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EXPERIMENTAL AND ANN-BASED INVESTIGATION OF RUBBERIZED GEOPOLYMER CONCRETE FOR SUSTAINABLE CONSTRUCTION

EKSPERIMENTALNA IN NA NEVRONSKIH MREŽAH TEMELJEČA RAZISKAVA GUMIRANEGA GEOPOLIMERNEGA BETONA ZA TRAJNOSTNO GRADNJO

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This study develops a mix design for geopolymer concrete (GPC) incorporating waste tyre rubber as a partial replacement for fine aggregate. Standard cube and beam specimens were cast and tested for compressive strength, and the resulting experimental data were used to train an artificial neural network (ANN) model for strength prediction. The proposed AI-driven framework enables the early estimation of compressive strength, reducing reliance on extensive laboratory testing and supporting timely decision-making in material design and quality control. The ANN model achieved R^2 values of 0.70, 0.42, and 0.57 on the training, validation, and test datasets, respectively, indicating moderate and consistent predictive performance. The network employs a two-layer feedforward architecture with seven input parameters, a sigmoid activation function in the hidden layer, and a linear output layer. While the model demonstrates reliable performance, further improvements through hyperparameter tuning and expanded datasets are anticipated. By integrating recycled tyre rubber into the GPC, the study addresses environmental and economic concerns, promotes sustainable construction practices, and supports circular-economy principles by valorising waste materials.

Keywords: ANN model, compressive strength, geopolymer concrete, waste tyre rubber, fly ash

V članku avtorji predstavljajo študijo razvoja in zasnovo mešanice za geopolimerni beton (GPC) z vključitvijo gume iz odpadnih pnevmatik, kot delne zamenjave za drobni agregat. Standardne vzorce v obliki kock in nosilcev so avtorji ulili in po utrjevanju določili njihovo tlačno trdnost. Dobljene eksperimentalne podatke so nato uporabili za učenje modela na osnovi umetne nevronske mreže (ANN; angl.: artificial neural network) za napovedovanje trdnosti. Predlagani okvir, ki ga poganja umetna nevronska mreža (ANN), omogoča zgodnjo oceno tlačne trdnosti, kar zmanjšuje odvisnost od obsežnih laboratorijskih testiranj in podpira pravočasno odločanje pri načrtovanju materialov in nadzoru kakovosti. Z ANN modelom so avtorji dosegli R^2 vrednosti 0,70, 0,42 in 0,57 na učnih, validacijskih in testnih naborih podatkov, kar kaže na zmerno in dosledno napovedno delovanje. Omrežje uporablja dvoslojno arhitekturo predhodne povratne zveze s sedmimi vhodnimi parametri, sigmoidalno aktivacijsko funkcijo v skriti plasti in linearno izhodno plastjo. Čeprav model kaže zanesljivo delovanje, avtorji pričakujejo nadaljnje izboljšave z uglaševanjem hiperparametrov in razširjenimi nabori podatkov. Z vključitvijo reciklirane gume iz pnevmatik v GPC predstavljena študija obravnava okoljske in ekonomske vidike, spodbuja trajnostne gradbene prakse ter podpira načela krožnega gospodarstva z izkoriščanjem odpadnih materialov.

Ključne besede: model umetnih nevronskih mrež (ANN), tlačna trdnost, geopolimerni beton, odpadna guma iz pnevmatik, elektrofilterski pepel

1 INTRODUCTION

Concrete is one of the most widely used construction materials due to its durability, mechanical strength, versatility, and availability of constituents. Conventional concrete primarily consists of natural fine and coarse aggregates, water, and a binder, typically Ordinary Portland Cement (OPC). However, OPC production is highly resource-intensive and contributes greatly to environmental degradation through emissions of CO_2, nitrogen oxides, and sulphur trioxide, thereby accelerating global warming and acid rain.[1] As a result, sustainability-driven research has increasingly focused on incorporating alternative binders and waste materials into concrete production to reduce environmental impact.[2]

Geopolymer technology, first introduced by Davidovits,[3] emerged as a promising alternative to OPC-based systems by utilizing aluminosilicate-rich materials activated with alkaline solutions at relatively low temperatures. Geopolymers exhibit favourable mechanical performance, high-temperature stability, and strong resistance to acid and chemical attacks.[4–6] Various industrial by-products and natural materials such as fly ash, metakaolin, calcined clays, agricultural ashes, slag, and red mud have been successfully used as geopolymer precursors.[7–10] Among these, Class-F fly ash-based

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geopolymer concrete (GPC) has received particular attention due to its abundance and advantageous mechanical and durability properties, including a high compressive strength, low shrinkage, and superior resistance to chemical exposure.[11–15]

In parallel to geopolymer research, the utilization of waste tyre rubber in concrete has gained momentum as a sustainable solution to address the growing environmental burden of discarded tyres. Numerous studies have demonstrated that waste rubber can partially replace natural aggregates in cement-based and GPCs, producing lightweight materials with enhanced energy absorption and impact resistance while reducing landfill disposal.[16–22] When applied to geopolymer systems, this approach yields rubberized geopolymer concrete (RGPC), which combines the environmental advantages of geopolymer binders with waste tyre recycling.[23–27] Existing studies on RGPC predominantly focus on evaluating the effects of rubber content, curing conditions, alkaline activator concentration, and aggregate characteristics on mechanical properties, including compressive, splitting tensile, and flexural strengths.[23–25]

Despite the extensive experimental investigation of rubberized GPC, comparatively fewer studies have employed machine-learning (ML) or deep-learning (DL) techniques to predict its mechanical performance. Existing research in conventional and eco-friendly concretes has demonstrated that artificial neural networks (ANNs), deep neural networks (DNNs), and other ML models can effectively capture complex nonlinear relationships between material composition and strength development.[28–30] Comparative studies have shown that ensemble and tree-based models, such as Random Forest and Decision Tree Regressors, can sometimes outperform stand-alone ANNs, particularly in handling data variability.[31–35] Hybrid approaches integrating optimization algorithms such as particle-swarm optimization or simulated annealing with neural networks have further enhanced the predictive capability.[36] At the same time, neuro-fuzzy models like ANFIS have demonstrated advantages in geopolymer-based applications.[37] Recent findings suggest that although DL models offer strong potential, their effectiveness is often constrained by limited dataset size, making hybrid and optimized ANN frameworks more suitable for experimental concrete datasets.[38,39]

A critical limitation in prior AI-based studies is the reliance on externally compiled datasets derived primarily from cube specimens, often without experimental control over mix design or structural elements such as beams. Concrete beams, which better represent real structural behaviour, are frequently excluded from predictive modelling. Addressing this gap, the present study is based on experimentally cast and tested standard cubes and beams with controlled variations in rubber content, aggregate proportions, fly ash, and curing conditions. By integrating experimentally generated data with an ANN framework using seven key input variables, this research provides a more application-oriented predictive model. This study incorporates waste tyre rubber as a partial replacement for fine aggregates, with the resulting mix cast into beams designed explicitly for strength testing. In accordance with IS 10086 – 1982, the concrete beams measure 150 mm × 150 mm × 700 mm and undergo water curing to ensure consistent hydration. These beams are prepared alongside standard concrete cubes (150 mm × 150 mm × 150 mm) from the same batch to provide a reliable basis for comparative analysis and model validation. This study primarily focuses on the compressive strength test to develop and validate an ANN model for accurately predicting the compressive strength of rubberized GPC.

Accordingly, the primary objective of this study is to develop and validate an ANN-based framework for predicting the compressive strength of rubberized GPC using experimentally designed specimens. The study aims to bridge the gap between laboratory experimentation and data-driven modelling, offering a practical tool for early-stage strength prediction that supports sustainable construction practices through waste-tyre utilization and geopolymer technology. This innovative method enables researchers to examine the intricate relationships between variables such as tyre composition, concrete-mix proportions, curing conditions, and environmental factors. Consequently, it allows the precise predictions of concrete strength and the development of optimization strategies tailored to the properties of waste rubber tires. The flexibility of neural network models ensures reliable predictions across various types of waste tyres and concrete formulations. Adopting this approach enhances the construction efficiency and promotes sustainability by utilizing waste materials in concrete production, thereby contributing to a greener, more resource-efficient construction industry.

2 EXPERIMENTAL PART

In this study, the mix design for GPC is formulated by partially replacing fine aggregate (FA) with rubber. Based on this mix design, standard cubes and concrete specimens are cast. These specimens undergo compressive strength testing to assess their performance, and the ANN model is trained to automatically predict compressive strength, eliminating the need for continuous experimental testing. **Figure 1** illustrates the methodology flowchart, illustrating the overall framework of the study. The process begins with the selection of materials, including fly ash, M-sand, coarse aggregate, waste tyre rubber, sodium silicate (Na_2SiO_3), sodium hydroxide (NaOH), and water. The experimental setup involves casting standard cubes and beams with partial replacement of fine aggregates by rubber (10 %, 20 %, 30 %), followed by 28 days of curing. Compressive strength tests are conducted on the cured specimens. The result-

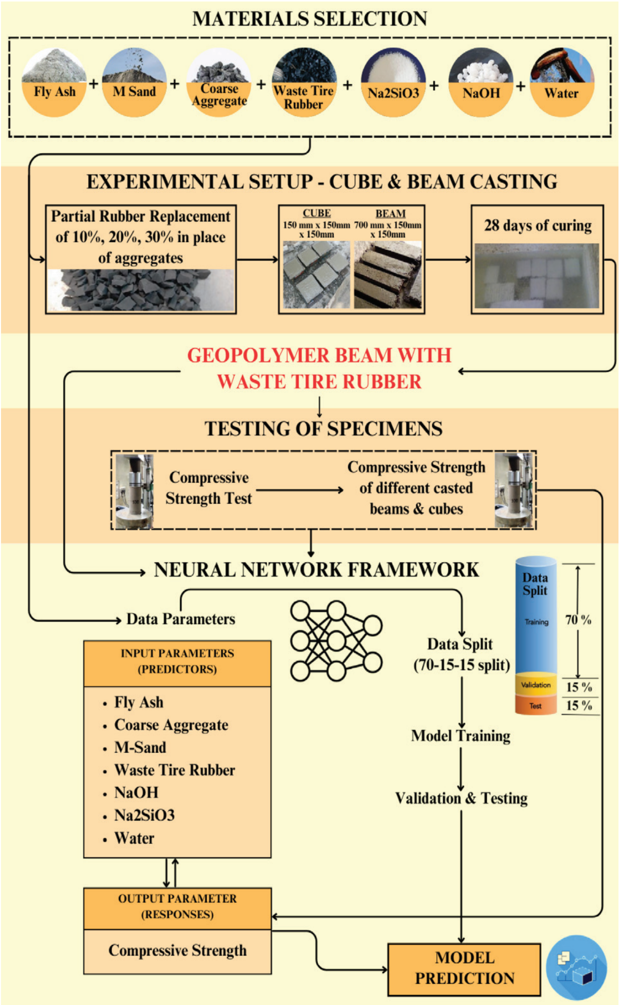


Figure 1: Flowchart illustrating the methodology adopted in the study

ing data, including material proportions and test results, are then used to train an artificial neural network (ANN) model. The ANN framework employs key input parameters to predict compressive strength, using a 70-15-15 split for training, validation, and testing to assess model performance.

2.1 Material Description

Geopolymer concrete: GPC is a material made from low-calcium fly ash (ASTM Class F) obtained from coal-burning power plants.[40] This fly ash has a carbon content determined by mass loss upon ignition. Based on the ASTM C618 classifications, this qualifies it as Class-F fly ash.[41] The specific gravity of the fly ash, measured according to IS 2386 (Part III) – 1963 standards,[42] is 2.89. The fly ash fineness was evaluated according to IS 3812 Part 1 2003,[43] yielding 27 % across three trials. Coarse aggregates, which are retained on a 4.75-mm sieve, have a specific gravity of 2.81 in all three experiments, calculated by comparing their density to that of a standard reference material.

M-Sand: Manufactured sand (M-Sand) serves as a substitute for river sand in concrete construction. M-Sand particles are smaller than 4.75 mm in diameter, and the average specific gravity across all three trials is 2.64.

Waste Tyre Rubber: To mitigate the depletion of natural resources, waste tyre rubber has been partially substituted for these aggregates. Waste rubber fiber, an elastic material derived from the rubber latex industry, contains many carbon atoms and is combustible, producing large amounts of thick black smoke when ignited.[44]

Alkaline Activator: A blend of sodium hydroxide (NaOH) and sodium silicate (Na_2SiO_3) solutions. The NaOH used was laboratory-grade pellets with a specific gravity of 2.15 and a purity of 97 %. Distilled water was used to prepare the activator solutions to avoid any potential contamination from unknown impurities.

Aluminium and silicon in the aluminosilicate source materials were dissolved using sodium hydroxide (NaOH) and sodium silicate (Na_2SiO_3). Based on previous research,[27] the sodium hydroxide concentration and the ratio of alkaline activators were maintained at 10 M and 1:2.5, respectively. NaCl and NaOH had specific gravities of 1.60 and 1.47, respectively. Preparing the alkaline solution by combining both solutions at least 24 h before use is advisable. Sodium silicate solutions are commercially accessible in different grades, and their solids must be dissolved in water to achieve the required concentration. The concentration of sodium hydroxide (NaOH) solution can range from 8 to 16 Molar, with the mass of NaOH solids in the solution varying accordingly.[45]

Water is a crucial element in construction, essential for preparing mortar and mixing concrete. Water quality directly affects the strength of mortar and concrete. Generally, potable water is considered suitable for mixing. The pH value of the water should be at least 6. The water used for manufacturing and curing concrete specimens in this study had a pH of 7.0, meeting the requirements of IS 456 – 2000.[46] **Figure ECF1** illustrates all the materials used to produce this geopolymer rubberized concrete.

2.2 Mix Design Calculations

The GPC mix components consist of fly ash with a specific surface area of 367 m^2/kg. The alkaline activator is composed of sodium silicate (Na_2SiO_3) and sodium hydroxide (NaOH), where NaOH is used at a concentration of 12 M, and the sodium silicate solution contains 50.32 % solid content. The coarse aggregate consists of crushed stone with a maximum particle size of 20 mm and a water absorption rate of 0.5 %. The fine aggregate used is M Sand (coarse sand), classified under Zone 1 according to IS 383:1970,[47] with a fineness modulus of 3.2 and a water absorption rate of 1 %. Waste tyre rubber is also incorporated into the mix, featuring a water absorption rate of 1.28 % and a particle size range of 3.35 mm to 4.5 mm.

(a) Fly ash (ASTM Class F) (b) Coarse aggregate (c) Manufactured sand (M-Sand) (d) Waste tyre rubber

(e) Sodium hydroxide (NaOH) (f) Sodium silicate (Na2SiO3) (g) water

Figure ECF1: Materials used for the Geopolymer Rubberized Concrete

2.2.1 Design Steps

A standard deviation of 4 N/mm^2 determines the target mean strength as per IS 10262:2009.[48] The quantity of fly ash required to achieve this strength is 500 kg/m^3, based on a solution-to-fly ash ratio of 0.35 and a fly ash fineness of 367 m^2/kg. The solution (Na_2SiO_3 and NaOH) to fly ash mass ratio is 0.35, requiring a solution mass of 175 kg/m^3. The Na_2SiO_3-to-NaOH ratio of 2.5 equates to 50 kg/m^3 of NaOH and 125 kg/m^3 of Na_2SiO_3. The solid content in the Na_2SiO_3 solution is 62.9 kg/m^3, while the solid content in the NaOH solution is 19.25 kg/m^3, resulting in a total solid content of 82.15 kg/m^3 in the alkaline solution. For the water content, considering medium workability and the fineness of fly ash, 95 kg/m^3 is selected, and for the other concrete workability, the required water content is tabulated in **Table ECT1**. An adjustment of –1.5 % for grading one sand results in a total quantity of water needed of 93.575 kg/m^3. Considering the water content in the alkaline solution is 92.85 kg/m^3, the water required is 0.725 kg/m^3.

Table ECT1: Quantity of required water for different concrete workability (IS 10262 : 2019 Š48Ć)

Degree of workability	Flow (in %)	Water quantity required (kg/m^3)			
		Fly ash Fineness (m^2/kg)			
		< 300	300–400	400–500	> 500
Low	0–25	80	85	100	110
Medium	25–50	90	95	110	120
High	50–100	100	110	120	135
Very high	100–150	120	130	140	160

The wet density of the GPC measures 2478 kg/m^3, with the proportion of fine-to-total aggregate content fixed at 35 % based on a sand fineness modulus of 3.2. The total aggregate content, calculated by subtracting the quantities of fly ash, alkaline solutions, and extra water from the wet density, is 1802.275 kg/m^3. The M Sand content, determined as 35 % of the total aggregate, is 630.79 kg/m^3, and the coarse aggregate content is the remainder, 1171.485 kg/m^3. When replacing 10 % of the sand, 63.079 kg/m^3 of rubber is required to achieve the specified rubber content. For 20 % and 30 % replacements, the required rubber contents are 126.158 kg/m^3 and 189.24 kg/m^3, respectively. The quantities of all materials for different beam castings are listed in **Table ECT2**.

Table ECT2: Amount of materials needed per cubic meter for geopolymer concrete with 10 %, 20 %, and 30 % rubber replacement.

Ingredients of geopolymer content	Quantity (kg/m^3)	Quantity (kg/m^3)	Quantity (kg/m^3)
Flyash	500	500	500
NaOH	50	50	50
Na_2SiO_3	125	125	125
M Sand	630	630	630
Rubber content	63.079	126.158	189.24
Coarse aggregate	1171	1171	1171
Total water	0.725	0.725	0.725

2.3 Casting of Concrete Specimens

In the casting process, concrete specimens are fabricated using beams measuring 700 mm in length, 150 mm in breadth, and 150 mm in depth, and standard cubes of

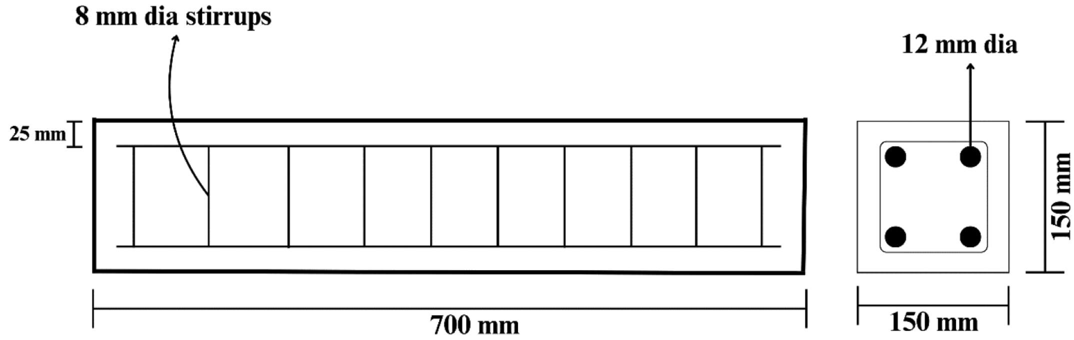


Figure ECF2: Cross section and longitudinal section of the beam

size 150 mm. The beams comprise four 12-mm-diameter rebars and 8-mm mild-steel stirrups, with a 25-mm cover for the stirrups. Different proportions of waste tire rubber replace the fine aggregate in the concrete specimens, based on these dimensions. **Figure ECF2** illustrates the structural representation, showing both the longitudinal and cross-sectional views of the beam.

The experimental plan includes a detailed schedule for casting, demolding, and water curing 118 concrete beams and cubes across three categories of rubber replacement percentages. On December 19, 2023, concrete mixes were cast with 10 % and 20 % rubber-replacement in the fine aggregate. Demoulded on December 20, 2023, and immediately placed into water curing. Additionally, a mix incorporating 30 % rubber replacement was cast on December 20, 2023, demoulded the following day, and water-cured. Testing of specimens demolded on December 20, 2023, is slated for January 17, 2024, while those demolded on December 21, 2023, will be tested on January 18, 2024, thereby ensuring that all specimens undergo the requisite 28-day curing period before testing.

2.4 Neural Network Framework

2.4.1 Data Collection and Processing

The dataset was meticulously compiled, documenting the precise quantities of materials used in all specimens of GPC mixes, incorporating various proportions of waste tyre rubber and other materials. Compressive strength measurements were experimentally obtained from 118 samples, serving as inputs (predictors) and outputs (responses) for the neural network model. **Table ECT3** presents a comprehensive tabulation of the predictor parameters and response parameters utilized in the study. This dataset serves as the foundation for training and evaluating the neural network model, ensuring the reliability and accuracy of predicting the compressive strength of rubberized GPC across various mix conditions.

The experimental data are the response variables used for the training, validation, and prediction of the neural network model. A crucial initial step in the framework involves preprocessing the data to eliminate noise or outliers. This process ensures the accuracy and reliability of the dataset. Each data point has been meticulously cross-verified with its corresponding material quantities and the resulting compressive strengths obtained from experimental setups, minimizing errors during data training. These rigorous steps are integral to the data-preprocessing phase. Subsequently, the input parameters are organized into a single Excel spreadsheet. At the same time, the compressive strengths (responses) are recorded in a separate Excel sheet, ensuring precise alignment of sample numbers between the datasets. Finally, these two Excel files (predictors and responses) are imported into MATLAB software to serve as inputs for developing the neural network framework. This rigorous approach ensures that the neural network is trained and tested with precise, meticulously validated data, thereby enhancing the reliability of its predictions.

Table ECT3: Variables of Neural Network Model

Input Predictors	Response
Fly ash	Compressive Strength
Coarse Aggregate	
M sand	
Waste Tyre Rubber	
NaOH	
Na_2SiO_3	
Water	

2.4.2 design and training of the ANN Model

In developing the neural network architecture for this study, a systematic approach was adopted to determine the optimal number of layers, the number of neurons per layer, the activation functions, and the training algorithms. The selected architecture is a two-layer feedforward ANN, designed to balance computational simplicity with sufficient representation capacity. The input layer consists of 7 neurons, corresponding to the seven key mix-design parameters. A single hidden layer with 15 neurons was selected after iterative experimentation with neuron counts ranging from 5 to 20; this configuration provided the most stable results with minimal signs of overfitting. The hidden layer employs a sigmoid activation function to capture the nonlinear interactions among the input variables. In contrast, the output layer uses a linear activation function suited to predicting continuous outcomes such as compressive strength.

The choice of this relatively simple yet effective architecture distinguishes this study from other frameworks that rely on deeper or hybrid models requiring large datasets. Since the present study is based on experimental data from cast rubberized GPC beams, a lean ANN design was adopted to ensure interpretability and practical deployment potential, particularly in resource-constrained construction environments. Unlike generic models trained on broad concrete datasets, the proposed framework is specifically tailored to rubberized GPC mixes, thereby contributing a focused tool that aligns with sustainable construction practices by promoting the reuse of waste tyre rubber in structural materials. **Figure ECF3** illustrates the finalized ANN structure, including the data flow across layers. This tailored configuration effectively addresses the complex relationships among the variables involved in rubberized GPC and enables accurate prediction of compressive strength from experimental inputs.

The model was trained on a dataset partitioned into training (70 %), validation (15 %), and test (15 %) subsets, ensuring that the network's performance was evaluated on unseen data to prevent overfitting. Scaled Conjugate Gradient Backpropagation was employed as the training algorithm, chosen for its efficiency and lower memory demands compared to alternatives such as Levenberg–Marquardt or Bayesian regularization.[49] This decision reflects a balance between computational efficiency and predictive accuracy for medium-scale experimental datasets.

Although the current work emphasizes ANN, exploratory trials with other machine learning models showed comparatively weaker performance for the given dataset and were not pursued further. A complete sensitivity analysis of ANN parameters was not included due to the scope of this study, but iterative trials informed the final architecture.[50] Model performance was evaluated using R-value and Mean Squared Error (MSE), as reported by MATLAB's Neural Network Fitting Toolbox. While additional error measures such as RMSE and MAE were not directly available in the native outputs, the chosen metrics provide a reliable indication of predictive precision and generalization. Visualization tools, including regression fit plots and error histograms, were employed to interpret discrepancies between predictions and actual outcomes. Overall, the proposed ANN framework demonstrates that a carefully designed, moderately complex network can reliably capture the nonlinear behavior of rubberized GPC and provide a foundation for developing AI-based tools that advance sustainable construction practices by efficiently reusing waste materials.

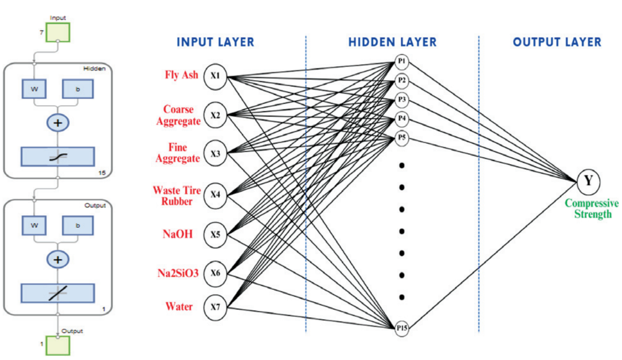


Figure ECF3: Neural Network Model Design

3 RESULTS

3.1 Compressive Strength Test

Compressive strength is a crucial property of concrete specimens, indicating their ability to withstand load. This experimental study replaced fine aggregate with waste tyre rubber at 10 %, 20 %, and 30 % by weight. The mean compressive strength, typically evaluated at 28 days, determines the mix's nominal water-cement ratio. Traditionally, compressive strength tests are vital in assessing concrete's suitability for structural applications. The developed model enables accurate prediction of compressive strength based on specific material proportions, thereby simplifying and enhancing the efficiency of the design process. This test is pivotal for validating in-situ concrete work and ensuring structural integrity. During testing, observations included recording the maximum load at failure, identifying anomalies in specimen appearance, and documenting the type of failure. Factors such as water-cement ratio, cement quality, and overall concrete production quality control measures all influence compressive strength—the gridlines in **Figure ECF4**. Enable precise measurement of crack lengths during beam testing. **Figure ECF4a** shows the image before the load is applied, while **Figure ECF4b** shows the

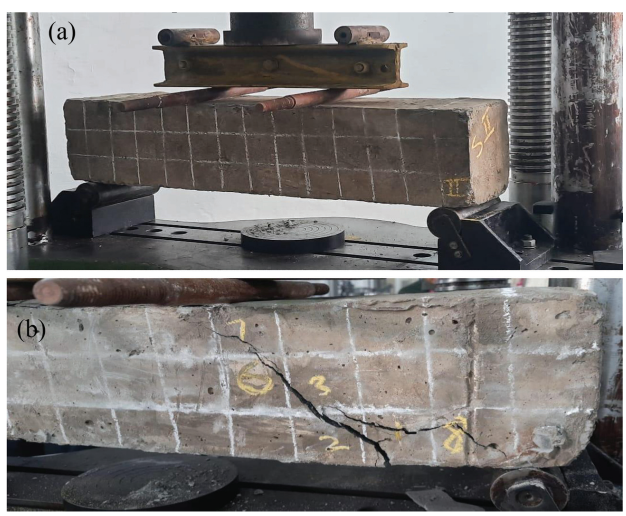


Figure ECF4: Plotted gridlines for the beam testing: a) before applying load, b) after applying load image after the load is applied. The gridlines help accurately measure the cracks.

The compressive strength results for GPC with different percentages of rubber replacement are as follows: For a 10 % replacement, recorded loads of 610 KN, 620 KN, and 600 KN corresponded to compressive strengths of 27.11 N/mm^2, 27.55 N/mm^2, and 26.67 N/mm^2, respectively, with an average of 27.11 N/mm^2. Similarly, with a 20 % rubber replacement, measured loads of 535 KN, 545 KN, and 540 KN yielded compressive strengths of 23.78 N/mm^2, 24.22 N/mm^2, and 24.00 N/mm^2, respectively, averaging 24.00 N/mm^2. Finally, for a 30 % rubber replacement, recorded loads of 475 KN, 450 KN, and 460 KN translated to compressive strengths of 21.11 N/mm^2, 20.00 N/mm^2, and 20.44 N/mm^2, respectively, with an average of 20.51 N/mm^2. These results are based on samples from 118 specimens across various rubber categories and thoroughly examine how increasing rubber content affects the compressive strength of GPC.

3.2 Abrasion Resistance

Substituting fine river aggregate with recycled granulated rubber (approximately the total volume) improves the hydro-abrasive resistance of concrete by up to 10 %. Including rubber in previous concrete significantly enhances its abrasion resistance compared to traditional mixes. Specifically, systematically increasing the rubber content enhances abrasion resistance, likely because rubber particles act as fibers that reinforce and protect the integrity of the cement paste. Fine crumb rubber performs better in improving abrasion resistance than tyre chips and larger rubber particles. For instance, replacing 20 % of natural aggregate with fine crumb rubber reduced wear depth from 0.91 % to 0.17 %, highlighting its effectiveness in lowering surface wear. Overall, rubberized concrete exhibits greater abrasion resistance than conventional concrete mixes, underscoring its potential to improve durability in construction applications.

3.3 Durability Properties under Acid Attack

The durability of rubberized concrete under acid attack was evaluated using two curing methods to assess its effects on concrete specimens. Both sulphuric acid and hydrochloric acid were used to assess durability, with compressive strength measured after exposure. Sulphuric acid was more detrimental than hydrochloric acid because it can generate ettringite within the concrete matrix, increasing internal pressure and propagating cracks. Rubberized concrete demonstrated superior resistance to acid attack compared to mixes containing alccofine and conventional concrete. This suggests that rubberized concrete is well-suited for applications where exposure to chemical agents, such as in coastal environments, is a regular concern. Specifically, the study highlights that sulphuric acid has a more pronounced effect on concrete durability than hydrochloric acid under similar conditions. This assessment underscores the potential benefits of using rubberized concrete in environments prone to chemical exposure, emphasizing its enhanced durability and suitability for challenging construction settings.

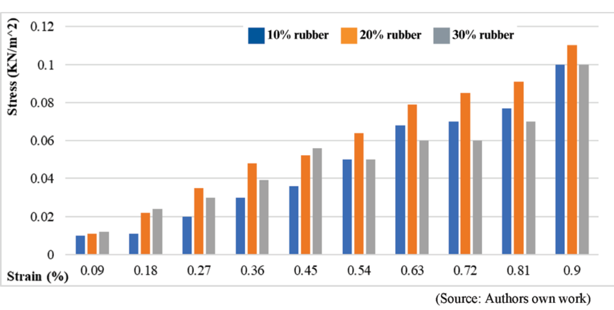


Figure 2: Stress–strain curve representing the compressive behavior of the concrete specimens

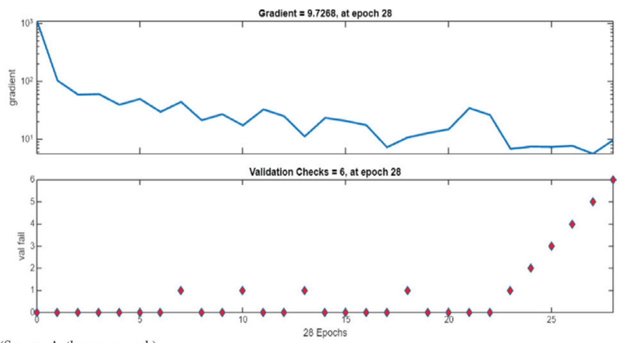
3.4 Stress Versus Strain Interrelation

The stress-strain relationship for three GPC mixes with varying waste tyre rubber contents (10 %, 20 % and 30 %, respectively) was plotted and shown in **Figure 2**. The x-axis represents strain as a percentage, while the y-axis depicts stress in kN/m^2. The graph provides insights into how each series responds to increasing strain, showing distinct patterns of stress development.

10 %, 20 % and 30 % rubber-content concrete beams exhibit different stress levels at corresponding strain percentages, reflecting variations in mechanical properties attributed to the rubber content. Understanding the stress-strain behaviour is crucial for evaluating key mechanical properties, such as elastic modulus, Poisson's ratio, yield stress, and ultimate tensile strength. These properties are essential for engineers to assess the load-bearing capacity and suitability for various structural applications. The graph illustrates the material's deformation characteristics under multiple loads (tensile, compressive, or torsional) and offers valuable insights into its performance and reliability in practical construction scenarios. This analysis highlights the significance of rubber content in shaping the mechanical behaviour of GPC and its potential implications for structural engineering applications.

3.5 Analysis of Neural Network Framework Results

Neural networks are renowned for effectively fitting various functions, as evidenced by their capacity to approximate nearly any function. This study employed a 70-15-15 data split, where 82 observations were allocated to the training set, 18 to the validation set, and 18 to the test set. The neural network model underwent training, with the training progress depicted in **Figure 3**. The plot indicates that the model was trained for 28 epochs, reaching a final gradient of the loss function of

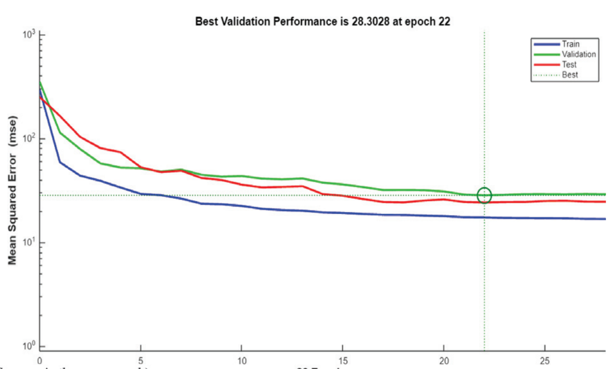


(Source: Authors own work)

Figure 3: ANN training state plot showing the convergence of training parameters over epochs

9.7268. This gradient indicates the rate of change in the loss function after training. The training process concluded after six validation checks, with measures implemented to prevent overfitting and ensure effective generalization to unseen data. These training observations and evaluation metrics are vital in assessing the model's ability to capture underlying patterns and its reliability in making accurate predictions from input data.

Evaluating the model's performance on the test dataset is a critical step, as shown in **Figure 4**, which illustrates changes in MSE across training epochs for the training, test, and validation datasets. The training concluded when the validation error equalled or exceeded the minor validation error from previous iterations for six consecutive checks. The performance plot serves as a crucial diagnostic tool, offering insights into the effectiveness of the neural network training process. The best validation performance, achieved with an MSE of 28.3028 at epoch 22, highlights the optimal training stage before potential overfitting. This information is instrumental in refining model parameters and ensuring robust generalization to new, unseen data. These findings underscore the model's readiness for practical deployment, demonstrating its ability to predict outcomes from input data accurately and to validate its performance in real-world scenarios.



(Source: Authors own work)

Figure 4: Model performance plot depicting MSE across training, validation, and testing phases

In **Figure 4**, the dotted line labelled "Best" indicates the epoch at which the model achieved its highest performance on the validation dataset. This point is crucial for identifying the optimal training stage before overfitting occurs. MSE, a metric that averages the squares of prediction errors, is a crucial indicator of model accuracy. Lower MSE values indicate superior performance, reflecting minimal deviation between predicted and actual values. **Table 1** below provides a detailed breakdown of MSE values across the training, validation, and test datasets. These values provide a numerical assessment of the model's generalization to new data and its consistency in maintaining accuracy across evaluation stages. Analysing MSE trends enables researchers to fine-tune model parameters effectively, ensuring robust performance in real-world applications.

Table 1: ANN Model Summary

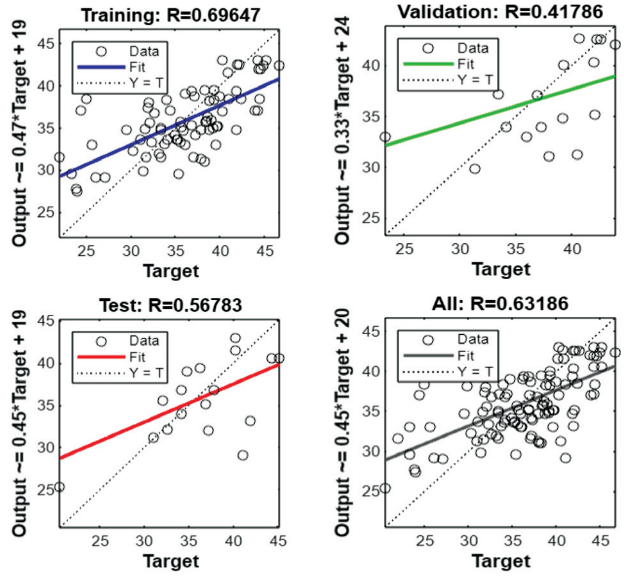
	Observations	MSE	R^2
Training	82	17.3762	0.6965
Validation	18	28.3028	0.4179
Test	18	24.1477	0.5678

(Source: Authors own work)

The best validation performance was 28.3028 at epoch 22. This means the lowest validation MSE during training was 28.3028, achieved at the 22nd epoch. This value is significant because it indicates the point at which the model achieved its best generalization performance on the validation dataset, potentially before it started to overfit the training data. The plot likely shows the MSE decreasing over the epochs as the model learns from the training data. Initially, the errors are higher and gradually decrease as the model parameters are optimized. The validation MSE is used to assess how well the model performs on data it has not been trained on. It typically decreases initially, then increases slightly as the model begins to overfit. The best validation performance is indicated by the lowest MSE on the validation dataset, suggesting the optimal point before overfitting occurs. The MSE test indicates how well the model performs on entirely new data, finalizing its generalization ability. An error histogram further verifies network performance: ideally, the data points align along a 45-degree line, indicating perfect prediction. The model shows a reasonably good fit across all datasets in this study. Each training session initializes network weights and biases differently, potentially leading to improved performance upon retraining.

In **Figure 5a**, blue bars correspond to training data, green bars represent validation data, and red bars indicate testing data. The histogram depicts the distribution of errors between the targets and outputs across training, validation, and test datasets. The histogram uses 20 bins to categorize the errors, showing a mix of training, validation, and test data. The histogram peak is centred around the zero-error mark, indicating that many predictions were close to the actual values. This distribution of errors illustrates the model's accuracy and generalization capability, as the mistakes are symmetrically distributed with a higher concentration near zero. The minimal validation and test errors near zero indicate that the model avoided overfitting the training data and effectively generalized to unseen data. This thorough error analysis underscores the neural network model's reliability in predicting the compressive strength of rubberized GPC. The test error histogram in **Figure 5b** further confirms the model's effectiveness. Most errors are within a narrow range, with the highest frequency around the zero-error mark. This consistent performance across training and test datasets validates the model's predictive accuracy for compressive strength, even with varying rubber content in the GPC.

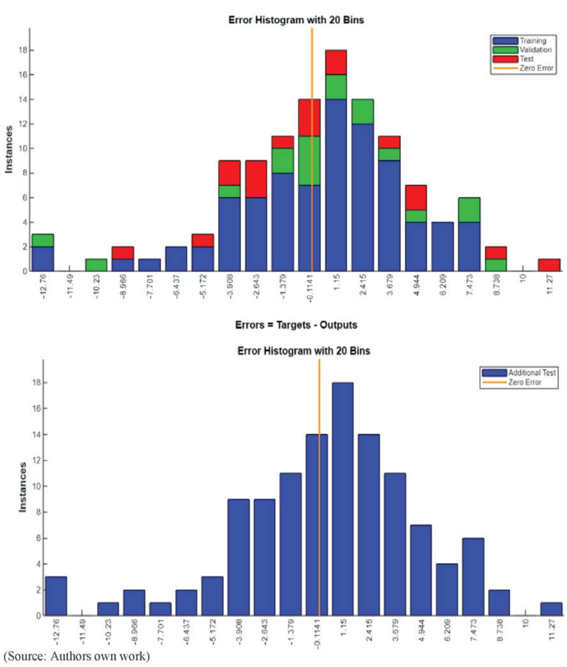
The regression plots for the training, validation, and test sets show the network predictions (outputs) versus the actual responses (targets), as represented in **Figure 6**. The plots indicate a good fit between the predicted and actual values, with R values of 0.70 (training), 0.42 (validation), 0.57 (testing), and an overall R of 0.63 for the combined dataset. These values suggest a positive moderate correlation between the predicted and actual compressive strengths, indicating that the model captures the underlying trend but has room for improvement. Future research can explore advanced optimization techniques, such as hyperparameter tuning, to improve the model's accuracy. This involves systematically adjusting parameters like the learning rate, activation functions, and the number of hidden layers or neurons. Alternative neural network architectures, such as deep feedforward networks, convolutional neural networks (CNNs), or ensemble-based models, may also enhance performance. Expanding the dataset with more diverse input variables and increasing data volume can also strengthen model generalization. Experimenting with various training algorithms and fine-tuning the initializations of weights and biases could further optimize learning efficiency. While the current ANN model exhibits moderate but consistent predictive strength, its outputs are satisfactory for predicting compressive strength in rubberized GPC, and it holds promise for practical applications with continued refinement.



(Source: Authors own work)

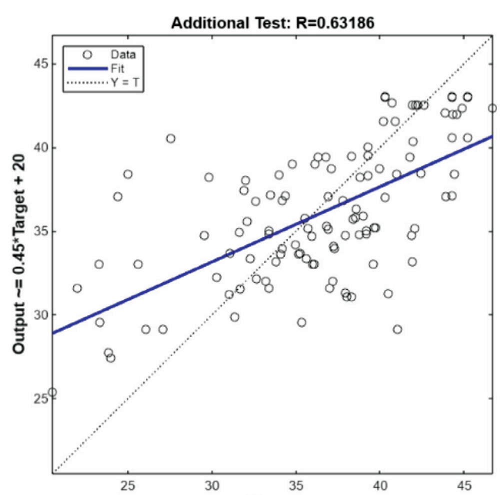
Figure 6: Regression plot comparing predicted vs. actual compressive strength

The additional regression plot in **Figure 7** evaluates the neural network model's performance on an independent test set, focusing on predicting the compressive strength of rubberized GPC. It illustrates the alignment between the model's predictions and actual values (tar-



(Source: Authors own work)

Figure 5: Histogram error plots of the model: a) Error histogram plot of the ANN model, b) Error histogram for the testing phase



(Source: Authors own work)

Figure 7: Regression plot showing prediction accuracy on the test dataset

gets). The R-value of 0.63 for this test set suggests a moderate yet consistent correlation, confirming the model's stable performance across various datasets. Previous studies primarily predicted the strength of GPC without rubber. For instance, Dong Van Dao's study using adaptive neuro-fuzzy inference (ANFIS) and ANN showed ANFIS achieving an R^2 of 0.879. In contrast, ANN achieved 0.851.[37] Another study comparing random forest and deep learning models for predicting the compressive strength of GPC concluded that, with a dataset of 61 samples, the random forest model was optimal, achieving an R^2 of 0.9321, compared to the deep learning model's R^2 of 0.7252.[38] A specific study on rubberized GPC, which compared ANN, MLP, and random forest using 129 samples, found that the ANN model achieved a higher R^2 value of 0.927.[31] These results highlight the robustness and minimal overfitting of the current model, demonstrating its reliability in predicting the mechanical properties of sustainable concrete mixes. Future research could explore adjustments to initial network parameters, such as weights and biases, expanding training datasets, incorporating relevant input features, or experimenting with different training approaches to enhance model accuracy.

4 DISCUSSION

To contextualize the performance of the developed ANN model, this section compares it with relevant studies involving AI-based approaches for predicting the compressive strength of eco-friendly concrete, including hybrid models and alternative machine learning architectures. The study developed an ANN with three hidden layers and compared its performance with that of the Random Forest (RF) and Multi-Layer Perceptron (MLP) models.[31] Using 129 data samples with input parameters like water, cement, supplementary cementitious materials (SCMs), superplasticizer, rubber aggregates, and age, the ANN achieved superior prediction accuracy with an R^2 of 0.927, and RMSE and MAE of 2.607 and 2.007, respectively. In another study,[32] eco-friendly concrete formulations incorporating Alccofine and graphene oxide were evaluated using ANN and tree-based regressors. The Decision Tree Regressor achieved a training precision of 0.4679 and testing precision of 0.2955, while the Random Forest Regressor yielded 0.4592 and 0.3010, respectively, indicating limited generalization capacity.

Gaussian Process Regression (GPR), Random Forest Regression (RFR), and Decision Tree Regression (DTR) were used to predict compressive and splitting tensile strengths of rice husk ash concrete.[33] DTR outperformed other models, with R^2 values of 0.9646 for compressive strength and 0.9691 for tensile strength, optimized using grid search. Hybrid machine learning models have also shown promise. One study applied a hybrid model combining simulated annealing and particle swarm optimization to an ANN for predicting rubberized concrete strength, achieving an R^2 of 0.9240, demonstrating the effectiveness of optimization-based enhancement. Another investigation observed that Gaussian Process Regression (GPR) outperformed Support Vector Machine (SVM) in predicting the compressive strength of rubberized concrete, reinforcing the advantage of probabilistic models in capturing material variability.[36]

Studies examined the prediction of GPC strength using input features such as fly ash, sodium hydroxide, sodium silicate solution, and water.[37] Their study compared ANN and Adaptive Neuro-Fuzzy Inference System (ANFIS), with ANFIS slightly outperforming ANN (R^2 = 0.879 vs. 0.851), highlighting the potential of neuro-fuzzy hybrids. Another Study compared Random Forest and deep learning models using 61 datasets with 11 variables.[38] The RF model yielded better accuracy, with lower RMSE (2.68 %) and MAE (37.47 %) than the deep learning model, which had higher RMSE (5.94 %) and error metrics, suggesting tree-based models' robustness on limited datasets.

In contrast, the current study's ANN model focused on rubberized GPC beams, achieving R-values of 0.696 (training), 0.417 (validation), and 0.567 (testing). While these values are moderate compared to hybrid or advanced models, the novelty lies in using experimental data from cast beam specimens with varied rubber content, offering a practical contribution to sustainable concrete applications. In future work, these comparisons underscore the potential for improving prediction performance through advanced model architectures, data expansion, and hybrid techniques.

3.7 Limitations and Future Research Directions

Although the developed ANN model demonstrates the capability to predict compressive strength of rubberized GPC, the relatively moderate R-values indicate that the model has limited generalization capacity. This may be attributed to the restricted dataset size and variability in rubberized concrete mixes, which can affect the network's ability to capture complex nonlinear relationships. Additionally, the performance evaluation is based on the R-value and MSE generated by MATLAB's Neural Network Fitting Toolbox, which does not directly provide RMSE or MAE outputs. For consistency, the study relied on the available performance metrics from MATLAB. However, future work could compute RMSE and MAE manually or via alternative platforms to provide a more comprehensive error analysis.

Future work should explore hybrid machine learning approaches to improve prediction accuracy and model robustness, such as combining ANN with optimization algorithms or ensemble models. Comparative studies with traditional regression and empirical models could enhance understanding of reliability and generalizability. Further refinement may involve optimizing the ANN architecture, incorporating advanced hyperparameter tuning, and expanding the dataset to include a wider range of material compositions. In addition to compressive strength, future predictive frameworks should integrate mechanical properties, such as flexural and tensile strengths, to better reflect structural performance. Investigating the long-term durability and microstructural behaviour of rubberized GPC will provide deeper insights into material behaviour and lifecycle performance.

Moreover, evaluating the economic feasibility of ANN-based predictions compared to conventional testing methods could establish the approach as a cost-effective tool for construction planning. Investigating this method's potential policy implications and relevance may also contribute to the evolution of construction standards and sustainability regulations. Extending this framework to other sustainable concrete types will broaden its applicability and encourage greener practices across construction sectors.

3.8 Scope and Broader Implications of the Study

This study presents an ANN-based framework for early prediction of compressive strength in rubberized GPC, offering potential integration into real-time construction workflows. The model enables rapid strength estimation, reducing dependency on traditional testing and facilitating timely decision-making in material selection, quality control, and resource planning. The framework supports sustainable construction practices and aligns with circular economy goals by enabling early assessments of rubberized GPC mixes, particularly those incorporating recycled tyre rubber.

From a broader societal perspective, the outcomes of this research hold potential implications across multiple domains. In public policy, the demonstrated benefits of rubberized GPC may encourage regulatory bodies to mandate or incentivize the use of recycled materials in infrastructure projects, thereby reducing landfill waste and supporting national sustainability targets. In the industry, embedding the proposed ANN model into digital construction platforms or design software could accelerate the adoption of eco-friendly concretes by simplifying decision-making for engineers and contractors. In education, the methodology and findings can be integrated into civil engineering curricula to strengthen knowledge on sustainable materials and AI-driven design practices, preparing future engineers for data-centric construction paradigms.

5 CONCLUSIONS

An innovative ANN model was developed in this study for predicting the compressive strength of rubberized GPC, using unique input variables including fly ash, M sand, coarse aggregate, waste tyre rubber, NaOH, Na_2SiO_3, and water. Experimental validation demonstrates that increasing the percentage of waste tyre rubber decreases the compressive strength of GPC across all tested ages. Specifically, compressive strength decreases from 27.11 N/mm^2 for a 10 % rubber replacement to 24.00 N/mm^2 for a 20 % replacement, and further to 20.51 N/mm^2 for a 30 % replacement. The ANN model demonstrates robust performance with R-values of 0.70 for training, 0.42 for validation, 0.57 for testing, and an overall R-value of 0.63 across the combined dataset.

This study proves the effectiveness of improving concrete properties using recycled materials and introduces an advanced deep-learning ANN model. This model reliably predicts the compressive strength of rubberized GPC, confirming the feasibility and reliability of using waste tyre rubber as an aggregate in GPC. This integrated approach supports environmental sustainability by reducing waste and mitigating pollution while fostering innovation in eco-friendly construction materials and technologies for the future.

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