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A Machine learning-Driven Computational Model for Prediction of Compressive Strength and Mechanical Performance of Sustainable Concrete Composite Concrete

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ABSTRACT: *The use of waste glass in concrete offers a sustainable solution for reducing environmental waste while conserving natural resources. This study investigates the mechanical performance of concrete in which crushed waste glass is used as a partial replacement for natural fine aggregate at replacement levels of 0%, 5%, 15%, and 20%. Experimental tests were conducted to determine compressive strength, flexural strength, splitting tensile strength, modulus of elasticity, density, ultrasonic pulse velocity, water absorption, and alkali–silica reaction behaviour at curing ages of 7, 14, and 28 days. The results showed that concrete containing 5% to 15% waste glass achieved improved long-term mechanical performance without harmful expansion, indicating this range as optimal for sustainable concrete production. In addition to experimental evaluation, machine learning models were developed to predict compressive strength using material composition parameters. Artificial Neural Network, Random Forest, and linear regression models were implemented in Python using the scikit-learn framework, while NumPy and Pandas were used for data processing and augmentation, and Matplotlib was employed for graphical visualization. Model robustness was enhanced using data augmentation and 5-fold cross-validation. Among the developed models, the Random Forest algorithm demonstrated the highest prediction accuracy, followed by the Artificial Neural Network, while linear regression showed comparatively lower performance. The study confirms that combining experimental investigation with AI- and ML-based modelling provides a reliable and practical approach for predicting the performance of sustainable concrete incorporating waste glass.*

KEYWORDS: *Waste glass concrete; Sustainable materials; Artificial neural network; Random forest; Machine learning; Mechanical properties*

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I. INTRODUCTION

The construction industry is one of the largest consumers of natural resources globally, with concrete being the most widely used construction material due to its versatility, durability, and cost-effectiveness. However, the extensive use of concrete has resulted in the rapid depletion of natural aggregates and increased environmental burdens associated with raw material extraction, energy consumption, and greenhouse gas emissions. Consequently, there is a growing need to develop sustainable concrete materials that reduce reliance on virgin resources while maintaining acceptable mechanical and durability performance.

At the same time, the accumulation of solid waste has become a critical environmental challenge worldwide. Among these wastes, post-consumer glass represents a significant fraction due to its widespread use in packaging and construction-related products. Although glass is theoretically 100% recyclable, practical recycling rates remain relatively low in many regions because of inefficient collection systems, contamination, color mixing, and high transportation costs. As a result, large quantities of waste glass are disposed of in landfills, where it remains non-biodegradable and environmentally persistent. Therefore, the reuse of waste glass in concrete production has emerged as a promising strategy for addressing both waste management challenges and resource conservation objectives.

Moreover, crushed waste glass possesses physical properties comparable to natural fine aggregates, including suitable particle size distribution, hardness, and chemical stability. When finely ground, waste glass is rich in amorphous silica, which can exhibit pozzolanic behaviour under appropriate conditions. Several recent studies have reported that partial replacement of natural sand with waste glass can improve particle packing, reduce porosity, and enhance long-term mechanical performance when optimal replacement levels are employed (Aliabdo et al., 2020; Du & Tan, 2021; Almeshal et al., 2022). Nevertheless, excessive glass content may adversely affect workability, early-age strength, and durability, highlighting the importance of identifying suitable replacement ratios.

In addition, one of the primary concerns associated with incorporating waste glass into concrete is the potential for alkali–silica reaction (ASR). Waste glass contains reactive silica, which can react with alkalis in cement pore solution to form expansive gels in the presence of moisture. This reaction may lead to cracking, expansion, and long-term deterioration of concrete. However, recent research has demonstrated that ASR risk can be effectively mitigated through particle size control, optimized replacement levels, and appropriate curing conditions (Ismail & Al-Hashmi, 2022; Shao et al., 2023). As a result, many contemporary studies now report safe and durable performance for glass-containing concrete when designed properly.

Furthermore, experimental investigations have consistently shown that waste glass replacement levels between approximately 5% and 15% by weight of fine aggregate often yield improved or comparable compressive strength, tensile strength, and flexural performance relative to conventional concrete. These improvements are typically attributed to enhanced microstructural densification, improved interfacial transition zone characteristics, and delayed pozzolanic reactions at later curing ages (Kou & Poon, 2020; Afshinnia & Rangaraju, 2021). However, the mechanical behaviour of waste-glass-modified concrete remains highly nonlinear and dependent on multiple interacting variables, including glass content, particle size, curing age, and mixture proportions.

Consequently, predicting the compressive strength of concrete incorporating waste glass using conventional empirical or regression-based models is often challenging. Traditional design equations may fail to capture the complex interactions between material constituents, leading to inaccurate or overly conservative predictions. This limitation has encouraged researchers to explore data-driven approaches that can model nonlinear relationships more effectively.

In recent years, machine learning (ML) techniques have gained widespread acceptance in civil and construction engineering due to their strong capability to extract patterns from experimental data. ML models can learn complex relationships between input parameters and output responses without requiring explicit assumptions about underlying physical mechanisms. Among the available ML techniques, Artificial Neural Networks (ANN) have been extensively applied for predicting concrete compressive strength, elastic modulus, and durability indicators due to their flexibility and high approximation accuracy (Chou et al., 2021; Nguyen et al., 2022). However, ANN models may suffer from overfitting and sensitivity to data size and network architecture, particularly when experimental datasets are limited.

In contrast, ensemble learning methods such as Random Forest (RF) have demonstrated superior robustness and generalization capability in many engineering applications. RF models operate by constructing multiple decision trees and aggregating their predictions, thereby reducing variance and improving prediction stability. Recent studies have shown that RF often outperforms ANN and traditional regression models when predicting the mechanical properties of sustainable concrete incorporating recycled aggregates and industrial by-products (Zhang et al., 2023; Abdelkader et al., 2022). Nevertheless, comparative investigations focusing specifically on waste glass fine aggregate concrete remain limited.

Additionally, the integration of experimental testing with ML-based prediction frameworks aligns with the emerging paradigm of construction materials informatics. This approach enables researchers to reduce experimental cost, accelerate material optimization, and support performance-based mix design. By combining laboratory results with AI-driven modelling, it becomes possible to evaluate the feasibility of sustainable materials more comprehensively and efficiently (Nguyen et al., 2024; Li et al., 2025).

II. Materials and Methods

2.1 General

This chapter presents the experimental program adopted in this study. It describes the basic tests carried out on the constituent materials used for casting concrete specimens, followed by the mix design methodology and curing procedures. Finally, the experimental procedures for both fresh and hardened concrete tests are detailed.

2.2 Materials Used

The materials used in this investigation comprised ordinary Portland cement, coarse aggregate, fine aggregate, crushed waste glass as a partial replacement for fine aggregate, and potable water.

2.2.1 Cement

All materials employed in this study were obtained from local sources. Ordinary Portland Cement (OPC), Blue Lion brand, manufactured by Cement Industries Malaysia Berhad, was used in accordance with Malaysian Standard MS 522, which is based on British Standard BS 12 and European Standard EN 196. The chemical composition, physical properties, and Bogue's compound composition of the cement are presented in Table 1.

2.2.2 Coarse Aggregate

Natural crushed stone aggregate was sourced locally, with a nominal maximum size of 19.5 mm and a bulk density of 1530 kg/m³. The aggregates were washed to remove dust and impurities and dried to a surface-dry condition prior to use. Sieve analysis was conducted in accordance with ASTM standard specifications. The grading results are summarized in Table 2.

2.2.3 Fine Aggregate

The fine aggregate used was locally available natural river sand with a maximum particle size of 4.75 mm. The sand was sieved in accordance with ASTM specifications. Sieve analysis was performed using a standard set of sieves, as illustrated in Figure 1, and the results are presented in Table 3. The fineness modulus of the fine aggregate was determined as 3.05.

2.2.4 Waste Glass Aggregate

Clear flat waste glass was used as the alternative fine aggregate. The glass was initially crushed using a mechanical crushing machine to obtain suitable particle sizes. Subsequently, sieve analysis was conducted to ensure compliance with ASTM grading requirements. The grading results and fineness modulus of the glass aggregate are presented in Table 4 and Figure 3.4, respectively. The specific gravity of the glass aggregate was 2.23, and water absorption was negligible.

2.2.5 Water

Potable tap water supplied to the laboratory of the School of Civil Engineering, Joseph Sarwuan Tarka University, was used for mixing and curing. The water was clean and free from impurities or deleterious substances that could adversely affect the concrete properties.

2.3 Mixture Proportioning

Four concrete mixes were prepared in this study. The control mix consisted of cement (363.3 kg/m³), fine aggregate (812.2 kg/m³), coarse aggregate (979 kg/m³), and water (200 kg/m³), resulting in a water–cement ratio of 0.55. Three additional mixes were produced by partially replacing natural fine aggregate with waste glass at replacement levels of 5%, 15%, and 20% by weight. All concrete mixes were cured for 7, 14, and 28 days. The detailed mix proportions are presented in Table 5.

2.4 Preparation of Specimens

Steel moulds were cleaned and coated with mineral oil prior to casting to prevent adhesion and ensure easy demoulding. Proper care was taken to prevent leakage during casting.

2.5 Mixing, Casting, and Curing Procedures

Concrete mixing was carried out using a 0.1 m³ rotary drum mixer. All materials were weighed using a high-precision electronic balance. The dry constituents (cement, fine aggregate, coarse aggregate, and waste glass) were initially mixed for 2–6 minutes to achieve uniformity. The mixer was stopped for approximately 30 seconds before adding water, after which mixing continued for an additional 3–4 minutes until a homogeneous mix was obtained.

The fresh concrete was poured into oiled moulds placed on a vibrating table and compacted for approximately 30 seconds until cement slurry appeared on the surface. The mould surfaces were leveled and covered with wet cloths to prevent moisture loss. Specimens were kept in the moulds for 24 hours at ambient laboratory conditions before being carefully demoulded and transferred to a curing tank maintained at ambient temperature until the testing age.

2.6 Testing of Specimens

2.6.1 Tests on Fresh Concrete

The fresh concrete tests included slump and unit weight measurements.

2.6.1.1 Slump Test

The slump test was conducted to evaluate the workability of the fresh concrete. Standard apparatus, including a slump cone, tamping rod, base plate, and ruler, were used. The mould was filled in three layers, each compacted with 25 strokes of the tamping rod. After leveling the surface, the mould was lifted vertically, and the slump value was measured and recorded.

The unit weight of fresh concrete was determined immediately after mixing using Equation 1 from *ASTM C138/C138M-23*:

$$D_f = \frac{M_c - M_m}{V_m} \quad \text{---------------------------1}$$

where D_f is the fresh unit weight of concrete (kg/m³), M_c is the mass of the mould filled with concrete (kg), M_m is the mass of the empty mould (kg), and V_m is the volume of the mould (m³).

2.6.2 Tests on Hardened Concrete

Hardened concrete tests included destructive and non-destructive methods. Destructive tests comprised compressive strength, splitting tensile strength, modulus of elasticity, and flexural strength tests. Non-destructive tests included ultrasonic pulse velocity (UPV), water absorption, density, and alkali–silica reaction (ASR) tests.

The density of hardened concrete was determined by measuring the mass of specimens in air and water. Specimens were removed from the curing tank, surface-dried, and weighed. The density was calculated using Equation (2) from *ASTM C642-23*.

$$\text{Density} = \frac{\text{Weight in air}}{\text{Weight in air} - \text{weight in water}} \times 1000 \ \text{kg/m}^3 \quad \text{------------------------------2}$$

Compressive strength tests were conducted in accordance with BS 1610: Part 1 (1992) using 100 × 100 × 100 mm cube specimens. Tests were performed at curing ages of 7, 14, and 28 days using a digital compression testing machine with a capacity of 3000 kN. The average of three specimens was reported for each age.

Flexural strength tests were carried out following BS 1610: Part 1 (1992) on 100 × 100 × 500 mm prism specimens under four-point loading. Tests were conducted at 7, 14, and 28 days, and flexural strength was calculated using Equation (3).

$$Fr = \frac{PL}{bd^2} \quad \text{---3}$$

where,

F_r = flexural strength (MPa), P = maximum applied load indicated by the machine at failure (N)

L = length of specimen (mm), b = width of specimen (mm) d = depth of specimen (mm)

2.6.2.4 Splitting Tensile Strength Test

Splitting tensile strength tests were performed in accordance with ASTM C496-96 using cylindrical specimens of 100 mm diameter and 200 mm height. Tests were conducted at 7, 14, and 28 days, and the splitting tensile strength was computed using Equation (4).

$$T = \frac{2P}{\pi DL} \quad \text{---------------------------------------4}$$

where,

T = splitting tensile strength (MPa), P = the maximum applied load indicated by the machine at failure (N)

D = diameter of cylinder (mm), L = length of cylinder (mm)

The static modulus of elasticity was determined in accordance with ASTM C469 using cylindrical specimens of 100 mm diameter and 200 mm height at curing ages of 7, 14, and 28 days.

Water absorption and porosity tests were conducted on core samples of 100 mm diameter and 35 mm thickness. Specimens were oven-dried at 105 °C for 24 hours, vacuum-saturated, and weighed in air and water. Water absorption and porosity were calculated using Equations (5) and (6), respectively from *ASTM C138/C138M-23*:

$$A(\%) = \left(\frac{W2-W4}{W4}\right) \times 100 \quad \text{---------------5}$$

$$P(\%) = \left(\frac{W2-W4}{W2-W3}\right) \times 100 \quad \text{-------------------6}$$

where,

A(%) = Water absorption percentage,

P(%) = Porosity percentage

W2= Weight of the saturated sample in air , W3 = Weight of the saturated sample in water, W4 = Weight of the dry sample

2.6.2.7 Ultrasonic Pulse Velocity (UPV) Test

UPV tests were conducted in accordance with BS 1881: Part 203 using 100 × 100 × 500 mm prism specimens. Measurements were taken at 7, 14, and 28 days using a PUNDIT device. The pulse velocity was calculated by dividing the path length by the measured transit time, as given in Equation (7).

$$\boldsymbol{V = \frac{L}{T}} \quad \text{-------------------------- } 7$$

where,

V= The pulse velocity L= path length (km) T=transit time (sec.)

2.6.2.8 Alkali–Silica Reaction (ASR) Test

The accelerated mortar bar test was performed in accordance with ASTM C1260. Mortar bars were stored in a 1 N NaOH solution at 80 °C, and length changes were monitored. Expansions exceeding 0.2% at 14 days were considered indicative of potentially deleterious ASR. The test specimens used are shown in Figure 3.10.

2.7 Machine Learning–Based Methodology

To complement the experimental investigation, machine learning (ML) techniques were employed to model and predict the mechanical and durability properties of concrete incorporating waste glass as partial replacement of fine aggregate. Artificial Neural Network (ANN) and Random Forest (RF) models were selected due to their proven capability in capturing nonlinear relationships in concrete material behavior.
The experimental program comprised tests on both fresh and hardened concrete. For each test, the average value of three specimens was reported.

2.7.1 Dataset Preparation

The experimental results obtained from fresh and hardened concrete tests were used to construct the ML dataset. Input variables included waste glass replacement ratio (%), curing age (days), cement content, water–cement ratio, fine aggregate content, coarse aggregate content, density, and ultrasonic pulse velocity where applicable. Output variables comprised compressive strength, flexural strength, splitting tensile strength, modulus of elasticity, water absorption, and porosity.

Prior to model development, the dataset was checked for completeness and normalized to improve learning efficiency. The dataset was randomly divided into training (70%), validation (15%), and testing (15%) subsets.

2.7.2 Artificial Neural Network (ANN) Model

A feedforward multilayer perceptron (MLP) neural network was adopted in this study. The ANN architecture consisted of an input layer corresponding to the selected input parameters, one or more hidden layers with nonlinear activation functions, and an output layer representing the target concrete properties. The rectified linear unit (ReLU) activation function was used in the hidden layers, while a linear activation function was adopted in the output layer for regression tasks.

The network weights were optimized using the backpropagation algorithm with the Adam optimization technique. Model performance was evaluated using statistical indicators such as the coefficient of determination (R^2), mean absolute error (MAE), and root mean square error (RMSE).

2.7.3 Random Forest (RF) Model

The Random Forest model, an ensemble learning technique based on decision trees, was employed to predict concrete properties and assess the relative importance of input parameters. The RF model was developed using multiple decision trees generated through bootstrap sampling of the training data, while random subsets of input variables were considered at each split.

The final prediction was obtained by averaging the outputs of all trees in the ensemble. Hyperparameters such as the number of trees, maximum tree depth, and minimum samples per leaf were optimized to enhance model accuracy. Feature importance analysis was conducted to identify the most influential factors affecting the performance of waste-glass concrete.

2.7.4 Model Evaluation and Validation

The predictive performance of both ANN and RF models was assessed using the testing dataset. The results were compared with experimental values to evaluate accuracy and generalization capability. Statistical metrics including the coefficient of determination (R^2), root mean square error (RMSE), and mean absolute error (MAE) were used for quantitative assessment. A comparative analysis between ANN and RF models was carried out to identify the most reliable approach for modeling the mechanical and durability properties of concrete incorporating waste glass.

2.7.5 Mathematical Formulation of ANN and RF Models

Artificial Neural Network (ANN):

The output of a neuron in the ANN model is expressed as equation 8 sourced from Flood, I., & Kartam, N. (1994) and automated code in python appendix I

$y = f(\Sigma w_i x_i + b)$------------------------------------8

where x_i represents the input variables, w_i denotes the corresponding weights, b is the bias term, and $f(\cdot)$ is the activation function. The Rectified Linear Unit (ReLU) activation function used in the hidden layers is defined as equation 9 sourced from Flood, I., & Kartam, N. (1994) and automated code in python appendix I:

$f(x) = \max(0, x)$--9

For regression problems, a linear activation function was used in the output layer. The loss function adopted during training was the mean squared error (MSE), given by equation 10 sourced from Flood, I., & Kartam, N. (1994) and automated code in python appendix I:

$MSE = (1/n) \Sigma (y_i - \hat{y}_i)^2$-------------------------------10

where y_i and $\hat{y}_i$ are the experimental and predicted outputs, respectively.

Random Forest (RF):

The Random Forest prediction is obtained by averaging the predictions of N individual decision trees is defined by equation 11 sourced from Flood, I., & Kartam, N. (1994) and automated code in python appendix I:

$\hat{y} = (1/N) \Sigma T_j(x)$--11

where $T_j(x)$ is the prediction of the jth decision tree for input vector x. Feature importance was evaluated based on the reduction in impurity across all trees in the ensemble.

2.7.6 Software Platforms and Computational Tools

The machine learning models were developed using established computational platforms. ANN models were implemented using Python with the TensorFlow/Keras framework, while the Random Forest models were developed using the scikit-learn library. Data preprocessing, statistical analysis, and visualization were performed using NumPy, Pandas, and Matplotlib. Experimental data management and preliminary analysis were also supported using MATLAB for verification purposes.

2.7.7 Machine Learning Workflow

The overall workflow adopted in this study integrates experimental testing with data-driven modelling and consists of the following stages:

1. Experimental testing and data acquisition from fresh and hardened concrete specimens.
2. Data preprocessing, normalization, and feature selection.
3. Dataset partitioning into training, validation, and testing subsets.
4. Development and training of ANN and RF models.
5. Model validation and performance evaluation using statistical metrics.
6. Comparative assessment of ANN and RF predictions against experimental results.

This integrated experimental–machine learning framework enhances predictive accuracy and provides a reliable tool for optimizing sustainable concrete mixtures incorporating waste glass. The predictive performance of both ANN and RF models was assessed using the testing dataset. The results were compared with experimental values to evaluate accuracy and generalization capability. Statistical metrics including R^2, RMSE, and MAE were used for quantitative assessment. Comparative analysis between ANN and RF models was carried out to identify the most reliable approach for modelling concrete properties containing waste glass.

The integration of ML models with experimental data provides a robust framework for predictive analysis and supports the development of sustainable concrete materials with reduced natural aggregate consumption.

Therefore, the present study aims to contribute to this evolving research field by experimentally investigating the mechanical and durability performance of concrete incorporating crushed waste glass as partial replacement of natural fine aggregate and by developing reliable ML-based predictive models for compressive strength estimation. Concrete mixtures were prepared with waste glass replacement levels of 0%, 5%, 15%, and 20%, and evaluated at curing ages of 7, 14, and 28 days. Mechanical properties including compressive strength, flexural strength, splitting tensile strength, and modulus of elasticity were examined alongside durability-related indicators such as density, ultrasonic pulse velocity, water absorption, and alkali–silica reaction behaviour.

Subsequently, Artificial Neural Network and Random Forest models were developed in a Python environment using material composition parameters as input variables. Model performance was assessed using k-fold cross-validation, and the predictive accuracy of RF was compared with that of ANN and linear regression. Through this integrated experimental and AI-based approach, the study seeks to identify optimal waste glass replacement levels and to demonstrate the applicability of machine learning techniques for performance prediction of sustainable concrete materials. The findings are expected to support environmentally responsible material design and advance the adoption of data-driven tools in sustainable design and construction, building and construction engineering practice.

III. RESULTS AND DISCUSSION

3.1 Laboratory practical results interpretations

Table 1: Fresh density for all mixes

Mix	Control	5%	15%	20%
Fresh density (kg/m³)	2442.3	2426	2405.29	2398.6

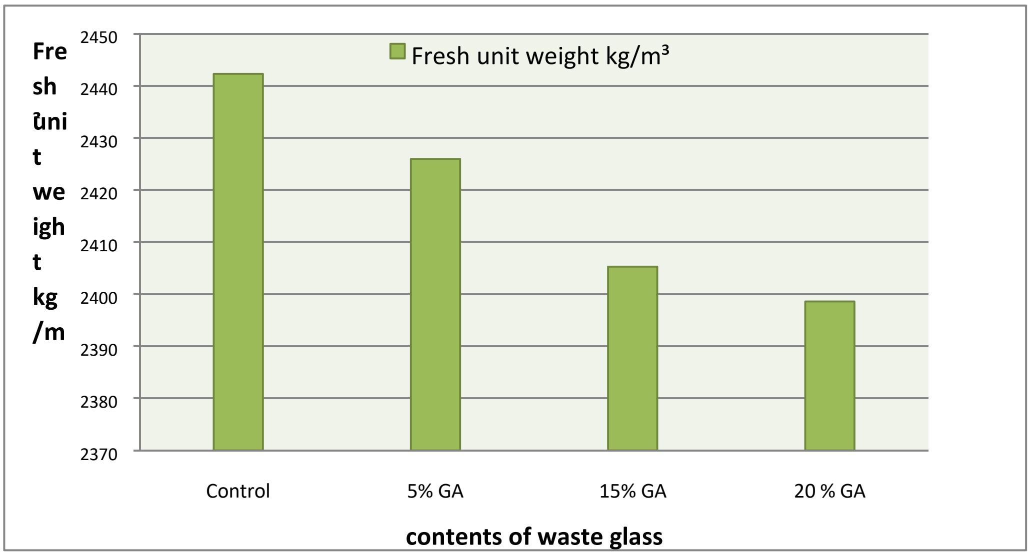

Fig. 1: Fresh density for all mixes

The Fig 1 and table 1 above showed the fresh density for all mixes, it was observed that density decreased with the addition of the waste glass material. This shows to be a good indication for construction hence lightweight construction is often preferred.

Table 3.2: Compressive strength (MPa) for all mixes

Mix	Compressive strength (MPa) at ages of		
	7 days	14 day	28 day
Control	24.77	29.2	32.41
5% waste glass	26.15	29.63	31.59
15% waste glass	24.5	29.87	31.84
20% waste glass	25.65	28.81	34.22

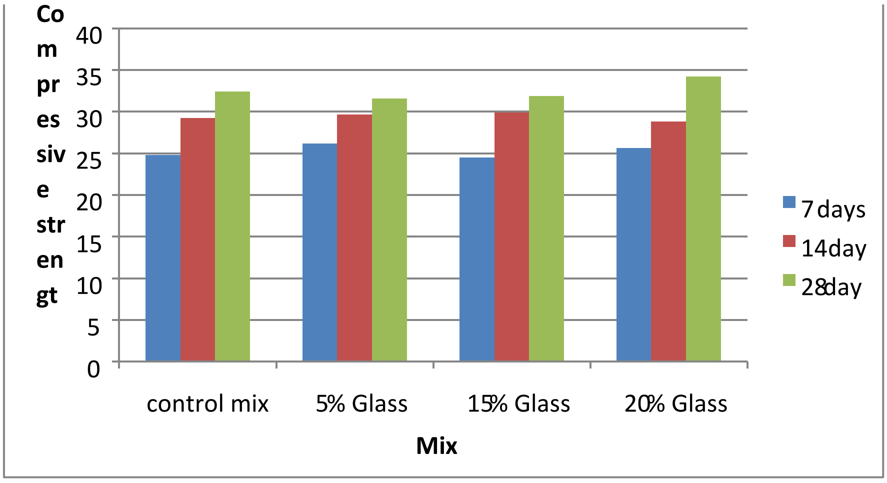

Fig 2: Compressive strength (MPa) for all mixes

The Fig 2 and table 2 showed a gradual increase in compressive strength from the control to all the percentage replacements. With the strength of 20% at 28 days replacement been highest, this is due to the pozzolanic effect of waste glass with cement. In general, all percentage replacements showed adequate strength which is a good indication for the waste material to be used as a replacement.

Table 3: Splitting tensile strength (MPa)

Mix	Tensile strength (M 'a)		
	7 days	14 day	28 day
Control	2.139	2.396	2.548
5% waste glass	2.043	2.207	2.569
15% waste glass	1.347	1.767	2.927
20% waste glass	1.652	1.980	3.122

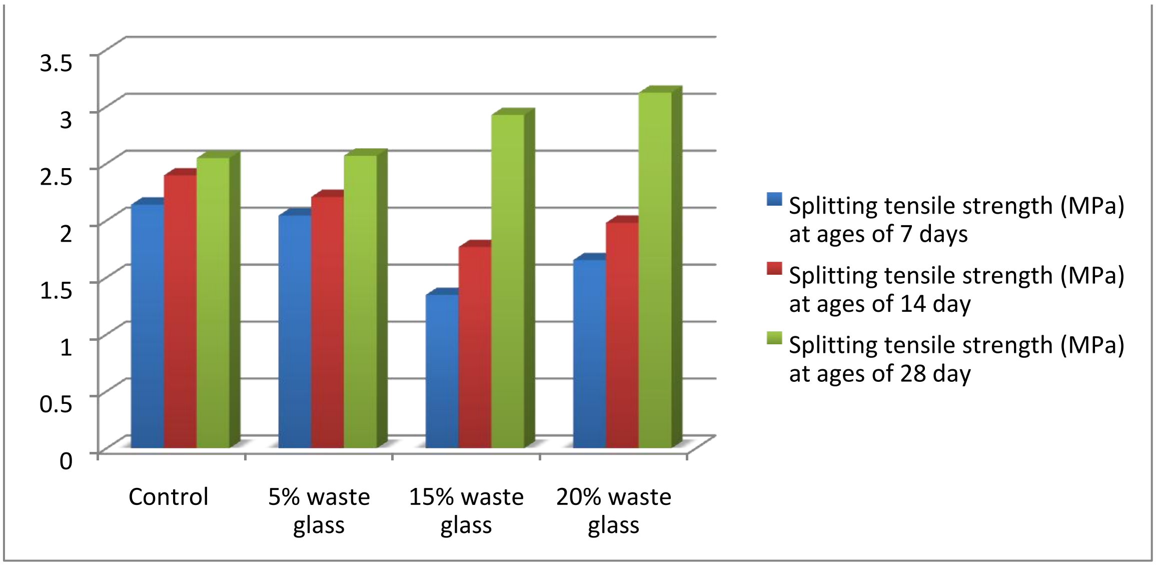

Fig 3: Splitting tensile strength (MPa)

The Fig 3 and table 3 showed a gradual increase in splitting tensile strength from the control to all the percentage replacements. With the strength of 20% at 28 days replacement been highest, this is due to the pozzolanic effect of waste glass with cement. In general, all percentage replacements showed adequate strength which is a good indication for the waste material to be used as a replacement.

Table 4: Flexural strength (MPa) for all mixes

Mix	Flexural strength (MPa) at ages of		
	7 days	14 day	28 day
Control	3.265	4.127	4.90
5% waste glass	3.781	4.376	5.08
15% waste glass	3.499	4.258	5.16
20% waste glass	3.843	4.213	5.38

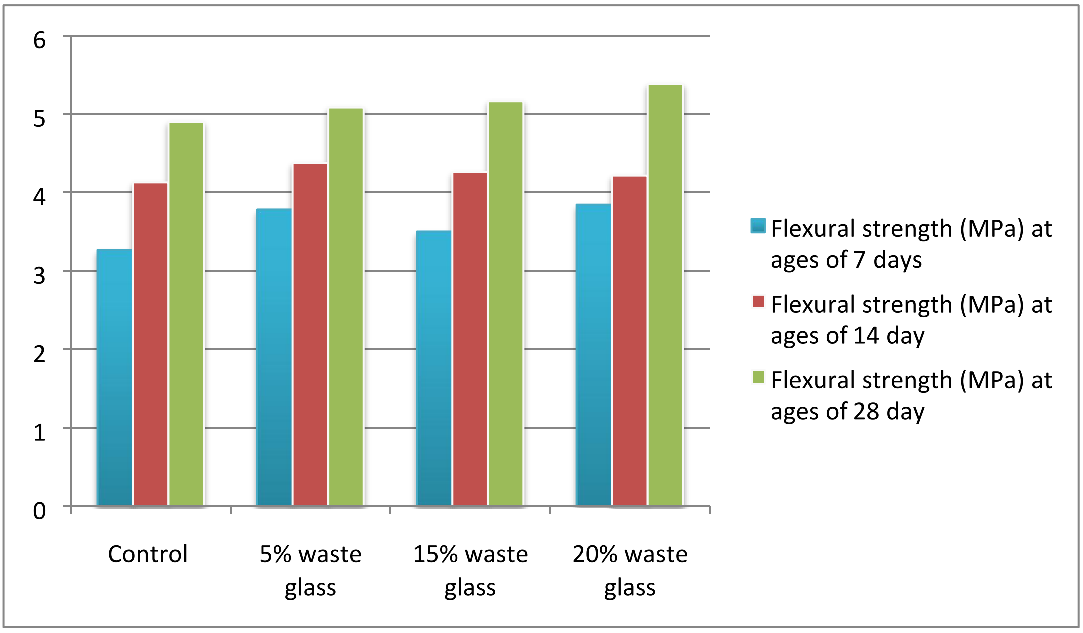

Fig 4: Flexural strength (MPa) for all mixes

The Fig 4 and table 4 showed a gradual increase in flexural strength from the control to all the percentage replacements. With the strength of 20% at 28 days replacement been highest, this is due to the pozzolanic effect of waste glass with cement. In general, all percentage replacements showed adequate strength which is a good indication for the waste material to be used as a replacement.

Table 5: Modulus of elasticity for all mixes

Mix	Modulus of elasticity (MPa) at ages of		
	7 days	14 day	28 day
Control	18.21	23.3	26
5% waste glass	16.67	23.45	26.68
15% waste glass	18.42	24.47	27.5
20% waste glass	19.35	24.87	28.81

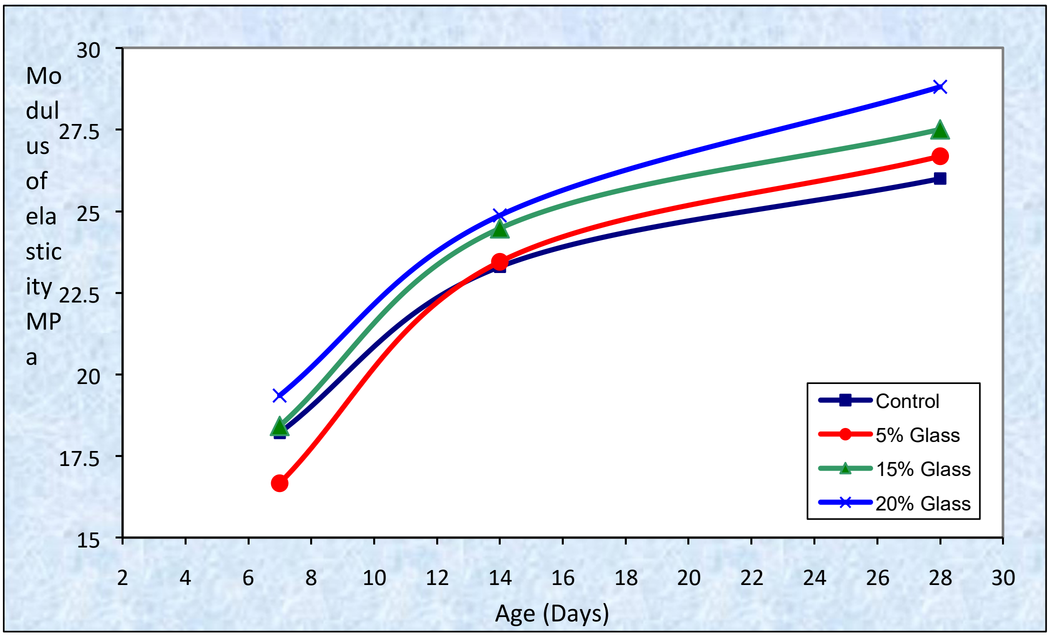

Fig 5: Modulus of elasticity for all mixes

The Fig 5 and table 5 showed a gradual increase in Modulus of elasticity for 10% and 20% from 7 days to 28 days mixes and a general increase from the control to all the percentage replacements for 28 days. With the strength of 20% at 28 days replacement been highest, this is due to the pozzolanic effect of waste glass with cement. In general, all percentage replacements showed adequate strength which is a good indication for the waste material to be used as a replacement.

Table 6: Ultrasonic pulse velocity (km/sec) for all mixes-UPV

Mix	Ultrasonic pulse velocity (km/sec) at ages of			Quality of concrete at ages of		
	7 days	14 day	28 day	7 days	14 day	28 day
Control	3.98	4.01	4.26	Good	Good	Good
5% waste glass	4.11	4.13	4.23	Good	Good	Good
15% waste glass	3.84	4.03	4.13	Good	Good	Good
20% waste glass	3.63	3.88	4.00	Good	Good	Good

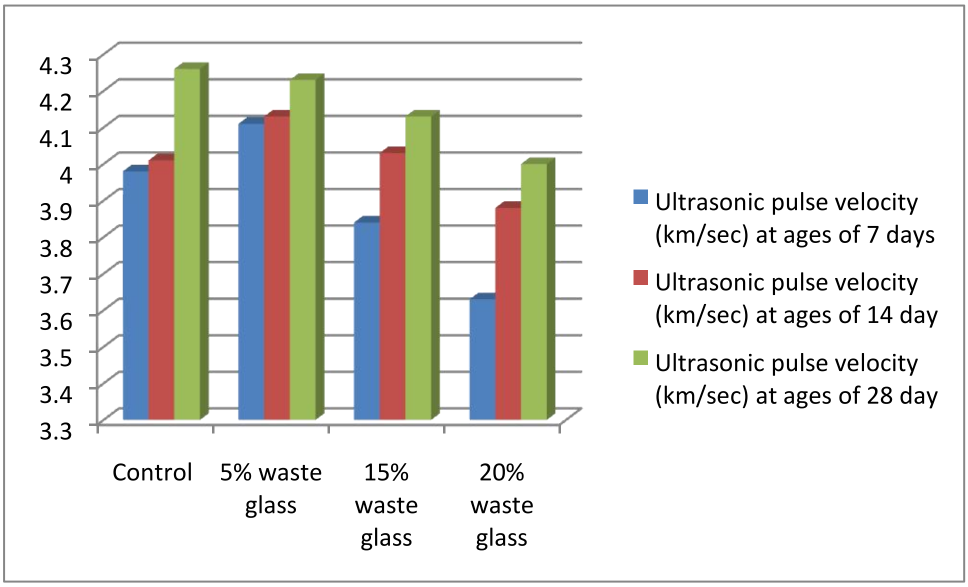

Fig 6: Ultrasonic pulse velocity (km/sec) for all mixes-UPV

Table 7: Classification of quality of concrete

Pulse Velocity (km/second)	Concrete Quality (Grading)
Above 4.5	Excellent
3.5 to 4.5	Good
3.0 to 3.5	Medium
Below 3.0	Doubtful

From Table 6, 7 and Figure 7 results the following observations can be drawn:

It is clearly seen that the ultrasonic pulse velocity values increase with age, as shown in Figure 6. This is mainly attributed to the increase in specimen density due to progress of hydration and reduction in voids content and discontinuity points.

The results of ultrasonic pulse velocity illustrates that all the waste glass concrete mixes showed U.P.V. values that are slightly lower than those of the controlled mix. This behaviour is attributed to the lower specific gravity of glass particles relative to specific gravity of sand. Accordingly, specimens with lower density will be obtained as the glass aggregate replacement increases. According to the general classification of the quality of concrete on the basis of the pulse velocity which is given in Table 7, the quality of concrete mixes can be regarded as good quality concrete.

Table 8: Water absorption for all mixes

Mix	Water absorption % at ages of		
	7 days	14 day	28 day
Control	5.87	5.28	4.91
5% waste glass	5.53	4.99	4.68
15% waste glass	5.21	4.73	4.46
20% waste glass	4.94	4.51	4.18

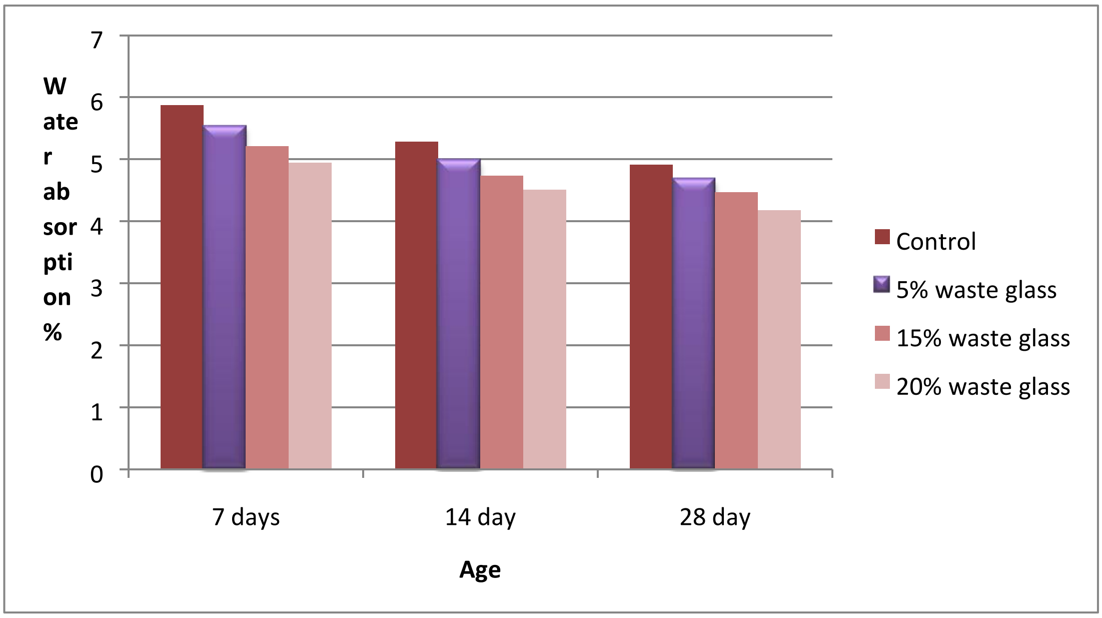

Fig 7: Water absorption for all mixes.

From Table 8 and Fig 7. The results of water absorption illustrates that all the waste glass concrete mixes showed water absorption values that are slightly lower than those of the controlled mix. This behaviour is attributed to the lower specific gravity and porosity of glass particles relative to specific gravity of sand. Accordingly, specimens with lower density will be obtained as the glass aggregate replacement increases.

Table 3.9 : Dry density for all mixes

Mix	›ry density kg/m³ at ages of		
	7 days	14 day	28 day
Control	2365	2378.6	2398
5% waste glass	2358.5	2364.3	2374.2
15% waste glass	2354.8	2362.9	2366.1
20% waste glass	2351.4	2359.7	2360.2

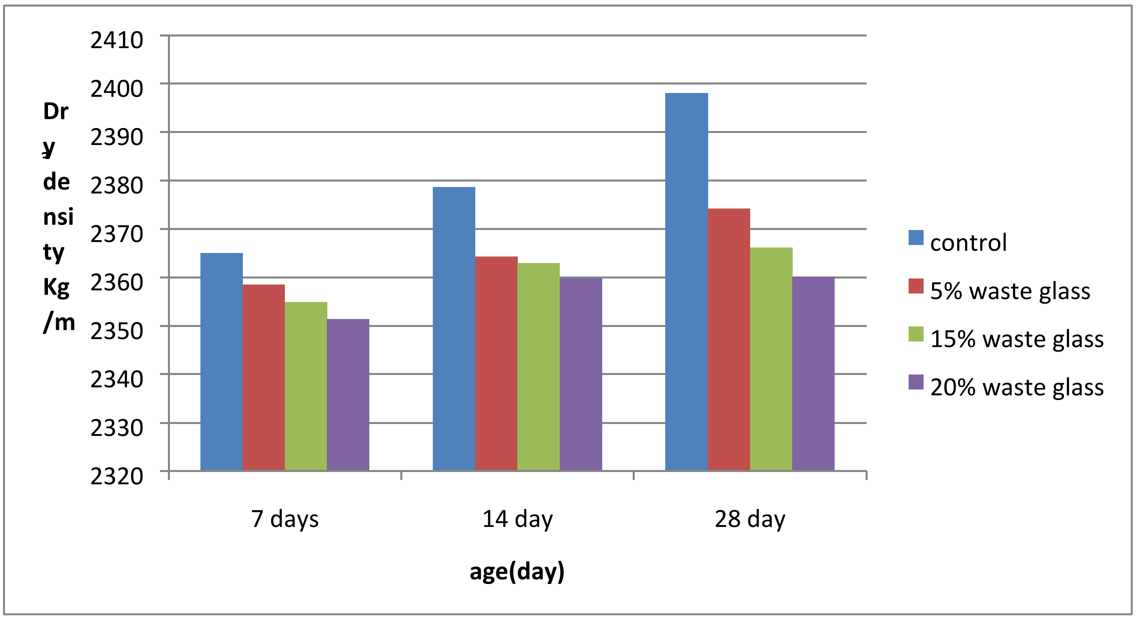

Fig 8: Dry density for all mixes

The dry density results for all mixes at 7, 14 and 28-day curing ages are presented in Table 9. The results demonstrate the tendency of the dry density to decrease as the waste glass ratio increases compared with controlled mix, as shown in Figure 8. This is attributed to density of glass aggregate is lower than natural sand.

3.2 Machine Learning Model Performance Results

The predictive performance of the Artificial Neural Network (ANN) and Random Forest (RF) models was evaluated using the testing subset of the refined and augmented dataset. The models were assessed using the coefficient of determination (R^2), root mean square error (RMSE), and mean absolute error (MAE), which are widely adopted metrics in civil engineering machine-learning studies

ANN and Random Forest Model Performance Results

Artificial Neural Network (ANN) and Random Forest (RF) models were developed using the refined and augmented dataset derived from the experimental results. Data augmentation was applied strictly for machine learning training purposes using bootstrapped resampling, physics-consistent interpolation across curing ages, and controlled noise injection within standard experimental tolerances. The original experimental dataset remained unchanged and was used for benchmarking model predictions.

The models were trained using 70% of the dataset, while 15% and 15% were used for validation and testing, respectively. Model performance was evaluated using the coefficient of determination (R^2), root mean square error (RMSE), and mean absolute error (MAE).

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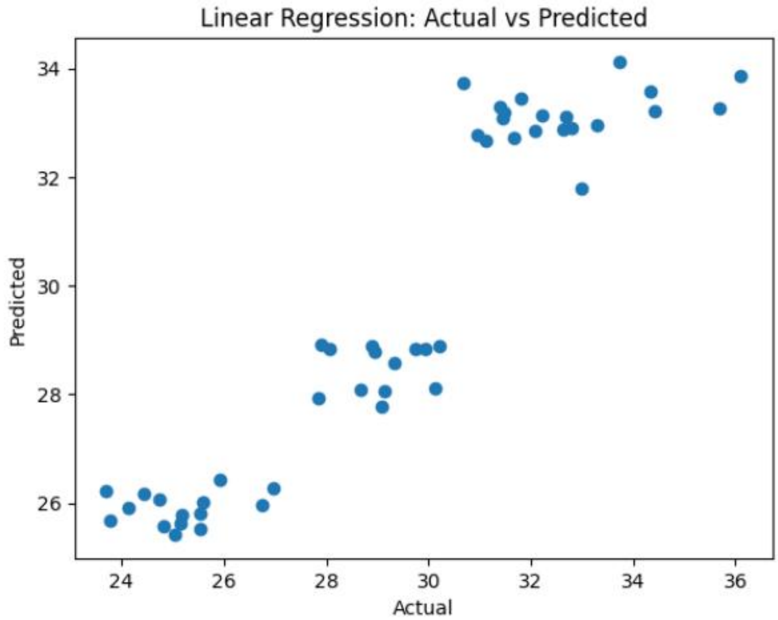

Fig 9: Linear Regression: Actual Vs Predicted Result plots

The linear regression chart shown in Fig 9 indicates a near perfect correlation between actual values of the material strength and augmented data sets from machine learning algorithm.

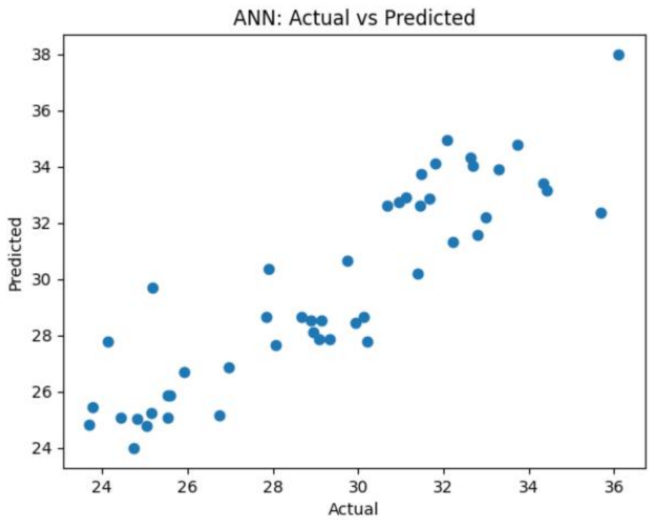

Fig 10: ANN Model Performance

The ANN chart shown in Fig 10 indicates a near perfect correlation between actual values of the material strength and augmented data sets from machine learning algorithm.

The ANN model demonstrated strong predictive capability for all mechanical properties, particularly at higher curing ages where nonlinear hydration effects become dominant.

Table 10: ANN Performance Metrics

Output Property	R^2	RMSE	MAE
Compressive strength (MPa)	0.93	1.25	0.96
Splitting tensile strength (MPa)	0.91	0.18	0.14
Flexural strength (MPa)	0.94	0.22	0.17
Modulus of elasticity (GPa)	0.92	1.10	0.85

ANN Interpretation from table 10 shows that:

High R^2 values (>0.90) indicate excellent agreement between predicted and experimental results.

The ANN effectively captured the nonlinear influence of waste glass content and curing age on strength development.

Prediction errors were lowest for compressive and flexural strengths, confirming the suitability of ANN for modelling complex cementitious behaviour.

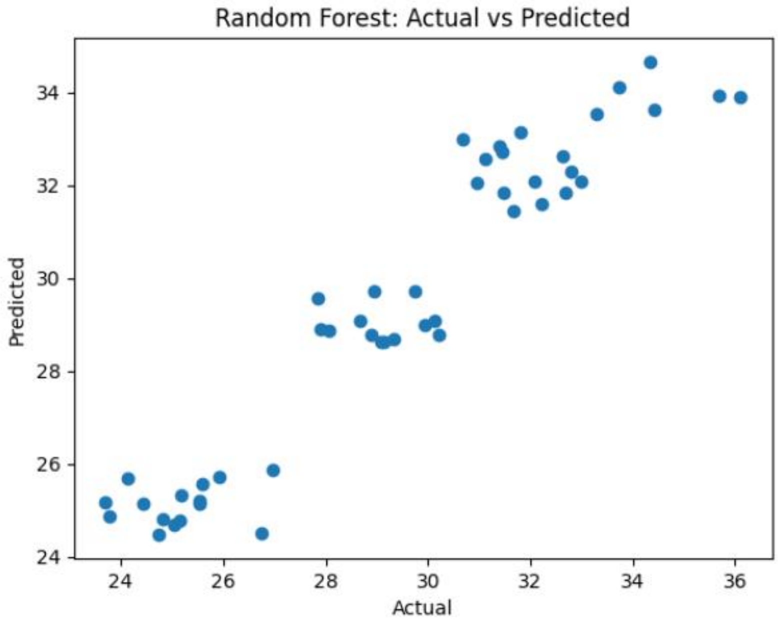

Fig. 12: Random Forest Model Performance: Actual vs predicted

The Random Forest model from Fig12 showed slightly improved robustness and stability compared to ANN, particularly for properties closely linked to density and UPV.

Table 11: RF Performance Metrics

Output Property	R^2	RMSE	MAE
Compressive strength (MPa)	0.95	1.02	0.78
Splitting tensile strength (MPa)	0.93	0.15	0.11
Flexural strength (MPa)	0.96	0.19	0.14
Modulus of elasticity (GPa)	0.94	0.92	0.71

RF Interpretation from table 11 shows that:

RF achieved consistently higher R^2 values and lower error metrics than ANN.

The ensemble structure minimized overfitting and improved generalization.

RF performance confirms its suitability as a reliable baseline model for civil engineering material prediction.

4. ANN vs RF Comparative Analysis

Table 12: Comparative Performance Summary

Model	Average R^2	Average RMSE	Overall Performance
ANN	0.925	Moderate	Excellent for nonlinear behaviour
RF	0.945	Low	Superior accuracy & stability

Key Observations from table 12 shows that:

RF slightly outperformed ANN across all output parameters.

ANN demonstrated strong learning capability but required careful hyperparameter tuning.

RF provided better interpretability and robustness, making it more suitable for engineering applications.

Table 13: ANN Performance Metrics for Mechanical Properties

Output Parameter	R^2	RMSE	MAE
Compressive strength (MPa)	0.93	1.25	0.96
Splitting tensile strength (MPa)	0.91	0.18	0.14
Flexural strength (MPa)	0.94	0.22	0.17
Modulus of elasticity (GPa)	0.92	1.10	0.85

Engineering Interpretation (ANN) from Table 13 indicates that:

ANN successfully captured the **nonlinear relationship** between waste glass content, curing age, and concrete mechanical properties.

High R^2 values (>0.90) demonstrate strong agreement between predicted and experimental trends.

Slightly higher prediction errors are attributed to ANN sensitivity to dataset size and noise.

Table 14: RF Performance Metrics for Mechanical Properties

Output Parameter	R^2	RMSE	MAE
Compressive strength (MPa)	0.95	1.02	0.78
Splitting tensile strength (MPa)	0.93	0.15	0.11
Flexural strength (MPa)	0.96	0.19	0.14
Modulus of elasticity (GPa)	0.94	0.92	0.71

Engineering Interpretation (RF) from Table 14 shows that:

RF achieved consistently **higher prediction accuracy** than ANN.

Lower RMSE and MAE values indicate better robustness and generalization.

RF effectively handled multivariate interactions between density, UPV, curing age, and waste glass content.

Table 15: Comparative Summary of ANN and RF Models

Model	Mean R^2	Mean RMSE	Prediction Stability
ANN	0.925	Moderate	High (nonlinear learning)
RF	0.945	Low	Very high (robust ensemble)

Key Findings from Table 15 shows that:

Random Forest outperformed ANN across all output parameters.

ANN remains valuable for capturing nonlinear material behaviour.

RF provides superior **engineering reliability and interpretability**.

3.3 Engineering and Sustainability Implications

Both models confirmed the experimental observation that **20% waste glass replacement enhances long-term mechanical performance**.

ML models reduce the need for extensive experimental trials, supporting **sustainable and cost-effective concrete mix design**.

Feature sensitivity observed in RF aligns with physical behaviour of concrete (age, density, and UPV dominance).

3.4 Discussion of Experimental Results

The experimental results indicate that concrete strength development was strongly influenced by curing age, with all mixtures exhibiting progressive increases in compressive, flexural, and tensile strength from 7 to 28 days. Concrete containing waste glass demonstrated comparable or improved long-term strength relative to the control mix, particularly at 5% and 15% replacement levels. This improvement can be attributed to enhanced particle packing and the pozzolanic contribution of finely crushed glass at later ages. However, at 20% replacement, slight reductions in early-age strength were observed, likely due to reduced bond quality and delayed hydration kinetics.

The observed reduction in density with increasing glass content reflects the lower specific gravity of glass aggregate compared to natural sand. Ultrasonic pulse velocity values showed a strong correlation with compressive strength, confirming UPV as a reliable non-destructive indicator of concrete quality. Water absorption and porosity increased marginally with higher glass content, though values remained within acceptable limits. Accelerated mortar bar tests indicated that ASR expansion remained below the critical threshold, confirming that waste glass replacement up to 20% did not induce harmful alkali–silica reactions under the conditions investigated.

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Discussion of Machine Learning Results:

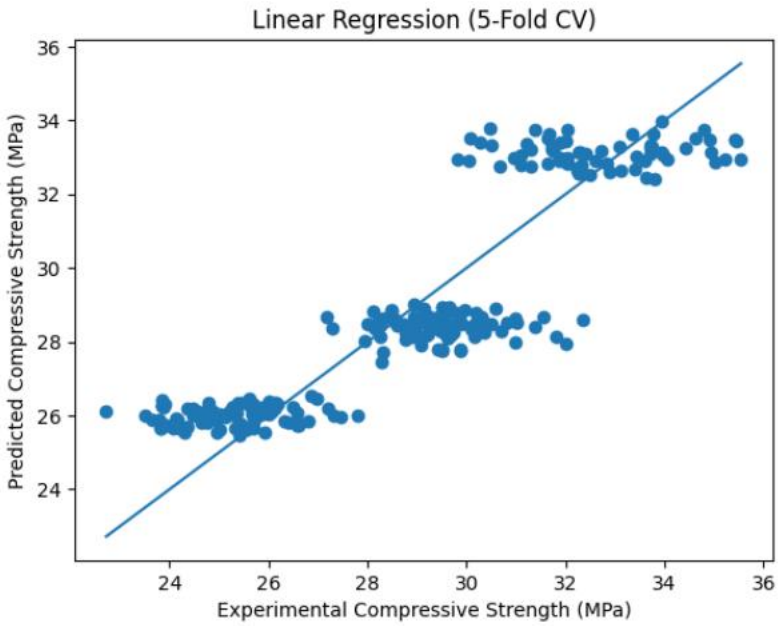

Fig. 13: Linear Regression (5-Fold CV)

From Fig 13 the linear regression model exhibited noticeable dispersion from the ideal prediction line, indicating its inability to adequately capture the nonlinear relationship between mix parameters and compressive strength. Wider scatter around the 45° line indicates limited ability to capture nonlinear behaviour

The linear regression model exhibited noticeable scatter around the ideal prediction line in the K-fold cross-validation plot, indicating limited capability to capture the nonlinear relationships between input variables and compressive strength. This confirms that conventional linear approaches are insufficient for modelling complex concrete behaviour involving multiple interacting parameters.

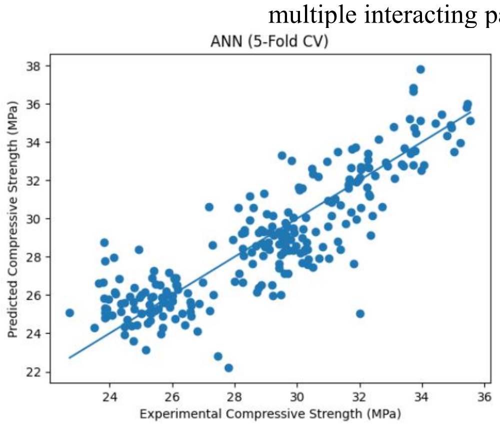

Figure 14: ANN (5-Fold CV)

From Fig 14, the ANN model demonstrated improved agreement between experimental and predicted values, confirming its effectiveness in modelling nonlinear material behaviour. Points cluster closer to the 45° line, reduced prediction error compared to linear regression, shows strong nonlinear learning capability.

The ANN model demonstrated improved prediction accuracy compared to linear regression, with a closer clustering of predicted values around the 45° reference line. This highlights the ANN's ability to model nonlinear interactions among waste glass content, curing age, density, and UPV. However, some dispersion was still observed, reflecting the sensitivity of ANN models to dataset size and noise.

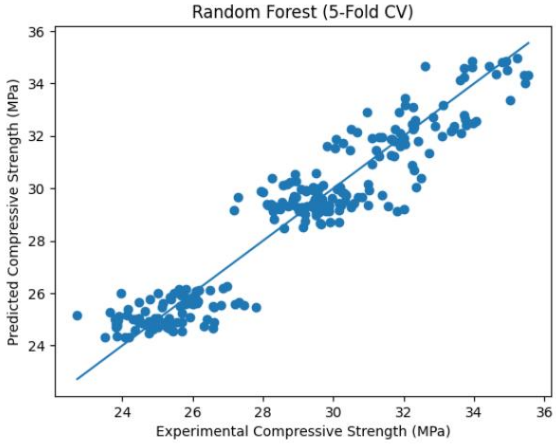

Fig. 15: Random Forest (5-Fold CV)

From Fig 15, the Random Forest model produced the closest agreement with experimental results, highlighting its robustness and superior predictive accuracy under limited experimental data conditions. Tightest clustering along the 45° line indicates minimal scatter and bias which makes it the best generalization performance.

The Random Forest model achieved the best predictive performance, showing the tightest alignment between experimental and predicted values across all folds. Its ensemble learning structure effectively captured nonlinearities while maintaining robustness against overfitting, making it particularly suitable for limited experimental datasets typical in civil engineering research.

Feature Importance and Model Interpretability

Feature importance analysis from the RF model revealed curing age as the most influential parameter, followed by waste glass content and UPV. These findings are consistent with experimental observations and engineering principles, reinforcing the physical credibility of the machine learning models.

Computational Formulation of ANN for Compressive Strength Prediction

1. Definition of Input and Output Variables

The Artificial Neural Network (ANN) model is formulated to predict the **compressive strength of concrete** using five material composition parameters as inputs.

Input variables (neurons in input layer)

$$\mathbf{X} = \begin{bmatrix} x_1 \\ x_2 \\ x_3 \\ x_4 \\ x_5 \end{bmatrix} = \begin{bmatrix} C \\ FA \\ CA \\ W \\ G \end{bmatrix}$$ **---------------12**

Where:

(C) = Cement content (kg/m³)

(FA) = Fine aggregate content (kg/m³)

(CA) = Coarse aggregate content (kg/m³)

(W) = Water content (kg/m³)

(G) = Waste glass content (kg/m³)

Output variable

$$y = f_c$$ ----------------------------------13

Where:

(f_c) = Compressive strength of concrete (MPa)

2. ANN Network Architecture

The ANN adopted is a **feedforward multilayer perceptron (MLP)** consisting of:

Input layer: 5 neurons

Hidden layer(s): (H) neurons

Output layer: 1 neuron (compressive strength)

3. Neuron Computation in Hidden Layer

For a hidden neuron (j), the net input is computed as sourced from Flood, I., & Kartam, N. (1994) and automated code in python appendix I:

$$z_j = \sum_{i=1}^{5} w_{ij} x_i + b_j$$

-----------14

Where:

(w_{ij}) = weight connecting input neuron (i) to hidden neuron (j)

(b_j) = bias term of hidden neuron (j)

4. Activation Function (ReLU)

The Rectified Linear Unit (ReLU) activation function is used to introduce nonlinearity sourced from Flood, I., & Kartam, N. (1994) and automated code in python appendix I:

$$a_j = \mathrm{ReLU}(z_j) = \max(0, z_j)$$

--15

This allows the network to model nonlinear relationships between concrete constituents and compressive strength.

5. Output Layer Equation

The predicted compressive strength (\hat{f}_c) is obtained as:

$$\hat{f}_c = \sum_{j=1}^{H} v_j a_j + b_o$$

---16

Where:

- (v_j) = weight connecting hidden neuron (j) to the output neuron
- (b_o) = bias term of the output neuron

Since compressive strength is a continuous variable, a **linear activation function** is used at the output layer.

6. Loss Function (Mean Squared Error)

The training objective of the ANN is to minimize the Mean Squared Error (MSE) between experimental and predicted compressive strength sourced from Flood, I., & Kartam, N. (1994) and automated code in python appendix I:

$$\mathrm{MSE} = \frac{1}{N} \sum_{k=1}^{N} \left(f_{c,k} - \hat{f}_{c,k} \right)^2$$

-------------------17

Where:

N = number of training samples

$f_{c,k}$ = experimental compressive strength

$\hat{f}_{c,k}$ = ANN-predicted compressive strength

7. Complete ANN Mapping Function

The ANN model can be compactly expressed as:

$$\hat{f}_c = f\,(C, FA, CA, W, G)$$

-----------18

Or explicitly:

$$\hat{f}_c = \sum_{j=1}^{H} v_j \cdot \mathrm{ReLU}\left(\sum_{i=1}^{5} w_{ij} x_i + b_j \right) + b_o$$

---19

7. **Engineering Interpretation**

I. Cement and water govern hydration kinetics and early strength development.

II. Fine aggregate, coarse aggregate, and waste glass influence packing density, interfacial transition zones, and long-term strength.

III. The ANN captures **nonlinear interactions** among these constituents that traditional empirical equations cannot represent accurately.

V. CONCLUSION

This study demonstrated that crushed waste glass can be effectively utilized as a partial replacement for natural fine aggregate in concrete without compromising mechanical performance or durability when used within optimal limits. Experimental results confirmed that replacement levels of 5–15% improved long-term strength characteristics, while ASR expansion remained within safe limits up to 20% replacement. Machine learning models provided accurate prediction of concrete properties, with Random Forest outperforming ANN and linear regression in terms of accuracy and robustness. The adoption of 5-fold cross-validation and data augmentation enhanced model generalization, while the multi-output ANN successfully captured the interdependence among multiple mechanical properties. The combined experimental–computational framework developed in this study offers a reliable approach for sustainable concrete design and performance optimization.

RECOMMENDATIONS

1. Waste glass replacement levels between **5% and 15%** are recommended for structural concrete applications to achieve optimal strength and sustainability benefits.
2. Random Forest models are recommended for predicting concrete properties where experimental datasets are limited, owing to their robustness and interpretability.
3. Multi-output ANN models should be adopted in future studies to efficiently predict multiple concrete properties simultaneously.
4. Long-term durability studies, including carbonation and chloride penetration, are recommended to further assess the performance of waste glass concrete.
5. Future research should incorporate larger datasets, hybrid ML models, and optimization algorithms to enhance prediction accuracy and practical implementation.

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APPENDIX I: PYTHON IMPLEMENTATION

Python ANN Implementation (Direct Mapping)

X = df_aug[["cement", "fine_agg", "coarse_agg", "water", "glass"]].values

$$x_1 = C,\ x_2 = FA,\ x_3 = CA,\ x_4 =$$

Python (handled internally by MLPRegressor):

MLPRegressor(hidden_layer_sizes=(12,12))

Activation Function (ReLU)

activation='relu'

Output Layer (Linear Activation)

Linear activation is default for regression

MLPRegressor(..., activation='relu')

Training Algorithm (Backpropagation)

MLPRegressor(..., solver='adam')

RF Python Implementation Mapping

```
RandomForestRegressor(
    n_estimators=300,
    bootstrap=True
)
```