone tests and mechanical attributes like compressive, split tensile, and flexural strengths, the study entailed mixing concrete with different proportions of RCA and silica fume. Higher RCA content decreased mechanical performance due to weaker interfacial zones and increased water absorption, according to the results. For example, a mix containing 60% RCA exhibited a decrease in compressive strength from 38.6 MPa in the control mix to 30.2 MPa. On the other hand, adding silica fume produced notable benefits; the ideal mixture (20% RCA and 10% silica fume) produced improved results in other characteristics as well as a compressive strength of 42.5 MPa. In order to forecast concrete qualities based on mix ratios, water-cement ratios, and other variables, an Artificial Neural Network (ANN) model was also created using MATLAB. This model achieved a high prediction accuracy with a regression value of R = 0.984. By comparing predictions with experimental findings, the model's dependability was validated, and the results showed little differences. The study backs the idea that ANN models offer a practical way to estimate concrete parameters, thereby reducing costs and resources in infrastructure projects, and that RCA combined with silica fume can produce effective sustainable concrete.

Keywords: Artificial Neural Network; Compressive Strength; Recycled Coarse Aggregate; Silica Fume.

1. Introduction

Because of its affordability, durability, and adaptability, concrete is the most often used building material. Environmental deterioration and resource depletion are the results of the construction industry's continuous expansion, which has led to a large consumption of natural resources like cement and aggregates. The significant amount of waste produced during building and deconstruction also presents a number of environmental and disposal issues. As a result, RCA made from destroyed concrete has become a viable substitute for natural aggregates, despite the fact that it frequently shows poorer mechanical performance because to adherent mortar, increased water absorption, and weaker interfacial transition zones [1-4].

Additional cementitious ingredients, such as silica fume, are often used to address these problems. By strengthening the pore structure and the link between aggregate and cement paste, silica fume, a reactive pozzolanic ingredient, increases strength and durability. However, the complex interactions in material characteristics caused by the combination of RCA and silica fume make it more difficult to forecast compressive strength using conventional empirical approaches. Therefore, proper modeling of these nonlinear connections requires sophisticated computational approaches, especially ANN [5-6].

Inspired by the human brain, ANN models are computational structures made up of interconnected neurons that collaborate to learn from input and solve complicated problems. In the field of concrete technology, a number of interconnected parameters, including mix proportions and curing age, affect compressive strength. While ANN can learn directly from experimental data without requiring explicit mathematical formulations, standard prediction approaches frequently ignore these nonlinear interactions.

An ANN may find complex and nonlinear correlations between parameters because of its structure, which is similar to that of a real neuron: inputs are given weights, summed, biased, and then processed through an activation function to produce an output. The feed-forward neural network (FFNN) is the most popular and efficient type of ANN, usually used for concrete strength prediction because of its robustness and ease of installation.

A variety of ANN architectures, such as feed-forward neural networks (FFNN), backpropagation neural networks (BPNN) for error minimization, radial basis function networks (RBFNN) for approximation, and deep neural networks (DNN) that handle complex patterns but require large datasets, have been investigated in civil engineering for strength prediction. For predicting concrete strength, the FFNN with backpropagation has shown exceptional efficacy [7-9].

RCA is made from concrete that has been destroyed and deals with disposal and environmental problems brought on by construction waste. The use of RCA concrete encourages resource conservation and sustainable waste management, despite the fact that it frequently has different mechanical and physical properties from conventional concrete. The potential environmental benefits and structural applications of RCA are significant, notwithstanding issues like decreased compressive strength and durability associated with the old mortar on RCA particles. Through suitable mix design modifications, the microstructure of RCA concrete can be enhanced and strength losses reduced, underscoring the need for sophisticated prediction methods, such as ANN, to precisely evaluate the compressive strength of RCA-based concrete.

In order to give real-time concrete strength predictions for scheduling and form removal during construction, the paper describes the creation of the I-PreConS (Intelligent Prediction system of concrete Strength), which makes use of ANNs. A modular ANN system made up of five interconnected networks was implemented as a result of the previous ANN architecture's inability to predict strength fluctuations brought on by changes in curing temperature. While ANN-II to ANN-V estimate strength from the second to the 28th day after pouring, ANN-I predicts strength within 24 hours. To increase accuracy, improvements like input neuron weighting and parameter condensation have been used [10].

The article also describes an ANN model that predicts the compressive strength of both regular and high-strength concrete by utilizing the Levenberg-Marquardt Backpropagation (LMBP) training technique. Eight input variables—cement concentration, blast furnace slag, fly ash, fine and coarse aggregate, water content, superplasticizer, and testing age were included in the extensive dataset of 1,637 samples used to evaluate this model. Analysis was used to determine the ideal architecture, which included the number of hidden layers and neurons. The model's efficacy was evaluated using k-fold cross-validation and statistical metrics like the correlation coefficient (R), coefficient of determination (R^2), Root Mean Square Error (RMSE), and Mean Absolute Error (MAE). Notably, it was discovered that superplasticizer and unit cement content had a major impact on compressive strength.

Because of its great durability and compressive strength, concrete is the most extensively used building material worldwide. These characteristics are tested and evaluated using conventional, time-consuming, and expensive procedures in both the fresh and hardened phases of concrete. An ANN built using a variety of input factors relevant to concrete mix design (such as coarse and fine aggregate qualities, cement content, water/cement (W/C) ratio, additive type and dosage, etc.) was used in this study to predict the compressive strength and slump of concrete. Compressive strength and slump data gathered through experimentation over many years for various materials and mix designs in Sudan were compared with the expected strength. The MATLAB neural network toolkit was used to create an ANN model. The anticipated and experimental values showed good correlations, with regression values of 0.915 and 0.931 for strength and slump, respectively. It is determined that the ANN approach can produce reasonable forecasts for slump and compressive strength.

The most crucial mechanical property of concrete is its compressive strength, which is frequently determined via destructive testing (Hosseinzadeh et al., 2024). However, these tests are costly and time-consuming [21]. Over the past ten years, ANNs have become the "second-best method for doing almost anything" in structural engineering because to its capacity to forecast complex, nonlinear interactions between mix ingredients (cement, water, admixtures) and final strength (Altunci, 2024) [20].

ANNs are now being developed for fly ash-modified SCC and alkaline-activated slag concrete (AASC), where normal empirical formulas often fail due to the chemical complexity of the binders (Ismael Jaf, 2023; Tang et al., 2022) [22,23].

Recent models have successfully predicted the strength of "Self-Healing Concrete" (SHC) by utilizing crystalline and mineral admixtures as input factors (Tang et al., 2022). ANNs are currently employed in new frameworks to predict the mechanical properties of steel-fiber-reinforced concrete at elevated temperatures (Frontiers, 2025).

For the purpose of predicting compressive strength, an ANN model with a single hidden layer and a Back Propagation (BP) network topology was also developed. The thresholds and synaptic weights required for precise predictions based on concrete mix proportions were effectively confirmed by this model, which was trained and tested against historical data. One important feature of concrete is its compressive strength, which is usually evaluated using expensive and time-consuming destructive testing techniques. Therefore, this study demonstrates how well the ANN model predicts concrete's compressive strength and slump utilizing a variety of mix design-related input factors. In concrete sourced from various materials and mix designs throughout Sudan, good correlations between projected and experimentally measured values of compressive strength and slump were found, with regression values of 0.915 and 0.931, respectively.

Alkaline-activated slag concrete (AASC) and fly ash-modified, self-compacting concrete (SCC) are two examples of concrete properties that can be optimized with ANNs, according to the document. The mechanical characteristics of "Self-Healing Concrete" (SHC) and the analysis of steel-fiber-reinforced concrete at high temperatures have been successfully predicted by recent models. There are still issues, nevertheless, such as the restricted applicability of models created on datasets from certain areas or circumstances, especially in diverse ecosystems like tropical settings. The lack of standardized theoretical guidelines for determining the ideal number of hidden layers or neurons, which frequently results in reliance on trial-and-error methods in complex mix designs, is highlighted along with the urgent need for hybrid architectures that can integrate multiple datasets without sacrificing accuracy.

The reviewed literature highlights a number of important research gaps concerning RCA concrete, with a particular emphasis on predictive modeling and the restricted use of material diversity in ANN models. Without sufficiently addressing the nonlinear behaviors of sustainable concrete mixes, the majority of studies place an emphasis on experimental evaluation. There is a significant chance to increase prediction accuracy because, in particular, few studies use ANN to evaluate the combined impacts of silica fume and RCA.

The goal of the current work is to develop an ANN-based model that integrates silica fume and RCA to accurately predict the compressive strength of concrete. Among the goals of the research are:

- The creation of sustainable concrete mixes for environmentally friendly building applications using silica fume and RCA.
- An analysis of how these materials affect concrete's fresh and hardened qualities.
- A variety of strength tests are used to assess mechanical performance.
- Examining how various RCA replacement levels affect the durability, strength, and stiffness of concrete.
- Using silica fume as a mineral addition to improve the performance of RCA concrete.
- Determining the best mixes of silica fume and RCA to enhance concrete performance.
- Using MATLAB, an ANN model trained on experimental data is created and validated.
- Using statistical metrics like R2, RMSE, MAE, and MSE, actual experimental findings are compared with ANN forecasts to evaluate accuracy and dependability.
- Creating regression plots and performance curves for ANN validation using MATLAB.
- An example of how ANNs may be used to quickly and accurately forecast sustainable concrete properties, which will lessen the need for labor-intensive laboratory work and encourage the use of recycled materials and AI approaches in sustainable concrete practices.

2.Materials & Methodology

The creation of an ANN model to forecast the compressive strength of concrete including RCA and silica fume is explained in this chapter. It includes a detailed explanation of the materials, mix ratios, experimental techniques, and approaches used during the study.

In accordance with IS 12269, Ordinary Portland Cement (OPC) of grade 53 was used. As required by IS 4031, tests for specific gravity, consistency, and setting time were carried out. Natural river sand that complies with Zone II of IS 383 was utilized. Before being used, the sand's specific gravity and water absorption were measured. It was clean, well-graded, and devoid of organic debris.

In accordance with IS 383, crushed angular coarse aggregates were chosen, and bulk density, water absorption, and specific gravity were assessed. In accordance with IS 456, potable water free of dangerous contaminants was utilized for the mixing and curing procedures. RCA was made from concrete that had been completely cleansed of impurities before being crushed. Its physical characteristics were analyzed and contrasted with those of naturally occurring coarse aggregates. This ASTM C1240-compliant ultra-fine pozzolanic material was used in place of some of the cement, improving the concrete's microstructure and characteristics.

Figure 1 RCA

Figure 2 Silica fume

2.1 Mix Proportions

In accordance with IS 10262 rules, concrete was constructed using M30 grade. RCA was used to partially replace natural coarse aggregate at levels of 0%, 25%, and 50%, while silica fume was used to substitute cement at levels of 0%, 5%, and 10%.

- Proportions of Mix (per m³)380 kg of cement
- 650 kg of fine aggregate
- 1200 kg of natural coarse aggregate
- 171 liters of water
- The ratio of water to cement is 0.45.

Table 1 Specimen details

Mix ID	RCA (%)	Silica Fume (%)
M1	0	0
M2	25	0
M3	50	0
M4	0	5
M5	25	5
M6	50	5
M7	0	10
M8	25	10
M9	50	10

Table 2 Concrete Specimen details

Sl. No	Test Conducted	Specimen Shape	Specimen Size
1	Compressive Strength Test	Cube	150 mm × 150 mm × 150 mm
2	Split Tensile Strength Test	Cylinder	150 mm Diameter × 300 mm Height
3	Flexural Strength Test	Prism Beam	100 mm × 100 mm × 500 mm
4	Modulus of Elasticity Test	Cylinder	150 mm Diameter × 300 mm Height
5	Impact Resistance Test	Disc/Cylinder	150 mm Diameter × 63.5 mm Thickness

Figure 3 Casting and curing of specimens

2.2 Experimental Program

Using the slump cone method in accordance with IS 1199, it was discovered that silica fume and RCA both decreased workability. All blends, however, showed respectable workability appropriate for structural purposes. To prevent segregation, concrete specimens were meticulously cast, guaranteeing uniform mixing and compacting. Compressive strength, split tensile strength, modulus of elasticity, impact resistance, and flexural strength tests were conducted using various types. Following a day of initial setting, the specimens were demoulded and allowed to cure in water until testing.

Using a compression testing apparatus in accordance with IS 516, this test was performed on cube specimens after seven and twenty-eight days of curing. The highest load was divided by the cross-sectional area of the specimen to determine the compressive strength. In accordance with IS 5816 recommendations, the tensile behavior of concrete was assessed using cylindrical specimens. Conducted using prism beam specimens under two-point loading circumstances in accordance with IS 516 criteria to determine how well concrete mixtures bend. Using stress-strain curves, the stiffness behavior of concrete containing RCA was examined. Using a standardized equipment on cylindrical disc specimens, this test evaluated the specimen’s capacity to bear dynamic loads. Crucial data were taken on the first evident cracks and failures.

This thorough approach demonstrated the effects of RCA and silica fume on the mechanical characteristics of concrete and supplied vital information for the ANN model that forecasts compressive strength.

2.3 ANN

The basic procedures for modeling using ANN to forecast the mechanical properties of sustainable concrete specifically, including silica fume and RCA are described in the section on ANN dataset preparation. Normalization was applied to input variables before training, improving accuracy and convergence of the ANN training phase. The dataset included both experimental results and mix proportion parameters.

The approach demonstrated the ANN can handle challenging nonlinear engineering issues that arise in concrete technology. Traditional mathematical models frequently fail to appropriately describe the intrinsically nonlinear relationship between parameters like cement content, water-cement ratio, and aggregate characteristics. In order to predict important concrete metrics—compressive strength, split tensile strength, flexural strength, modulus of elasticity, and impact resistance this study built an ANN model using the MATLAB Neural Network Toolbox.

By using concrete mix proportions and curing factors as inputs and concrete's mechanical qualities as output responses throughout a training process, the ANN simulates how the brain works. By using backpropagation algorithms to modify internal weights and biases, the ANN gradually lowers prediction errors.

Important considerations while choosing an ANN architecture highlighted how important input and output parameter selections are for prediction accuracy. Three parts make up the model: an input layer that receives concrete mix parameters, hidden layers that process this data using weighted connections and activation functions, and an output layer that predicts compressive strength.

Critical input parameters, including cement content, water content, aggregate kinds, and other important characteristics representing material qualities and curing age, were discovered for efficient ANN operation. Compressive strength was the only output measure, supplemented by tests such as split tensile strength and flexural strength.

Initiatives for data preprocessing, such as normalization, were crucial for enhancing model performance by guaranteeing that input parameters stayed within a same range, facilitating faster convergence. By effectively adjusting weights and biases to reduce differences between expected and experimental outcomes, the Levenberg-Marquardt backpropagation method made training easier.

The dataset was split into three sections:

70% for training, 15% for validation, and 15% for testing. This allowed for accurate predictions on unknown data while maintaining an objective evaluation of ANN performance. While a linear activation function in the output layer made it possible to forecast continuous values, nonlinear activation functions in the hidden layers allowed for the modeling of complex relationships.

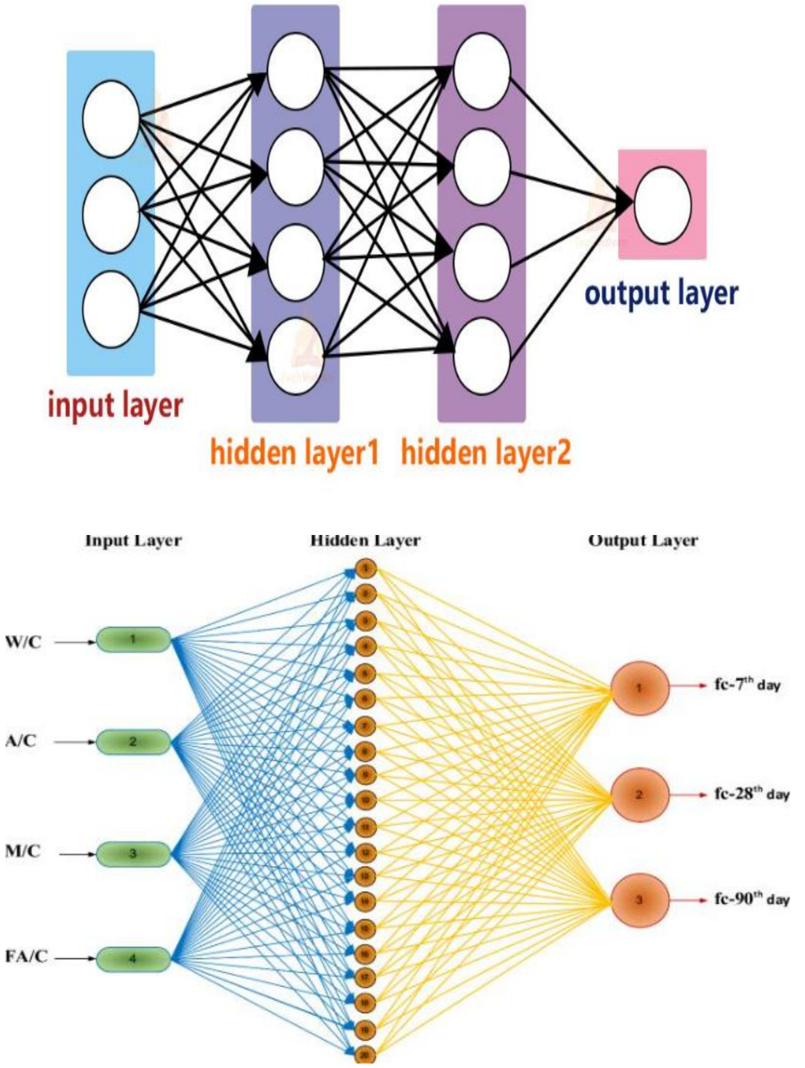

Figure 4 Layers in ANN network

Statistical metrics including the Coefficient of Determination (R^2), Root Mean Square Error (RMSE), and Mean Absolute Error (MAE) were used to evaluate post-training performance; data points that closely aligned with the line of equality in regression plots demonstrated good correlation. Through scatter plots, the model validation demonstrated a good connection between anticipated and experimental values, confirming the model's dependability.

In summary, this work uses the ANN technique to establish a strong correlation between the mechanical properties of sustainable concrete and its mix parameters. With significant regression coefficients and lower prediction errors, the resulting MATLAB-based model showed remarkable predictive skills, improving future applications in smart construction while requiring less testing.

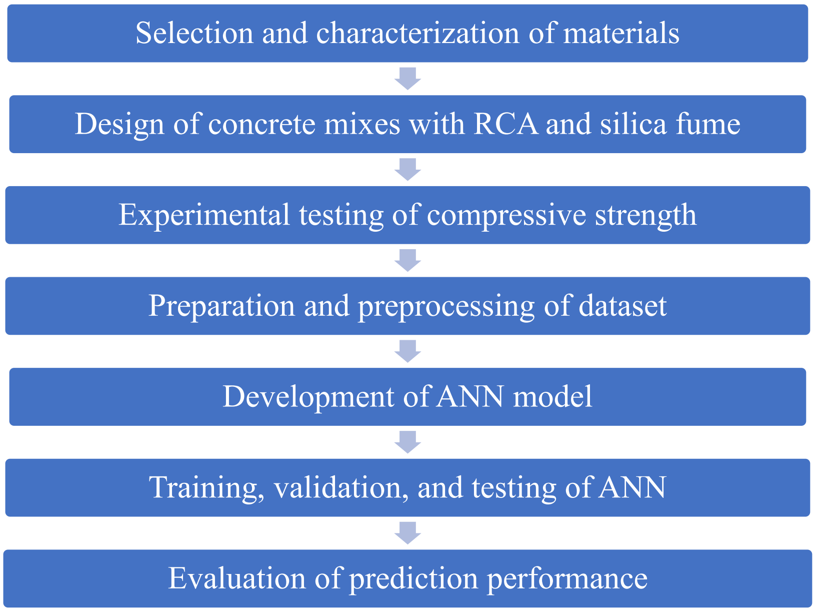

Figure 5 Flowchart methodology of ANN procedure

4.Results & Discussion

4.1Mechanical test results

The study looks into how adding silica fume and RCA affects the mechanical qualities and workability of concrete mixtures.

4.2 Test of Workability

The slump test showed that because of the recycled aggregates rough texture and enhanced water absorption, workability declined as the RCA percentage rose. Slump values were further reduced by the tiny particles in silica fume. With appropriate compaction, the mixes were still workable, and the slump values were within acceptable bounds for structural concrete.

4.3 Strength of Compression

Because of things like weak interfacial zones and increased porosity, the addition of RCA resulted in a decrease in compressive strength. Through pozzolanic processes, silica fume improved the microstructure and greatly increased compressive strength; the best combination was 10% silica fume and 20% RCA, which produced the maximum strength.

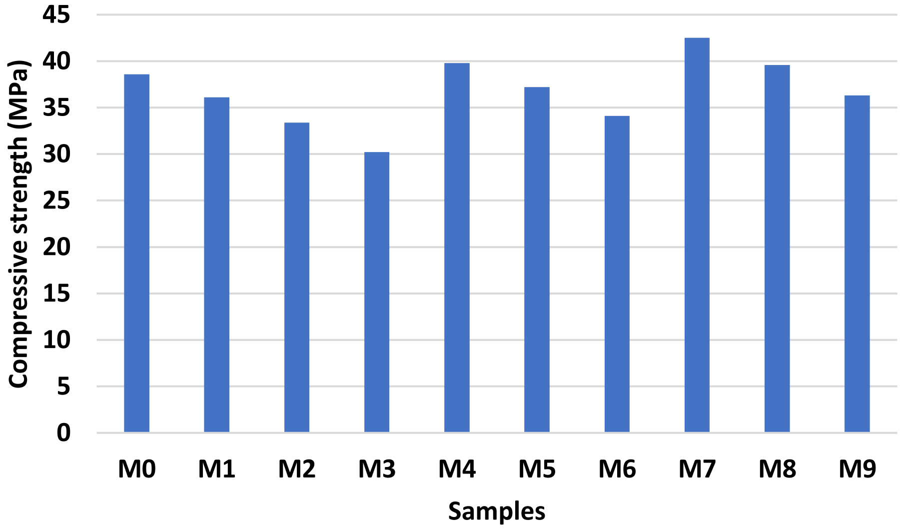

Figure 6 Compressive strength results

4.4 Split Tensile Strength

According to the split tensile strength tests, tensile strength was adversely influenced by increasing RCA content. RCA addition decreased strength, according to the results, while mixtures with silica fume performed better because of their improved microstructural integrity. In particular, the highest tensile strength was obtained by combining 10% silica fume with 20% RCA.

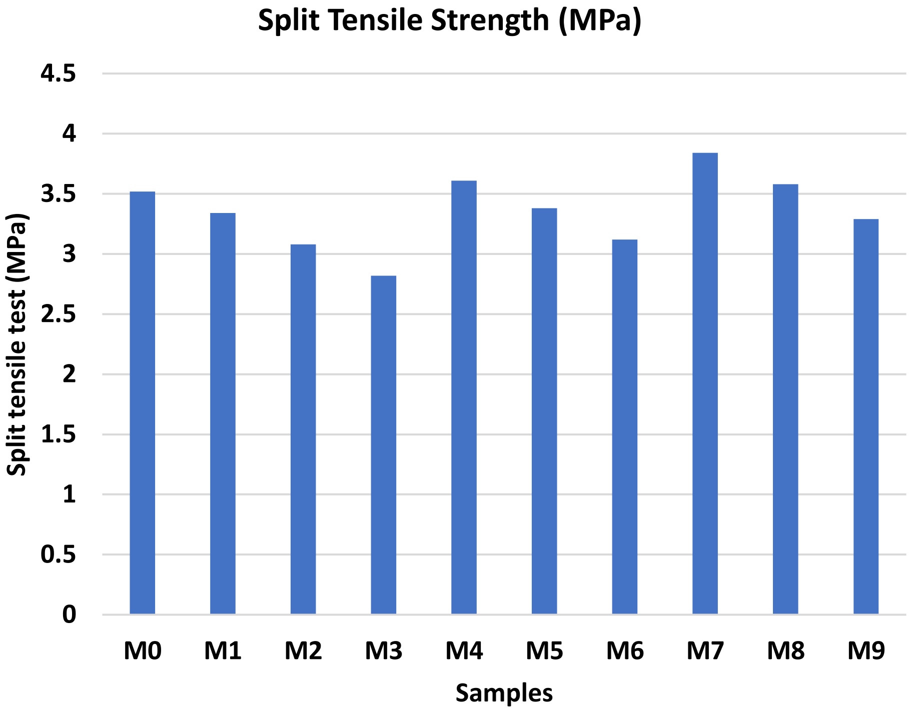

Figure 7 Split tensile strength results

4.5 Test of Flexural Strength

Due of weaker bonding and increasing porosity, flexural strength eventually dropped as RCA concentration increased. However, silica fume-containing mixes performed better; the mix with 20% RCA and 10% silica fume reached a flexural strength of 5.24 MPa, demonstrating significant improvements because of the micro-filling effects of silica fume.

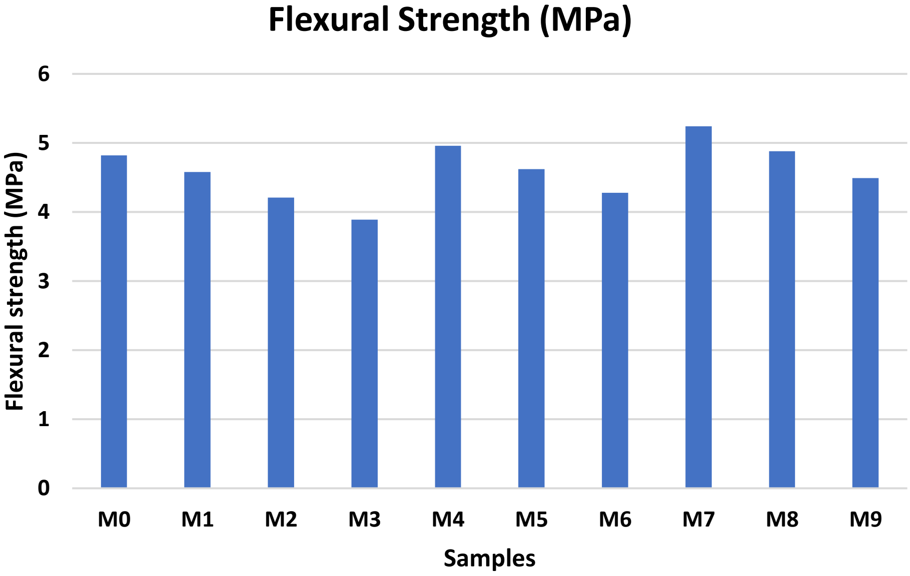

Figure 8 Flexural strength results

4.6 Elasticity Modulus Test

Similar to RCA levels, the modulus of elasticity gradually decreased. Mixes containing silica fume, however, perform better than control mixes in terms of stiffness and deformation characteristics because the addition of silica fume helped restore some lost stiffness.

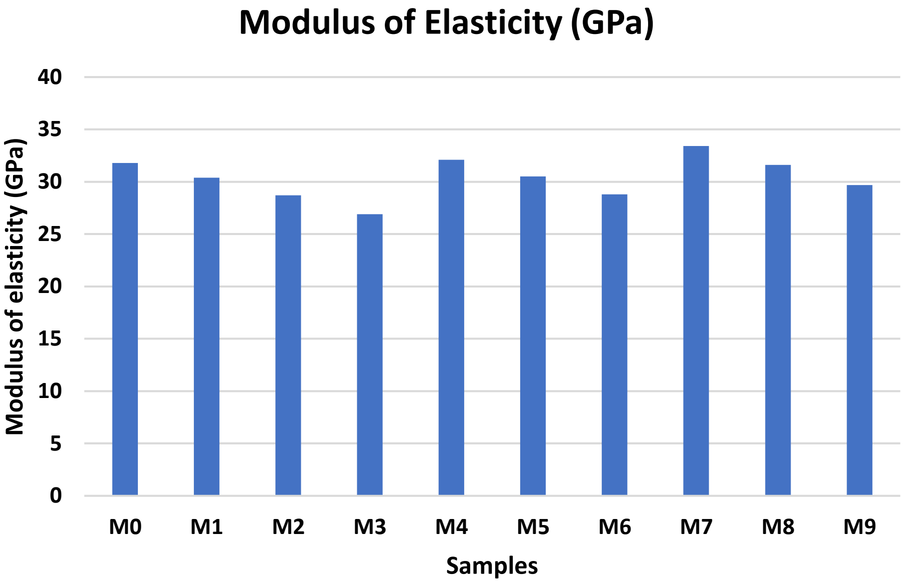

Figure 9 Elasticity modulus outcomes

4.7 Test for Impact Resistance

The impact resistance tests demonstrated how RCA affected energy absorption and toughness, with higher RCA resulting in fewer blow counts in first crack and final failure tests. However, impact resistance was greatly increased by the addition of silica fume in a number of ratios; mix M7 (20% RCA, 10% silica fume) showed the strongest resistance.

Table 3 Impact Resistance outcomes

Mix ID	RCA (%)	Silica Fume (%)	First Crack Blow Count	Final Failure Blow Count
M0	0	0	28	42
M1	20	0	25	39
M2	40	0	22	35
M3	60	0	19	31
M4	20	5	30	45
M5	40	5	27	41
M6	60	5	24	36
M7	20	10	34	51
M8	40	10	31	47
M9	60	10	27	41

The study concludes by highlighting the fact that silica fume and moderate amounts of RCA can create concrete mixes that are both sustainable and preserve the requisite structural performance for a variety of applications.

5 Comparison of experimental and ANN results

In this section, the mechanical characteristics of concrete mixes incorporating RCA and silica fume are compared with predictions from an ANN model.

5.1 Compressive Strength

The data in Table 4 shows that the ANN model accurately predicts compressive strength with little variation between experimental and predicted values. Since neither overprediction nor underprediction occurs considerably, the deviations are consistently minor, indicating the correctness of the model. The model's good generalization to new data is demonstrated by the high regression coefficients ($R^2 > 0.97$) in Table 5, which show a strong connection between ANN outputs and experimental values. The model's consistency and dependability are supported by the prediction error data in Table 5, which show that the maximum and minimum errors are within ±0.5 MPa.

Table 4 ANN-predicted compressive strength

Mix ID	Experimental Strength (MPa)	ANN Predicted Strength (MPa)	Deviation (MPa)
M0	38.6	38.1	−0.5
M1	36.1	35.7	−0.4
M2	33.4	33.9	0.5
M3	30.2	29.8	−0.4
M4	39.8	40.3	0.5
M5	37.2	36.7	−0.5
M6	34.1	34.6	0.5
M7	42.5	42	−0.5
M8	39.6	40.1	0.5
M9	36.3	35.9	−0.4

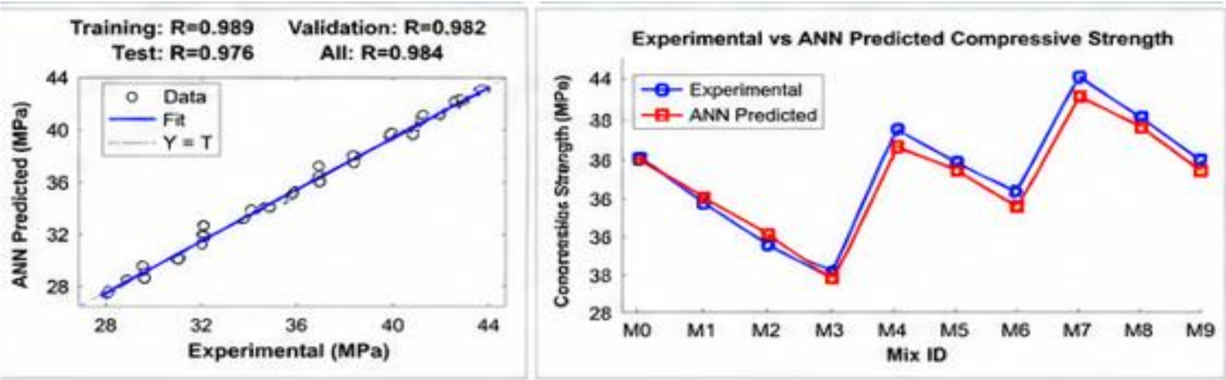

Figure 10 Regression (R) & comparison graphs of compressive strength results

5.2 Split Tensile Strength Test

With the experimental value for the control mix (M0) at 3.52 MPa compared to an ANN prediction of 3.48 MPa, and a noteworthy performance for mix M7, which reached 3.84 MPa experimentally compared to the projected 3.80 MPa, the ANN model successfully forecasts split tensile strengths. The model's capacity to represent tensile behavior is confirmed by the modest discrepancies, especially when it comes to the RCA content.

Table 5 Experimental and ANN Predicted Split Tensile Strength

Mix ID	Experimental Strength (MPa)	ANN Predicted Strength (MPa)	Deviation
M0	3.52	3.48	−0.04
M1	3.34	3.30	−0.04
M2	3.08	3.12	0.04
M3	2.82	2.79	−0.03
M4	3.61	3.65	0.04
M5	3.38	3.34	−0.04
M6	3.12	3.16	0.04
M7	3.84	3.80	−0.04
M8	3.58	3.62	0.04
M9	3.29	3.25	−0.04

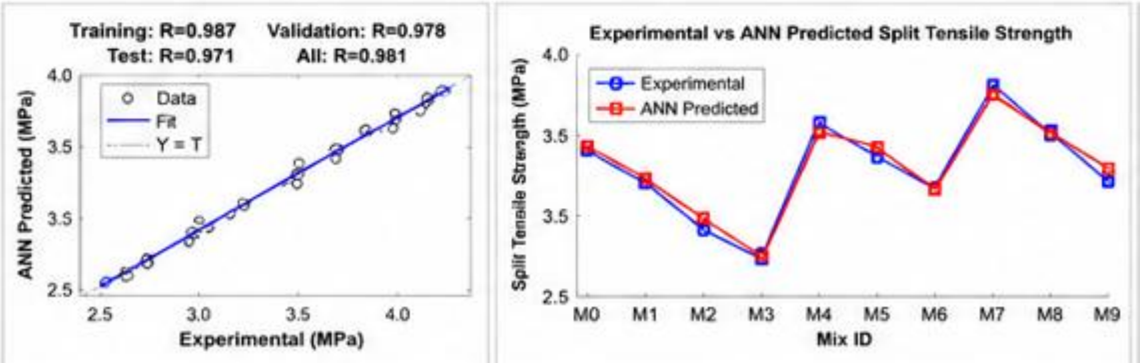

Figure 11 Regression (R) & comparison graphs of split tensile strength results

5.3 Analysis of Flexural Strength

Additionally, the ANN model predicts flexural strength with a high degree of accuracy (4.78 MPa vs. 4.82 MPa for the control mix (M0) and a high strength of 5.24 MPa for mix M7 versus a prediction of 5.19 MPa). This indicates the model captures the effects of silica fume and RCA on flexural characteristics.

Table 6 Flexural Strength Analysis

Mix ID	Experimental Strength (MPa)	ANN Predicted Strength (MPa)	Deviation
M0	4.82	4.78	-0.04
M1	4.58	4.54	-0.04
M2	4.21	4.26	0.05
M3	3.89	3.84	-0.05
M4	4.96	5.01	0.05
M5	4.62	4.57	-0.05
M6	4.28	4.33	0.05
M7	5.24	5.19	-0.05
M8	4.88	4.93	0.05
M9	4.49	4.44	-0.05

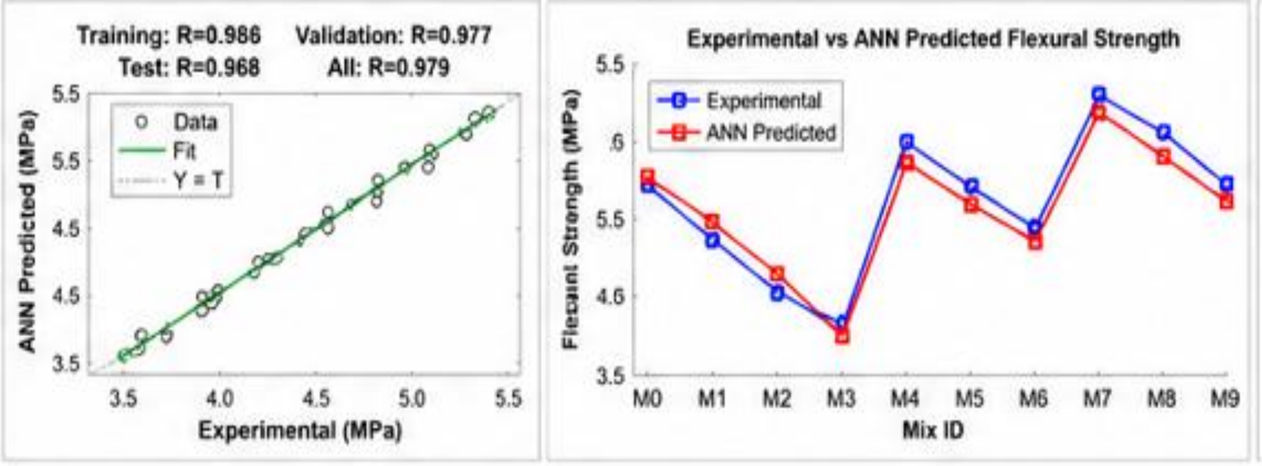

Figure 12 Regression (R) & comparison graphs of Flexural strength results

5.4 Analysis of the Modulus of Elasticity

As evidenced by a forecast of 31.4 GPa for M0, where the experimental value was 31.8 GPa, the ANN model has high prediction ability for modulus of elasticity, closely matching experimental values across mixtures. The model's comprehension of how RCA and silica fume alter concrete stiffness is reflected in this accuracy.

Table 7 Modulus of Elasticity results comparison

Mix ID	Experimental Value (GPa)	ANN Predicted Value (GPa)	Deviation
M0	31.8	31.4	−0.4
M1	30.4	30.0	−0.4
M2	28.7	29.1	0.4
M3	26.9	26.5	−0.4
M4	32.1	32.5	0.4
M5	30.5	30.1	−0.4
M6	28.8	29.2	0.4
M7	33.4	33.0	−0.4
M8	31.6	32.0	0.4
M9	29.7	29.3	−0.4

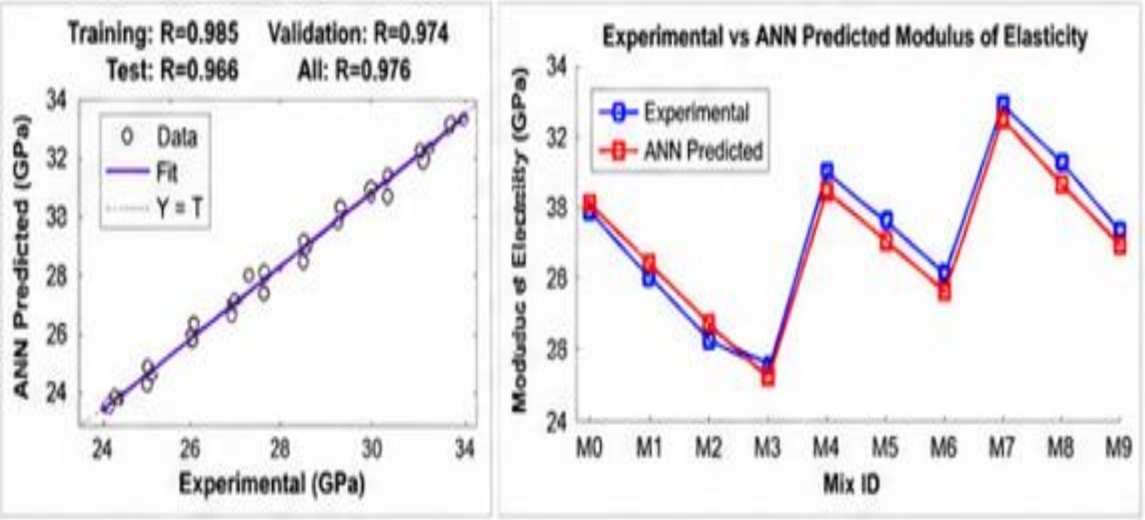

Figure 13 Regression (R) & comparison graphs of modulus of elasticity results

5.5 Analysis of Impact Resistance

Impact resistance is accurately predicted by the ANN model, with very little difference between the experimental and projected values for the control mix (M0). The model's dependability in evaluating toughness is further demonstrated by mix M7's maximum impact resistance, with experimental counts of 34 (first crack) and 51 (final failure) compared to predictions of 33 and 50.

Table 8 Experimental and ANN Predicted Impact Resistance

Mix ID	Experimental Final Failure Blow Count	ANN Predicted Blow Count	Deviation
M0	42	41	−1
M1	39	38	−1
M2	35	36	1
M3	31	30	−1
M4	45	46	1
M5	41	40	−1
M6	36	37	1
M7	51	50	−1
M8	47	48	1
M9	41	40	−1

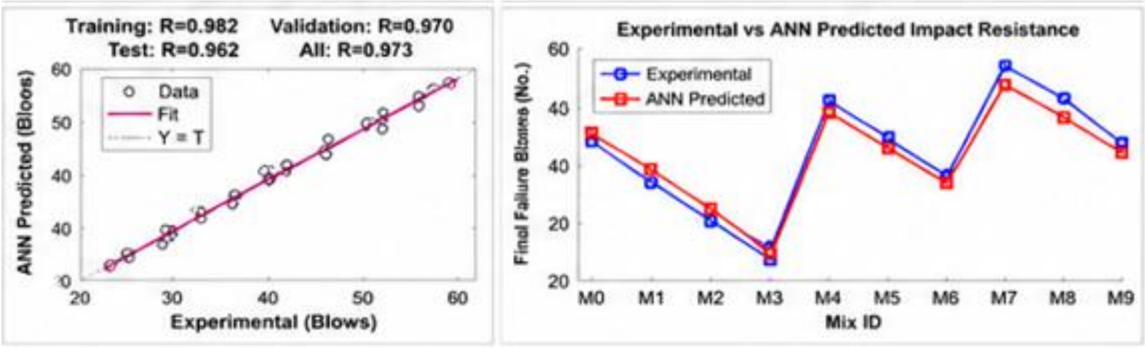

Figure 14 Regression (R) & comparison graphs of impact test results

5.6 Overall Assessment of ANN Performance

Low prediction errors and high regression coefficients support the model's excellent predictive ability for all mechanical characteristics examined. It effectively represents the nonlinear correlations between concrete's mechanical properties, curing age, silica fume content, and RCA %. For engineering applications using sustainable concrete, the ANN model's high prediction accuracy reduces the need for expensive laboratory testing and speeds up performance evaluation.

6. Conclusions

Several mechanical properties are impacted when RCA are added to concrete mixes. A slump decreases from 82 mm (control mix) to 61 mm at 60% RCA shows that workability decreases as RCA and silica fume concentrations increase because of RCA's abrasive texture and greater water absorption. With a strength of 30.2 MPa for the 60% RCA mix and 38.6 MPa for the control, the compressive strength also decreases with increasing RCA. The mix M7 (20% RCA and 10% silica fume) achieved the greatest strength of 42.5 MPa, indicating that silica fume considerably increases compressive strength.

According to split tensile strength data, M7 has a tensile strength of 3.84 MPa, which is higher than the control mix's 3.52 MPa. Flexural strength increases with silica fume but falls with increasing RCA levels; M7 reaches a maximum of 5.24 MPa. Although M7 shows higher stiffness at 33.4 GPa due to silica fume incorporation, the modulus of elasticity decreases from 31.8 GPa (conventional concrete) to 26.9 GPa (60% RCA). Despite RCA's detrimental impact on energy absorption, impact resistance demonstrates an increase in toughness from control mix blow counts of 42 to 51 for M7.

The study proves that silica fume and RCA-based sustainable concrete can function well in structural applications. Developed in MATLAB, an ANN model minimized the need for laboratory testing while reliably predicting mechanical parameters with small errors (±0.5 MPa for compressive strength). The results encourage the development of smart concrete technology and the use of sustainable materials in conjunction with artificial intelligence.

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