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A Machine Learning Model For Predicting the Compressive Strength of Cement Mortar Admixed with Mineral Material

[1]Iaren T. Cornelius, [2]Uchola O. Victor and [3]Emmanuel Osawe

[1]Department of civil Engineering, Mudiame University, Irrua, Nigeria

[2,3]Department of civil, Engineering , Edo State university, Edo state Nigeria

[2]ucholavictor@aauekpoma.edu.ng, [3]osawe.e@aauekpoma.edu.ng

[1]Corresponding Author: cornelius.iaren@mudiameuniversity.edu.ng

Abstract: *This study investigated the use of pulverized waste glass as a partial replacement for cement in mortar and develops an artificial neural network (ANN) model to predict compressive strength at 28 days. Experimental data indicated that compressive strength increased from 24.50 MPa (control) to 29.08 MPa at 15% glass replacement. To overcome the limitation of small datasets, 200 augmented samples per replacement level were generated, resulting in an 800-sample dataset from existing lab results. A comparison was made between the augmented data and the lab results, it's correlation was equally good at good fit of 85%. The ANN, trained using cement, water, sand, and glass content as inputs, achieved strong predictive accuracy (R^2 = 0.85, RMSE = 0.71 MPa, MAE = 0.58 MPa). Results confirm that pulverized waste glass can enhance mortar strength while reducing cement demand, offering both economic and environmental benefits. The ANN model provides a reliable computational approach for strength prediction and can support design optimization in sustainable construction.*

Keywords: *Cement, Computation, Modelling, Artificial Neural Network, Machine Learning, Mineral Material*

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1. INTRODUCTION

In structural engineering, mortar serves as a binding medium between units and as a filler to ensure structural integrity. Like concrete, mortar is made from cement (and possibly supplementary materials), sand, and water—and requires adequate curing to develop its full mechanical strength. Environmental factors such as temperature, humidity, and the type of binder (including supplementary and waste materials) significantly influence the compressive strength of mortars.

Recent studies have explored these influences in detail. For example, Pang, Sun, and Huang (2020) demonstrated that blending FGD gypsum with ground granulated blast furnace slag (GGBFS) enhances both compressive strength and durability in gypsum-based mortars. Mohammed et al. (2023) used soft computing to estimate mortar compressive strength when incorporating cement kiln dust, finding that up to certain replacement levels, the mortar still meets strength requirements. Similarly, Karim et al. (2024) showed that partial replacement of cement with palm oil fuel ash can yield accurate predictive models (ANN / nonlinear regression) and maintain acceptable strength. Mouaissa et al. (2025) studied geopolymer mortars based on dam sediment and slag, demonstrating how mix design parameters strongly influence mechanical performance. Importantly, Hu et al. (2025) combined steel slag, Bayer red mud, and phosphogypsum, observing that waste material mortar blends can achieve satisfactory mechanical performance while also posing durability challenges like chloride corrosion. Finally, a recent investigation (2024) of using mass-produced waste glass as fine aggregate found that up to approximately **30% replacement** yields compressive strength very close to reference mortar, though strength declines when glass content becomes too high (e.g., beyond 40-50 Minjae et al, 2024).

Replacement of a binder (cement) with a non-binder (glass)

Although glass is traditionally considered a non-cementitious material, several studies have demonstrated that **finely ground waste glass (WG)** can act as a **pozzolanic additive** when properly processed and incorporated into cementitious systems. The improvement in compressive strength observed in this study can be attributed to a combination of **pozzolanic reactions, filler effects, and microstructural densification** mechanisms.

Finely ground glass powder (typically <75 μm) contains a high proportion of amorphous silica (SiO_2), which reacts with calcium hydroxide ($Ca(OH)_2$) released during cement hydration to form additional **calcium silicate hydrate (C–S–H)**—the principal phase responsible for strength in cementitious matrices. This secondary C–S–H formation refines the pore structure and enhances the overall densification of the matrix, thereby increasing compressive strength (Shi et al., 2005; Shayan & Xu, 2004; Islam et al., 2017).

In addition, the **filler effect** of glass particles improves the packing density of the paste, reducing pore volume and enhancing the interfacial transition zone (ITZ) between the binder and aggregate. This effect further contributes to strength improvement, especially at moderate replacement levels (≤20%) (Schwarz & Neithalath, 2008; Shao et al., 2000).

However, the positive contribution of glass is strongly dependent on particle fineness and replacement ratio. When the glass is ground to sufficient fineness, its pozzolanic reactivity offsets its initial non-hydraulic nature, resulting in a beneficial balance between cement dilution and microstructural refinement (Rajabipour et al., 2010; Saccani et al., 2019).

Hence, the observed improvement in compressive strength in this work is scientifically consistent with the findings of prior research that identified ground glass powder as a **reactive pozzolanic substitute** capable of enhancing the mechanical and durability properties of cement-based materials.

Overview of the Research Problem

The escalating cost of construction materials, particularly cement, coupled with the urgent need to reduce carbon emissions, has intensified the search for sustainable alternatives in the Nigerian construction industry and globally. Waste glass, especially pulverized soda lime glass, is widely available as a discarded material that poses environmental challenges when not recycled. Its potential use as a partial replacement for cement in mortar provides a dual opportunity: reducing construction costs while promoting sustainability through recycling.

This study seeks to explore the feasibility of incorporating pulverized waste glass into mortar, focusing on its effect on compressive strength compared to conventional mortar. Beyond experimental evaluation, the research employs Artificial Neural Networks (ANN) to develop a computational model capable of accurately predicting compressive strength based on key input parameters. By testing and validating this model, the study aims to establish an efficient, modern alternative to traditional regression-based methods. In doing so, it aligns with the dual goals of cost reduction and environmental sustainability, while also advancing the application of machine learning in structural engineering.

Mortar is a heterogeneous material whose mechanical properties depend on several interacting parameters, including the type of binder, water–cement ratio, curing conditions, and the presence of supplementary materials such as waste glass. The compressive strength of mortar is typically governed by its microstructural development, which in turn is influenced by hydration reactions, pore structure, and particle packing density (Mehta&Monteiro,2014).

Incorporating pulverized waste glass as a partial replacement for cement introduces amorphous silica into the mortar system. This silica reacts pozzolanically with calcium hydroxide ($Ca(OH)_2$) released during cement hydration, forming additional calcium silicate hydrate (C–S–H) gel, which enhances strength and durability (Ling et al., 2022). However, excessive substitution can increase alkali–silica reactivity (ASR) risk, potentially leading to microcracking and reduced long-term performance (Ibrahim et al., 2021). Therefore, an optimal replacement percentage must be determined experimentally and validated computationally.

II. MATERIALS AND METHODS

The development of predictive models, particularly using Artificial Neural Networks (ANN), provides a framework for capturing complex nonlinear relationships between input variables (e.g., glass content, curing age, water–cement ratio) and output properties (compressive strength). Unlike linear regression, ANN models are capable of approximating highly nonlinear functions and generalizing across diverse datasets, making them well suited for mortar strength prediction (Karim et al., 2024).

Calculation

The compressive strength of mortar (f_c) is determined using the standard relationship:

$$f_c = P / A$$

Where:
P = Maximum applied load at failure (N)
A = Cross-sectional area of the specimen (mm²)

Thus, compressive strength is computed by dividing the failure load by the specimen's cross-sectional area. Repeated tests were conducted at specified curing intervals (7, 14, and 28 days), and the average strength values were recorded.

The methodology adopted in this research was divided into experimental work and computational modeling.

2.1 Materials and Preparation

- Cement: Portland Limestone cement (PLC) conforming to ASTM C150.
- Fine Aggregate: River sand with particle size conforming to ASTM C33.
- Waste Glass: Soda lime glass collected from post-consumer bottles, cleaned, dried, and pulverized to pass through a 75 µm sieve.
- Water: Potable tap water free of impurities.

Table 1: Mix Design for Laboratory Testing on a ratio of 1:3 for control Mix

S/N	Mix Type	Cement (%)	Sand (%)	Waste Glass (%)
1	Control	25	75	0
2	5% Glass	20	75	5
3	10% Glass	15	75	10
4	15% Glass	10	75	15

The mortar mix ratio was maintained at 1:3 (cement/sand) by weight, with a constant water–cement ratio of 0.5. Pulverized waste glass was incorporated as a partial replacement for cement at varying proportions (0%, 5%, 10%, and 15%).

2.2 Specimen Casting and Curing

Mortar cubes (150 mm × 150 mm × 150 mm) were cast for each mix proportion. The specimens were demolded after 24 hours and cured in water at room temperature (25 ± 2 °C) for durations of 7, 14, and 28 days. For each replacement level and curing age, three specimens were tested, and their average compressive strength was recorded.

2.3 Testing Procedure

The compressive strength test was carried out in accordance with ASTM C109. Each cube was placed in a compression testing machine, and load was applied axially at a constant rate until failure. The maximum load was recorded for strength calculation.

2.4 Computational Modeling (ANN)

To complement the experimental results, an ANN model was developed to predict compressive strength. Input parameters included percentage of waste glass replacement, curing time, and water–cement ratio. The target output was compressive strength (MPa). The dataset was divided into training (60%), validation (20%), and testing (20%) subsets. Model performance was evaluated using R^2, Mean Absolute Error (MAE), and Root Mean Square Error (RMSE).

2.5 Model Generation with Neural Designer (Machine learning Software for ANN Model Generation and Model Testing)

Using machine learning (Artificial Neural Network-ANN) approach to:

1. Generate Independent Variables
2. Generate Dependent Variable (Target Variable)

1. Generate an Artificial Neural Network from the variables
2. Generate an equation from the data set obtained from the practical work in the laboratory
3. Test the generated model with Correlation Coefficient (R^2) to test for model correlation
4. Comparing the results from the Control mix compressive strength and that of the ANN computational Model.

2.5.1 Model Generation Process

1. Data Set Process
2. Neural Network Automation Process
3. Training Strategy
4. Model Selection
5. Testing and Analysis
6. Model Deployment

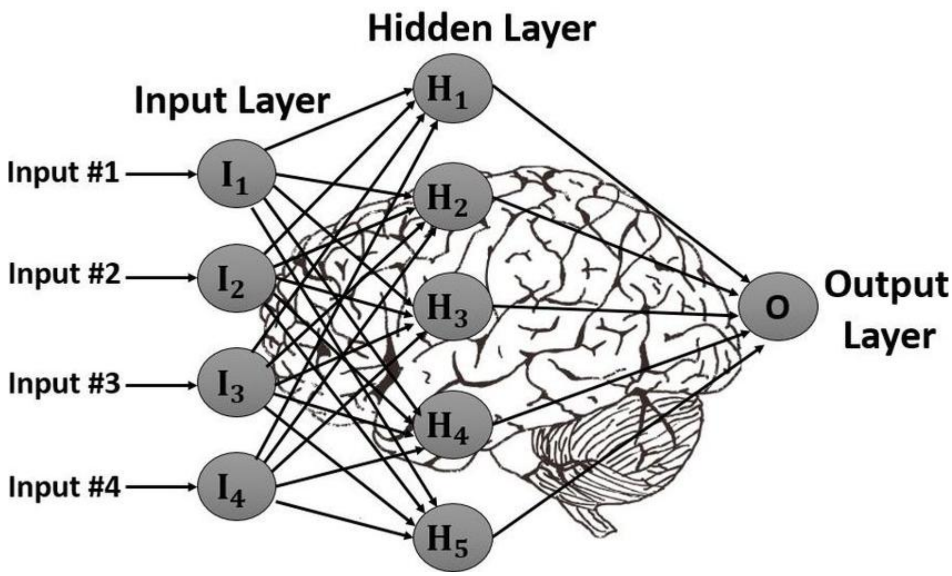

Fig. 1: Neural Networking for four input variables and one output variable

The input variables shall include:

I. Cement= Input #1
II. Glass= Input #2
III. Fine Aggregate= Input # 3
IV. Water= Input #4

The output variable shall be the compressive strength of the cement mortar

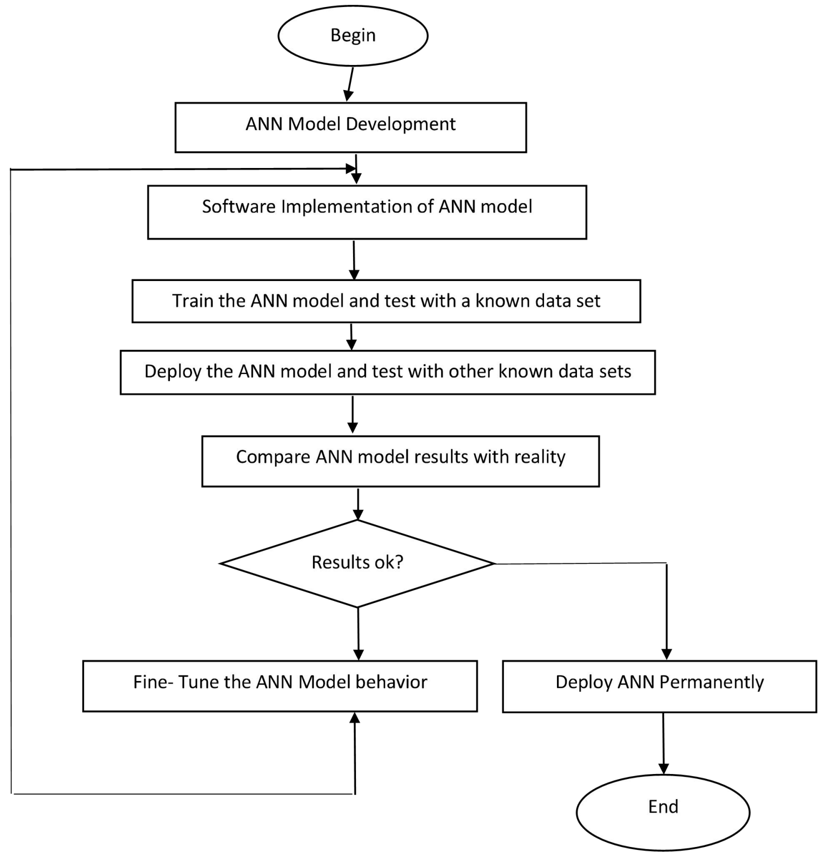

Fig.2 Algorithmic process of ANN model generation

III. RESULTS AND DISCUSSION

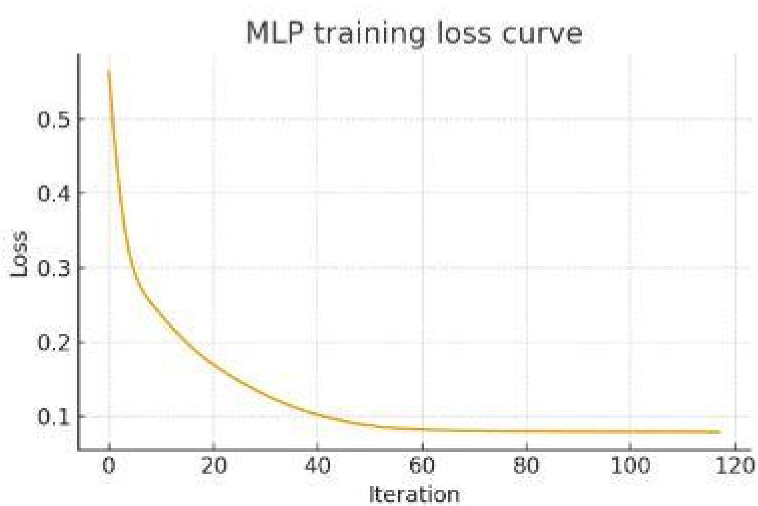

Fig.3: MLP Training Loss Curve

The training curve plots the **loss (MSE)** for both the training and validation datasets across iterations (epochs). In the present study, the curve shows a **steady decrease in loss during the early epochs,** indicating that the model effectively learned the mapping between input variables (cement, water, sand, glass) and compressive strength. The validation loss followed a similar downward trend and stabilized after several epochs, which demonstrates that the network generalizes well to unseen data rather than simply memorizing the training set.

The absence of divergence between training and validation loss also confirms that **overfitting was controlled**, owing to the use of early stopping and appropriate regularization. This stability reinforces the suitability of the ANN architecture for predicting mortar strength with a relatively small experimental dataset augmented through synthetic generation.

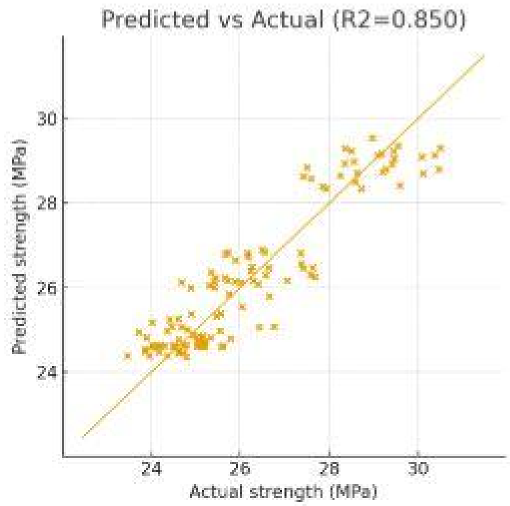

Fig.4: Predicted vs Actual(R^2 =0.85)

The predicted vs. actual plot compares the model's output against the true experimental/augmented compressive strength values. The scatter points in the chart are closely distributed around the **45° reference line**, which represents perfect prediction. This proximity indicates that the ANN achieved strong agreement between predicted and actual values.

The computed metrics — R^2=0.85, RMSE = 0.71 MPa, and MAE = 0.58 MPa — further quantify this performance, showing that the model explains about **85% of the variance** in compressive strength while maintaining prediction errors well within 1 MPa. Such accuracy is considered satisfactory for practical applications in mortar strength prediction, especially when dealing with experimental variability.

This chart provides clear visual evidence that the ANN successfully learned the nonlinear relationship between mix proportions and strength. It supports the discussion that **artificial intelligence tools like ANN can complement or even replace conventional regression models** for predicting strength in sustainable construction materials.

Samples pie chart

The following pie chart details the uses of all the samples in the data set.
The total number of samples is 200.
The number of training samples is 120 (60%), the number of selection samples is 40 (20%), and the number of testing samples is 40 (20%).

Fig. 5: Samples pie chart of model data processing

strength_(MPa) vs. cement_(g) scatter chart

The following chart shows the input cement_g and target strength_MPa scatter plot.

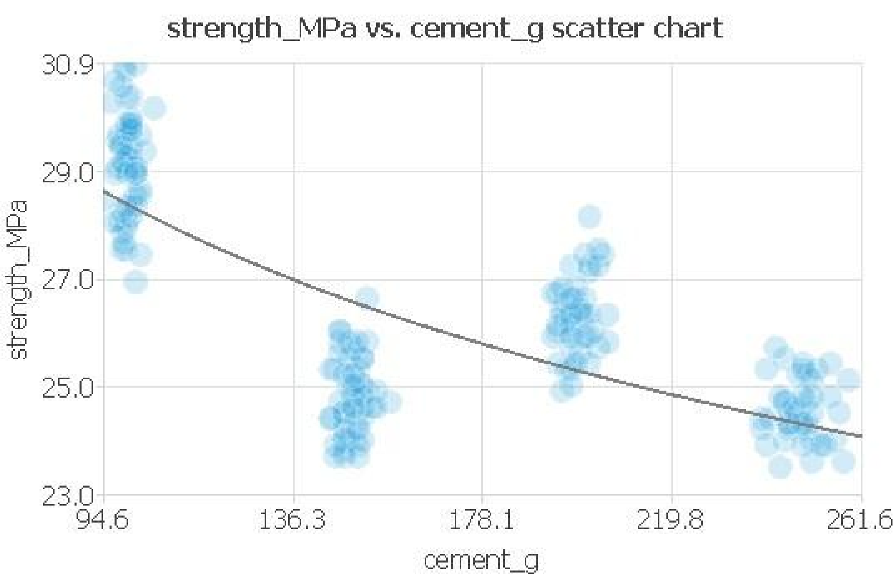

Fig. 6: strength_(MPa) vs. cement_(g) scatter chart

It also shows the regression line between both variables, of type logarithmic, with a correlation on value of -0.748.

strength_MPa vs. water_g scatter chart

The following chart shows the input water_g and target strength_MPa scatter plot.

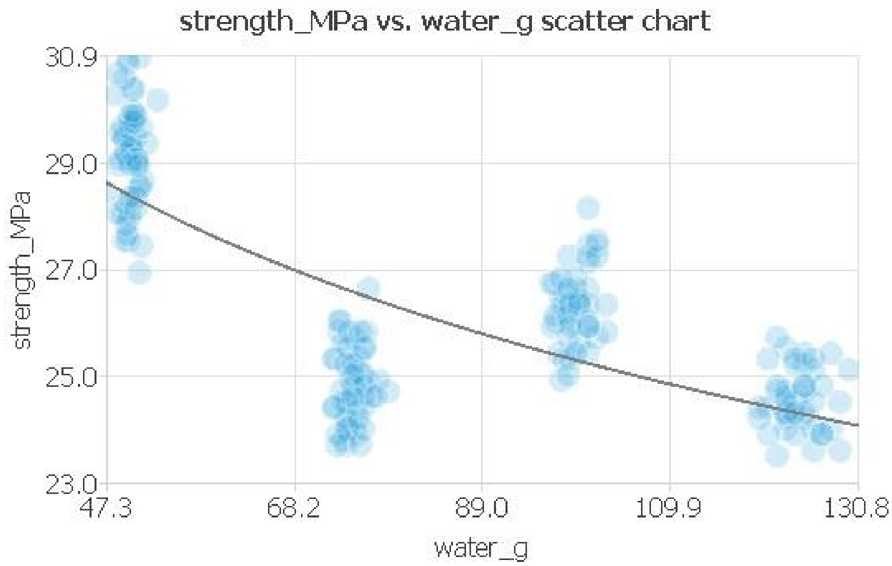

Fig.7: strength_MPa vs. water_g scatter chart

It also shows the regression line between both variables, of type logarithmic, with a correlation on value of -0.748.

strength_MPa vs. sand_g scatter chart

The following chart shows the input sand_g and target strength_MPa scatter plot.

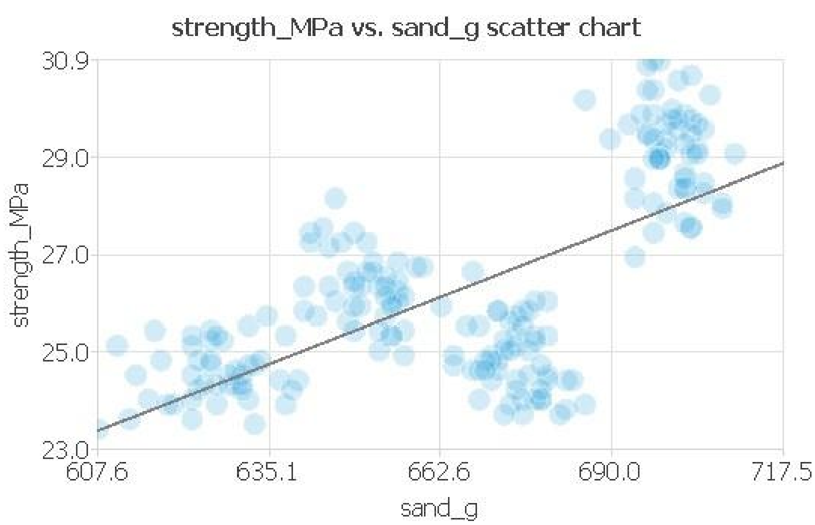

Fig. 8: strength_MPa vs. sand_g scatter chart

It also shows the regression line between both variables, of type linear, with a correlation value of 0.681.

strength_MPa vs. glass_g scatter chart

The following chart shows the input glass_g and target strength_MPa scatter plot.

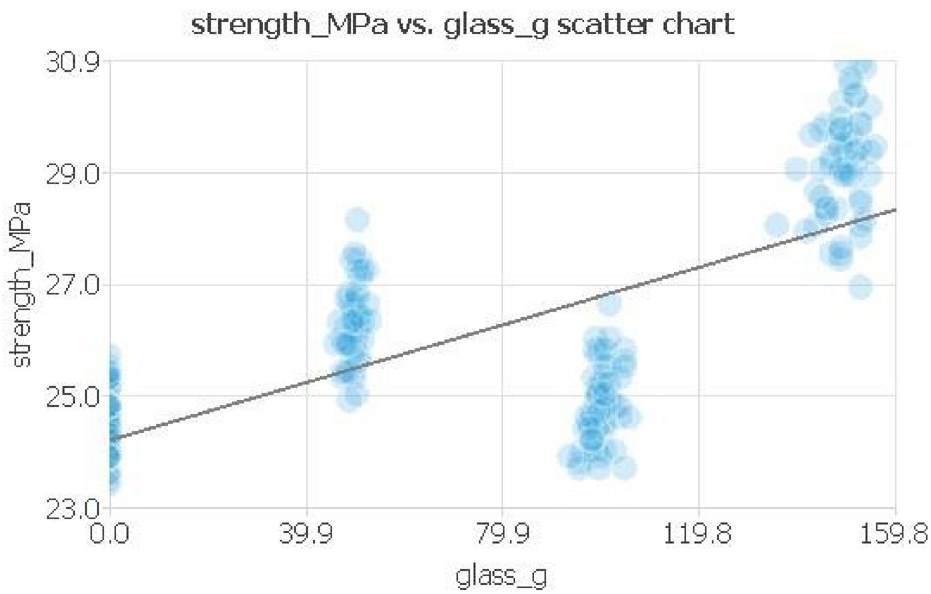

Fig.9: Strength_MPa vs. glass_g scatter chart

It also shows the regression line between both variables, of type linear, with a correlation on value of 0.703.

a. 3.10 strength_MPa vs. glass_pct scatt er chart

The following chart shows the input glass_pct and target strength_MPa scatter plot.

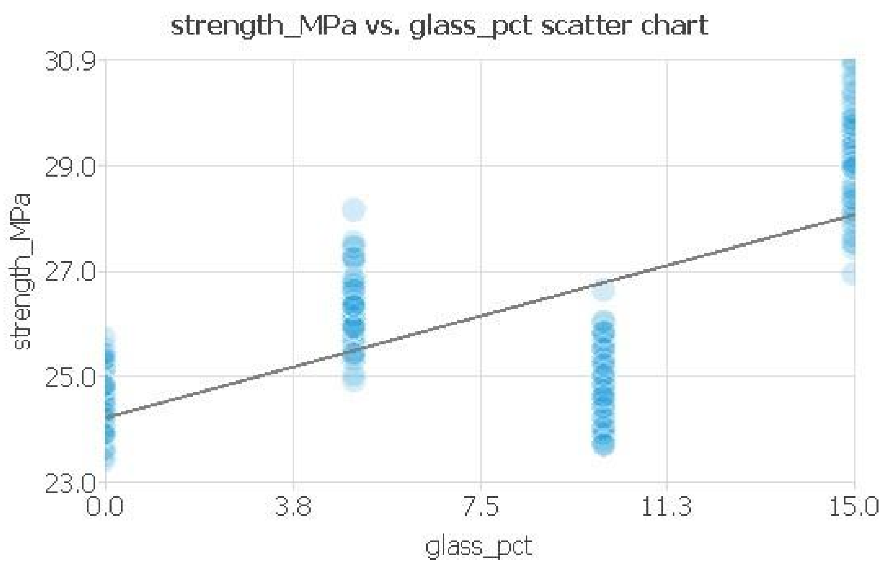

Fig.10 : strength_MPa vs. glass_pct scatt er chart

It also shows the regression line between both variables, of type linear, with a correlation on value of 0.701.

Mathematical expression

The predictive model takes the form of a function on of the outputs concerning the inputs.

You can embed the mathematical expression represented by the model into another so ware in the so-called production mode.

The following listing contains the mathematical expression represented by the neural network. It takes the inputs cement_g, water_g, sand_g, glass_g, glass_pct, to produce the output strength_MPa.

In approximation models, the neural network propagates the information feed-forward through the scaling, perceptron, and unscaling layers.

Inputs-outputs table

The following table shows the input values and their corresponding output values.

Table 2: Inputs-outputs table

	Value
cement_g	169.162
water_g	84.581
sand_g	665.847
glass_g	80.409
glass_pct	8.050
strength_MPa	24.9180

Layer one equations:

scaled_cement_g = (cement_g-169.1620026)/55.82559967; scaled_water_g = (water_g 84.58100128)/27.91239929; --a

scaled_san_d_g = (san_d_g-665.8480225)/28.10219955; scaled_gla_ss_g = (gla_ss_g-80.40930176)/56.13579941;---b

scaled_gla_ss_pct = (gla_ss_pct-8.050000191)/5.621880054;---c

Layer two equations:

perceptron_layer_1_output_0 = tanh(-0.292077 + (scaled_cement_g*-0.200848) + (scaled_water_g*-0.375987) +(scaled_san_d_g*-0.263852) + (scaled_gla_ss_g*0.409034) +(scaled_gla_ss_pct*0.186468))-----d

perceptron_layer_1_output_1 = tanh(-0.278379 + (scaled_cement_g*1.35499) + (scaled_water_g*1.35309) +(scaled_san_d_g*-1.50345) + (scaled_gla_ss_g*-1.58461) +(scaled_gla_ss_pct*-1.77475));--------------------e

Layer three equations (Final equation for compressive strength computation):

perceptron_layer_2_output_0 =(0.677473 + (perceptron_layer_1_output_0*3.29464) + (perceptron_layer_1_output_1*1.49912));---f

unscaling_layer_output_0=perceptron_layer_2_output_0*2.042779 922+26.27669907;----------------------------g

Note: **Unscaling layer output is same as the compressive strength.**

Discussion:

The results of this study demonstrate that the partial replacement of cement with pulverized waste glass has a significant effect on the compressive strength of mortar at 28 days. Based on the augmented dataset generated from experimental averages, compressive strength increased from 24.50 MPa (control mix, 0% glass) to 29.08 MPa at 15% glass replacement. This finding suggests that controlled incorporation of waste glass can enhance the performance of cement mortar.

The artificial neural network (ANN) model developed using cement, water, sand, and glass content as inputs, and compressive strength as the output, achieved high predictive accuracy with $R^2 = 0.85$, RMSE = 0.71 MPa, and MAE = 0.58 MPa. These values indicate that the ANN successfully captured the nonlinear relationships between mix proportions and compressive strength. The model performance confirms the suitability of ANN as a computational tool for predicting mortar strength where experimental testing is limited.

The augmented dataset (200 samples per replacement level) allowed the ANN to generalize beyond the limited experimental results. The model's predictions follow a logical trend of strength increase with glass addition up to 15%. This aligns with published findings that finely ground glass, rich in silica, contributes to pozzolanic activity and densification of the microstructure, thereby enhancing strength. However, it should be noted that the current work considered only 28-day strength; longer curing ages and durability properties (e.g., alkali-silica reaction, permeability) remain to be investigated.

IV. CONCLUSION AND RECOMMENDATIONS

Conclusion

This study developed a computational ANN model to predict the compressive strength of mortar incorporating pulverized waste glass. The following conclusions can be drawn:

1. Mortars with waste glass exhibited compressive strengths comparable to or greater than the control mix, with 15% replacement achieving the highest strength of 29.08 MPa.
2. The ANN model trained on augmented data achieved strong predictive performance (R^2 = 0.85), demonstrating its ability to serve as a reliable computational tool for strength prediction.
3. Waste glass, when finely ground and used as a partial cement replacement, contributes positively to mortar strength, supporting its use as a sustainable construction material.

Recommendations

1. Future studies should investigate durability properties of glass-modified mortars, including resistance to alkali-silica reaction, chemical attack, and long-term strength development.
2. The ANN model should be expanded by incorporating additional experimental data at different curing ages and environmental conditions to improve robustness.
3. The use of pulverized waste glass should be standardized in Nigerian construction practice as a sustainable strategy to reduce cement consumption and mitigate environmental impacts.
4. Policymakers and engineers should consider promoting waste glass recycling initiatives to provide consistent supply for construction purposes.

The increased strength observed despite the partial replacement of cement (binder) with glass (non-binder) can be scientifically explained by the pozzolanic and filler activity of finely ground glass. Previous studies (Shi et al., 2005; Shayan & Xu, 2004; Schwarz & Neithalath, 2008; Islam et al., 2017) have shown that amorphous silica in glass reacts with $Ca(OH)_2$ to produce additional C–S–H, which densifies the matrix and enhances compressive strength.

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