Journal of Information Systems Engineering and Management
2025, 10(59s)
e-ISSN: 2468-4376
https://www.jisem-journal.com/

Research Article

Artificial Neural Network-Based Prediction of the Compressive Strength of Eco-Friendly Concrete Incorporating PET Granules

Houcine Bentegri[1,2], Mohamed Rabehi[2], Samir Kherfane[2]

[1] *Built Environmental Research Laboratory, Civil Engineering Faculty, Sciences and Technology Department, University of Houari Boumediene, Algeria*

[2] *Civil Engineering and Sustainable Development Laboratory, Faculty of Sciences and Technology, Ziane Achour University of Djelfa, 17000 Djelfa ,Algeria.*

bentegri.houcine@univ-djelfa.dz

https://orcid.org/0009000103872950

ARTICLE INFO

Received: 10 Mar 2025

Revised: 11 May 2025

Accepted: 03 June 2025

ABSTRACT

The incorporation of polyethylene terephthalate (PET) granules as a partial replacement for traditional aggregates in concrete presents a promising strategy for addressing the pressing issues of plastic waste accumulation and environmental degradation. This study investigates the mechanical behavior of eco-friendly concrete mixtures containing PET granules and proposes an artificial neural network (ANN) model to predict their compressive strength with high accuracy. Experimental datasets from prior studies were used to train the ANN, with key input variables including water content, cement dosage, fine and coarse aggregates, and PET granule proportion.

The developed ANN model exhibited strong predictive performance, achieving a high correlation coefficient ($R^2 = 0.9444$), thereby confirming its robustness and reliability. Sensitivity analysis revealed that the water-to-cement ratio and PET granule content were the most influential factors affecting compressive strength. The findings indicate that PET granules can effectively replace natural aggregates up to an optimal threshold without compromising structural integrity, supporting their viability in sustainable concrete formulations.

This research underscores the dual environmental and engineering benefits of integrating recycled PET into concrete. The proposed ANN model offers a valuable tool for optimizing mix design while minimizing the need for extensive laboratory experimentation. Overall, the study contributes to sustainable construction practices by promoting the reuse of plastic waste and the development of greener building materials.

Keywords: PET granules, compressive strength, ecological concrete, artificial neural networks, sustainable construction.

INTRODUCTION

(PET) aggregate concrete is now frequently used to replace a certain percentage of gravel and sand aggregates in concrete due to many advantages such as low cost, light weight and the most important advantage is to recovery of plastic waste [1]. A recent study [2,3] looked at the feasibility of employing recycled plastic waste (Polyethylene terephthalate, or PET) at different concentrations as a fine aggregate alternative for natural sand in three-dimensional polypropylene. At the maximum replacement percentage of 50%, the results demonstrated a reduction in compressive and flexural strength of up to 48.9% and 51.9%, respectively.Using recovered plastic waste in place of fine aggregates is a step in the right direction toward establishing a circular economy using one type of plastic as a building material. Resin8 is the form of plastic trash employed in this investigation. Resin8 is an eco-aggregate made entirely of recycled plastic trash from Resins 1 through 7[38,39,40,41,42,43]

The disposal of waste materials, particularly the escalating production of plastic waste, has become a pressing global concern. The production of plastic garbage has increased significantly as a result of modern living and technological

Journal of Information Systems Engineering and Management
2025, 10(59s)
e-ISSN: 2468-4376
https://www.jisem-journal.com/
Research Article

improvements; in 2020, it reached 7000 million metric tons globally, and by 2050, it is expected to exceed 26,000 metric tons[4,5]. Australia, contributing 2.24 million metric tons annually, faces a substantial challenge, with 16% of its municipal waste stream comprised of plastic. Polyethylene terephthalate (PET), a widely used synthetic polymer in plastic bottles due to its cost-effectiveness, lightweight nature, and easy handling, plays a dominant role. In Australian households, PET waste constitutes a staggering 34.9% of domestic plastic waste, amounting to 1.2 million tons[5].

The persistent disposal of PET bottles, often discarded after use, emerges as a significant contributor to land and water contamination. These bottles, notorious for their poor biodegradability, take an alarming 400 years to disintegrate in nature. Consequently, urgent measures are needed to address the growing waste management crisis, with a particular focus on mitigating the environmental impact of PET waste. This study underscores the gravity of the situation, emphasizing the need for sustainable solutions to curb plastic pollution and promote responsible waste management practices[6,7,8,9,10,44,45,46,47,48].

Artificial Neural Networks (ANN) were used in the study to create models that predicted concrete's compressive strength based on ultrasonic pulse velocity. The findings showed that, in comparison to conventional linear regression techniques, machine learning (ML) models showed noticeably improved accuracy in predicting compressive strength. Furthermore, ML models have been applied in a number of research to forecast concrete behavior with respect to resistance to environmental deterioration and carbonation[11,12,13,49,50,51,52,53].

In view of the need to forecast ecological concrete's compressive strength (CCS) and tensile strength in advance and the demonstrated efficacy of artificial neural networks (ANN) in handling difficult issues, the current study aims to improve Support Vector Machine SVM parameters, a crucial component of model efficiency. The study suggests identifying the ideal SVM parameter values using a MATLAB software as a secondary optimization procedure. In a variety of industries, including energy consumption, the petroleum sector, civil engineering, and others, ML-based models have become more and more popular. [12, 13; 14; 15; 16; 17; 18,54,55,56].

By employing machine learning and pre-processing techniques to forecast concrete, this study advances current understanding. In order to investigate and improve the prediction of Environmentally friendly concrete compressive strength and tensile strength, the study explicitly uses ANN and GA together as a hybrid model Genetic Algorithm-Artificial Neural Network (GA-ANN), with an emphasis on the effectiveness and precision of handling experimental data. The paper's next sections describe the ML techniques that were applied to give the experimental dataset, go over the conclusions and outcomes, and offer suggestions for further study.

The overarching goal is to advance understanding and capabilities in predicting concrete compressive strength through computational models[12,13,14,15,16,17,18].

Neural networks, also known as artificial neural networks, or ANNs, are layered structures that mimic the organization of the human brain and are used as an adaptable system for learning. Neural networks are capable of learning from data, which enables them to be trained to recognize patterns, classify information, and make future prediction. A neural network splits an input into layers of abstraction. It can be trained by giving it many of examples, just how the human brain learns to identify patterns in speech or pictures. The behavior of a neural network is determined by the weights, or connections, between its various parts. In this study, we will use neural networks supported by the Matlab program to train the model collected through previous studies on environmentally friendly concrete whose granules contain plastic granules. The results of this program showed very great efficiency and accuracy, reaching up to 99%, This makes the results of using artificial intelligence simulated and its results close to the experiments used in the laboratory.

The use of PET (polyethylene terephthalate) granules as partial substitutes for traditional aggregates in concrete can influence several mechanical characteristics. Here are the key effects:

Compressive Strength: Compressive strength is a critical parameter for concrete in structural applications. Studies have shown that the incorporation of PET granules can affect compressive strength depending on factors like the percentage of substitution and the quality of PET granules used. Generally, lower percentages of PET substitution (up to around 10%) may have minimal impact on compressive strength. However, higher percentages or poor

Journal of Information Systems Engineering and Management
2025, 10(59s)
e-ISSN: 2468-4376
https://www.jisem-journal.com/
Research Article

bonding between PET and cement paste can lead to reductions in compressive strength due to decreased load-bearing capacity.

Tensile Strength: Tensile strength in concrete is typically lower than compressive strength, and it is important for resisting tensile stresses. PET granules, when well bonded with the cement matrix, can potentially enhance tensile strength by improving the overall ductility and crack resistance of concrete. This is particularly beneficial in applications where tensile strength is crucial, such as in earthquake-resistant structures.

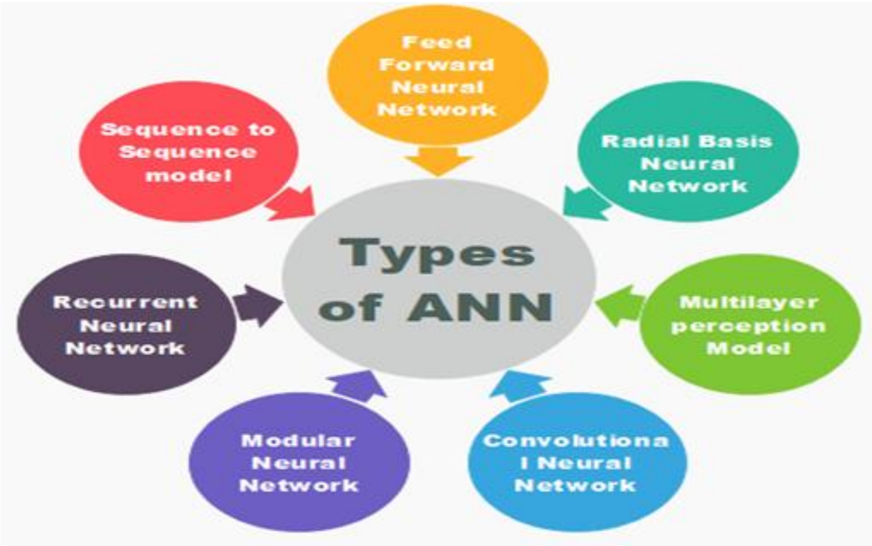


Figure 1. Types of ANN

Neural networks come in a variety of forms and may still be in the research and development phase. They can be categorized based on a variety of factors, including their structure, data flow, density and use of neurons, layers, and depth activation filters. To expand your knowledge, study about R's neural network. In figure 1 we see different neural networks.

MATERIALS AND METHODS

Artificial neural networks

In order to simulate the input/output connections present in the human brain structure, artificial neural networks are used as analytical models. They possess robust capabilities as pattern recognizers and classifiers, making them well-suited for addressing highly intricate problems that classical mathematics and traditional methods struggle to handle. These networks can effectively model input/output relationships, even in cases where explicit mathematical formulas are not available. Through procedures like weight modification and statistical optimization, networks are trained using known input/output data in order to do this modeling. Until the network accurately depicts the input/output space, this training process is repeated.

Based on field data, I have quickly categorized concrete using ANN data mining techniques and genetic algorithms. A collection of standardized quantitative field data collected through direct testing with specialized equipment serves as the operating platform for the machine learning techniques used in this work.

Designed to resemble brain neurons in terms of functionality, feed-forward backpropagation neural networks are made up of multiple-input neurons. Each input vector that reaches these neurons is multiplied by a distinct, initially random integer weight. After adding a constant bias and summing the weighted inputs, the neuron's output is shifted. The neuron's output is obtained by passing this corrected value via a transfer function, which acts as a normalization function and can take on several shapes such as a sigmoid function, piecewise-linear function, or threshold function.

Input and output layers of a neural network contain input and output data, respectively. Neural networks are layered systems. Nestled between the input and output layers are hidden layers, which are made up of weighted connections between neurons. In theory, a two-layer network can map any non-linear relationship; each layer is a vector with any number (R) of neurons it contains. Every layer produces a vector of length R that consists of the outputs from every

Journal of Information Systems Engineering and Management
2025, 10(59s)
e-ISSN: 2468-4376
https://www.jisem-journal.com/
Research Article

neuron within that layer. Through each hidden layer until the final output is reached, this output vector serves as the input vector for the subsequent hidden layer.

In this study, feed-forward backpropagation neural networks were utilized. Here, training entails modifying the synaptic weights, which are originally assigned random values. The training dataset is sent into the network to start

the training process and produce an output. The synaptic weights are modified in accordance with the output if it does not match the target. Until the network performs as intended, this iterative process is continued.

These characteristics collectively form the dataset used to train the ANN (Artificial Neural Network) model. ANN models are adept at capturing complex nonlinear relationships between inputs (such as those listed above) and

Data Collection and Preparation:

- **Data Gathering**: Gather a comprehensive dataset that includes various mixes of concrete with PET aggregates (and traditional aggregates for comparison).
- **Data Preprocessing**: Clean the data, handle missing values, normalize or standardize numerical inputs, and encode categorical variables if necessary.

Model Development:

- **ANN Architecture**: Select an appropriate ANN architecture based on the complexity of the problem and the dataset. This involves deciding the number of layers, number of neurons per layer, activation functions, and learning parameters (like learning rate and batch size).
- **Training**: Divide the dataset into training, validation, and testing subsets (e.g., 70% training, 15% validation, 15% testing). Use the training data to adjust the weights and biases of the ANN through backpropagation and optimization algorithms (e.g., gradient descent).
- **Validation During Training**: Monitor the performance of the ANN on the validation set during training to prevent overfitting. Adjust hyperparameters if necessary based on validation performance.
- **Model Evaluation**:
- **Testing Phase**: Once training is complete, evaluate the ANN model on the testing dataset that was not used during training. This step assesses the generalization capability of the model.
- **Performance Metrics**: Calculate performance metrics such as Mean Squared Error (MSE), Root Mean Squared Error (RMSE), Mean Absolute Error (MAE), and coefficient of determination (R-squared) to quantify how well the ANN predicts compressive and tensile strengths compared to actual values.

Sensitivity Analysis:

- **Feature Importance**: Conduct sensitivity analysis to determine the influence of each input variable (e.g., water content, cement content, PET aggregate fraction) on the predicted strengths. This helps in
- understanding which factors significantly affect the outcomes and can guide further optimization of concrete mixes.

Comparison and Benchmarking:

- **Comparison with Baselines**: Compare the ANN predictions with baseline models (e.g., traditional statistical models) or empirical formulas commonly used in concrete engineering to validate the superiority of the ANN approach.
- **Literature Validation**: Cross-validate the ANN results with findings from other studies or experimental data reported in the literature to ensure consistency and reliability.

Journal of Information Systems Engineering and Management
2025, 10(59s)
e-ISSN: 2468-4376
https://www.jisem-journal.com/
Research Article

Model Interpretation and Reporting:

- **Interpretability**: While ANNs are complex models, efforts can be made to interpret the trained model's behavior. Techniques like feature importance analysis and visualization of neural network weights can provide insights into how inputs contribute to predictions.
- **Documentation**: Document the entire process, including data preparation, model architecture, training parameters, validation results, and conclusions drawn from the sensitivity analysis.

By following these steps rigorously, researchers can validate the ANN model effectively for predicting the compressive and tensile strengths of concrete with PET aggregates. This validation process ensures that the developed model is robust, accurate, and suitable for practical applications in engineering and construction contexts.

The use of Artificial Neural Networks (ANNs) offers several advantages in predicting the mechanical properties of environmentally friendly concrete, especially when compared to traditional methods:

Ability to Capture Nonlinear Relationships: ANNs excel in capturing complex nonlinear relationships between input variables (such as water content, aggregate types, cement content, etc.) and output variables (compressive strength, tensile strength, etc.). In contrast, traditional methods like empirical formulas or statistical regression models may struggle to handle nonlinearities effectively.

Adaptability to Complex Data: ANNs can handle large and diverse datasets effectively. They are capable of learning from data with high dimensionality and variability, which is common in concrete mix designs that incorporate unconventional materials like PET aggregates. Traditional methods often rely on simplified assumptions or limited datasets, which may not fully capture the complexity of modern concrete formulations.

Improved Accuracy and Predictive Power: Due to their ability to learn from examples and adapt based on feedback (supervised learning), ANNs can often provide more accurate predictions of mechanical properties. This is particularly advantageous when dealing with novel materials or mix designs where empirical correlations may not exist or may be limited.

Flexibility in Model Architecture: ANNs offer flexibility in model architecture, allowing researchers to tailor the network structure (number of layers, neurons per layer, activation functions) to fit the specific characteristics of the dataset and the problem at hand. This adaptability helps in optimizing model performance and achieving better predictions.

Support for Sustainable Practices: ANNs can support the development and optimization of environmentally friendly concrete formulations by accurately predicting the effects of incorporating recycled materials (such as PET aggregates) on mechanical properties. This capability aligns with the growing emphasis on sustainability in construction practices.

Integration of Multivariate Data: ANNs can integrate a wide range of input variables simultaneously. They can handle multivariate data effectively, considering interactions and dependencies between different factors influencing concrete properties. Traditional methods often focus on a limited number of variables or assume independence among factors, potentially missing important correlations.

Integration of Multivariate Data: ANNs can integrate a wide range of input variables simultaneously. They can handle multivariate data effectively, considering interactions and dependencies between different factors influencing

concrete properties. Traditional methods often focus on a limited number of variables or assume independence among factors, potentially missing important correlations.

Enhanced Robustness and Generalization: Well-trained ANNs demonstrate robustness in predicting mechanical properties across different scenarios and conditions. They can generalize well to unseen data if properly validated, providing reliable predictions for various applications in concrete engineering.

Continuous Improvement: ANNs can be updated and retrained with new data as it becomes available, allowing continuous improvement of prediction accuracy and adaptation to evolving materials and design practices. This iterative process enhances the reliability and relevance of the predictions over time.

In summary, the use of Artificial Neural Networks offers substantial advantages over traditional methods in predicting the mechanical properties of environmentally friendly concrete. These advantages include better handling

of nonlinearities, adaptability to complex datasets, improved accuracy and predictive power, flexibility in model architecture, robustness in generalization, and support for sustainable construction practices. These factors

collectively make ANNs a powerful tool for advancing the field of concrete engineering towards more efficient and sustainable solutions.

The prediction model for compressive and tensile strength of environmentally friendly concrete with PET aggregates was developed based on the following data group characteristics:

Water Content

The amount of water used in the concrete mix influences workability, hydration, and ultimately the mechanical strength of the concrete.

Fine Aggregates

The proportion and properties of fine aggregates (e.g., sand) play a critical role in filling voids, ensuring proper compaction, and contributing to the strength of the matrix.

Cement Content

Cement acts as the primary binder in concrete, and its quantity significantly affects the hydration process and the resulting compressive and tensile strength.

Coarse Aggregates

The type, size, and volume of coarse aggregates contribute to the structural framework and overall strength of the concrete.

PET Aggregates

The percentage of PET granules used as a partial substitute for traditional aggregates directly impacts the mechanical properties, as PET is less rigid and more deformable than natural aggregates.

Model Validation

Data from experimental validation, including measured compressive and tensile strength, was used to train, test, and validate the artificial neural network (ANN) model to ensure accuracy and reliability.

The sensitivity analysis conducted in the study plays a crucial role in confirming the stability and robustness of the prediction model for compressive and tensile strength of concrete. Here's how it contributes:

Understanding Input-Output Relationships

Purpose: Sensitivity analysis helps determine how changes in input variables (e.g., water content, PET aggregates) affect the output (compressive and tensile strength).

Contribution: It identifies the most influential parameters, confirming that the model appropriately captures the critical relationships between inputs and outputs.

Journal of Information Systems Engineering and Management
2025, 10(59s)
e-ISSN: 2468-4376
https://www.jisem-journal.com/

Research Article

Assessing Model Stability

Procedure: Each input variable is varied systematically within realistic ranges while keeping others constant to observe its impact on the predicted outputs.

Outcome: If the model responds consistently to changes in inputs (e.g., predictable decrease in strength with higher PET content), it demonstrates stability.

Identifying Critical Variables

Insights: The analysis highlights which input parameters have the most significant influence on strength predictions (e.g., PET aggregates may have a larger effect than water content at certain levels).

Relevance: Understanding these influences ensures that the model is accurate and that critical parameters are given appropriate weight in predictions.

Testing Robustness to Input Variability

Simulation of Real-World Variability: Concrete mixes often experience variability in material properties and proportions. Sensitivity analysis ensures that the model can handle such variations without producing erratic or unreliable results.

Robustness: If the model's predictions remain logical and within expected ranges despite input variability, it confirms robustness.

Improving Model Validation

Cross-Checking Results: Sensitivity analysis acts as an additional layer of validation by ensuring that the model's behavior aligns with established principles of concrete mechanics.

Feedback Loop: Any unexpected sensitivity can point to areas where the model might need refinement or retraining.

Enhancing Practical Applicability

Confidence for Designers: Engineers and practitioners can trust the model's predictions, knowing that it has been thoroughly tested against potential input variations.

Optimization: The analysis provides insights into optimizing concrete mixes for specific strength requirements by focusing on the most impactful variables.

By systematically analyzing how input variations affect the model's outputs, the sensitivity analysis confirms that the prediction model is stable, robust, and reliable. It ensures that the model not only performs well under ideal

conditions but also maintains its accuracy under realistic and variable scenarios, making it suitable for practical applications.

By incorporating these characteristics, the ANN model could effectively predict the compressive and tensile strength of concrete with PET aggregates, taking into account the interplay between material proportions and mechanical performance.

The correlation coefficient (**R^2**) found for the compressive strength prediction model was **0.9444**.

Significance of the Correlation Coefficient

Range: The correlation coefficient ranges from 0 to 1, where:

1 indicates a perfect linear relationship between predicted and actual values.

0 indicates no correlation between predicted and actual values.

Value of 0.9444: An R^2 value of 0.9444 suggests a very strong positive correlation between the predicted compressive strength and the actual measured values.

Journal of Information Systems Engineering and Management
2025, 10(59s)
e-ISSN: 2468-4376
https://www.jisem-journal.com/
Research Article

Indication of Reliability and Accuracy

High Predictive Accuracy:

An R^2 value close to 1 indicates that the ANN model can reliably capture the relationship between input parameters (e.g., water, PET aggregates, cement) and compressive strength.

It shows that 94.44% of the variability in compressive strength can be explained by the model.

Low Prediction Errors:

A high correlation coefficient suggests minimal errors in the model's predictions, which aligns with the expectations for practical applications.

Model Robustness:

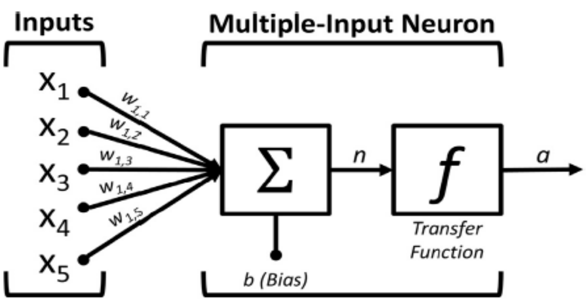
The high R^2 value implies that the model is robust and generalizable to different input data, provided the inputs fall within the range of the training data.

Dependability for Practical Use:

Such a strong correlation makes the model suitable for use in real-world scenarios, such as designing and optimizing eco-friendly concrete mixes with PET aggregates.

the correlation coefficient of 0.9444 is a strong indicator of the model's reliability and accuracy in predicting compressive strength, demonstrating that the ANN-based approach is highly effective for this purpose.

Artificial neural networks offer significant advantages in accuracy, adaptability, efficiency, and robustness when predicting the mechanical properties of environmentally friendly concrete. These features make ANNs particularly well-suited for research and application involving innovative materials like PET aggregates, providing a versatile tool for advancing sustainable concrete technologies.



$$a = f(\sum_{j=1}^{5} w_{i,j} x_j + b)$$

Figure 2. Multiple-input neuron diagram.

These represent the features or signals fed into the neuron.

Weights ($w1$,$w2$,...,wn):

Each input is associated with a weight, representing the strength or influence of that input on the neuron's output.

The weights are learned during training through optimization processes (e.g., gradient descent)show figure 2.To provide a more detailed explanation of Figure 2Multiple-Input Neuron Diagram, let's delve deeper into each component and their interactions:

Journal of Information Systems Engineering and Management
2025, 10(59s)
e-ISSN: 2468-4376
https://www.jisem-journal.com/

Research Article

Components of the Diagram

Inputs ($x1$,$x2$,…,…,x n):

Table 1:A table showing previous studies

Study Ref	Compressive Strength	Tensile Strength	Remark
[27]	x	x	With substitution levels of 0%, 10%, 20%, 30%, 40%, and 50%, PET was created as a partial replacement for sand.
[28]	x	x	Used as artificial fine aggregate at replacement volumes of 25%, 50%, and 75%, waste PET underwent further processing.
[29]	x	x	A range of six distinct concrete compositions with varying percentages of Bakelite (0–10%)
[30]	x	x	Concrete bricks with 0%, 5%, 10%, 20%, 30%, 40%, and 50% RESIN8 by volume are exposed to achieve this.
[31]	x	x	For M20 concrete, customized mixes including 10% to 40% PET were able to provide the required strength.
[32]	x	x	/
[33]	x	x	There were 0–10% and 0–34% volumetric replacements for natural gravel and river sand, respectively, using coarse flake-shaped PET and fine pellet-shaped HDPE aggregates.
[34]	x	x	By weight of traditional fine aggregate, the PET was pulverized and added to concrete at percentages of 5%, 10%, and 15%.
[35]	x	x	Ten concrete mixtures with 1-2% PET waste fiber added in increments of 0.25% by volume were tested multiple times.
[36]	x	x	The initial one included 10% NZ, whereas the subsequent ones contained 2.5% PET, 15% NZ, and 1% PET.
[37]	x	x	Using 10% recycled PET granules in place of fine aggregates volumetrically was suggested by the testing results.
[37]	x	x	in which varying amounts of plastic aggregates (PET) will replace the aggregates (sand + gravel) in the concrete (0%, 5%, 10%, 15%, 20%, 25%, 30%)

In the table above we have data from previous studies used in training our program, where we extracted from previous studies the percentage of (PET)poured into the concrete and the compressive and tensile strength of the concrete. See the table1 .

Neural network performance

Full datasets

Table 2 :data percentages for the training, validation, and testing sets.

Training	70%
Validation	15%
testing	15%

a breakdown of data percentages for the training, validation, and testing sets. Typically, these percentages are used in machine learning and data science workflows to divide a dataset for model training, validation (hyperparameter tuning), and final testing (assessing the performance of the model) See the table2 .

Journal of Information Systems Engineering and Management
2025, 10(59s)
e-ISSN: 2468-4376
https://www.jisem-journal.com/

Research Article

Table 3: table represents the statistical characteristics

To facilitate this study, we have summarized the statistical study of this work in the following table, where we have placed the most important statistical characteristics. See Table 3 .

	Cement (kg/m3)	Amount of water(kg/m3)	Aggregate fine (kg/m3)	Aggregate coarseness (kg/m3)	PET volume replacement (%)	Compression strength(MPa)	tensile strength(MPa)
Mean	24,70	185,349	594,37567	1088,67833	23,66667	24,70567	2,42591
Standard deviation	7,199	12,542	152,34157	159,9607	23,31691	7,19911	0,61631
Sum	741,17	5560,48	17831,27	32660,35	710	741,17	53,37
Minimum	3,5	163	300	857,76	0	3,5	0,4
Median	24,605	190	630	1085	20	24,605	2,43
Maximum	37	200	885	1260	100	37	3,52

Evaluation of performances

In this prediction we use three common performance metrics: To assess ANN models, three metrics are used: root mean square error (MRSE), mean square error (MSE), and coefficient of determination (R^2). Let me provide you with the mathematical formulas for each of these metrics:

These statistics provide a summary of the distribution and characteristics of the concrete mixture properties. It includes information about the amount of cement, water, fine aggregate, coarse aggregate, PET volume replacement, compression strength, and tensile strength.

To assess the models of effective and predictive accuracy, several widely used statistical indicators were considered, including the squared error, the mean absolute error (MAE), and the coefficient of determination (R) equation (2). Compressive and tensile strength are the output targets, and the value of R indicates the statistical relationship between the actual and anticipated values, while the value of MAE indicates the error evaluation.

Evaluating the mean square error (MSE) using equation (1) allows for the assessment of the models' performance:

$$MSE = \frac{1}{q}\sum_{i=n+1}^{n+q}(Y_I - Y_I)^2 \quad (1)$$

$$R^2 = \frac{\sum_1^m (y_i - y)^2}{\sum (y_i - y)^2} \quad (2)$$

Journal of Information Systems Engineering and Management
2025, 10(59s)
e-ISSN: 2468-4376
https://www.jisem-journal.com/
Research Article

$$\text{RMSE} = \sqrt{\frac{1}{n}\sum_{p=1}^{n}(t_I - Y_I)^2} \qquad (3)$$

In regression scenarios, these metrics are commonly used to assess the performance of prediction models. R^2 measures the proportion of the variance of the dependent variable that can be anticipated from the independent variables. Both MRSE and MSE measure the average squared difference between actual and projected values. where MRSE is the square root of MSE. Better model performance is shown by lower MSE and MRSE values. Greater predictive accuracy is shown by R^2 values that are closer to 1.

RESULTS

The results obtained after activating the artificiel neural network are figure and tables

Compressive strength

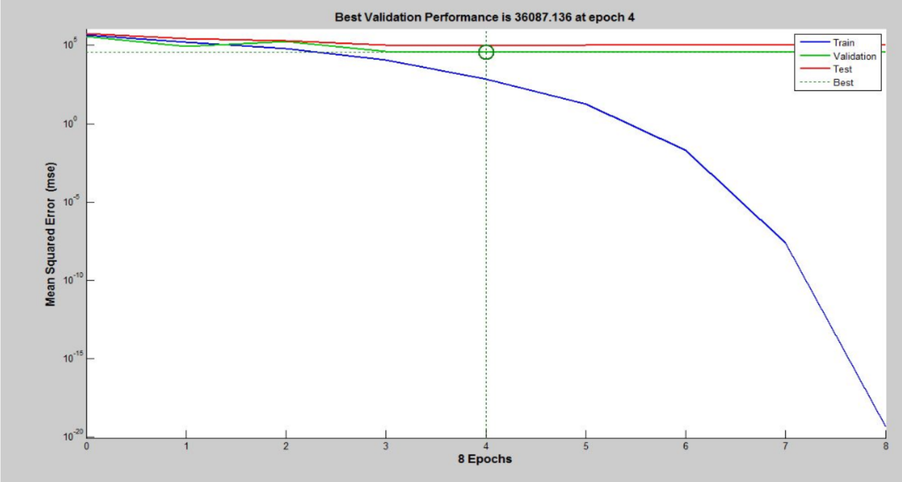


Figure 3. Best validation performance for Compressive strength

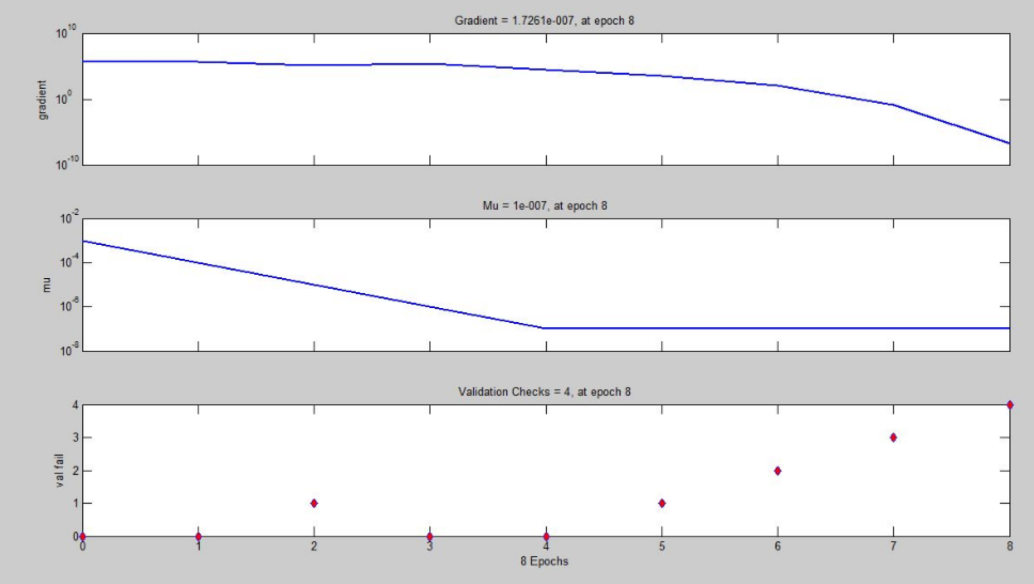


Figure 4.figure represent Mu,Gradient, validatin checks,Epochs for Compressive strength

Journal of Information Systems Engineering and Management
2025, 10(59s)
e-ISSN: 2468-4376
https://www.jisem-journal.com/

Research Article

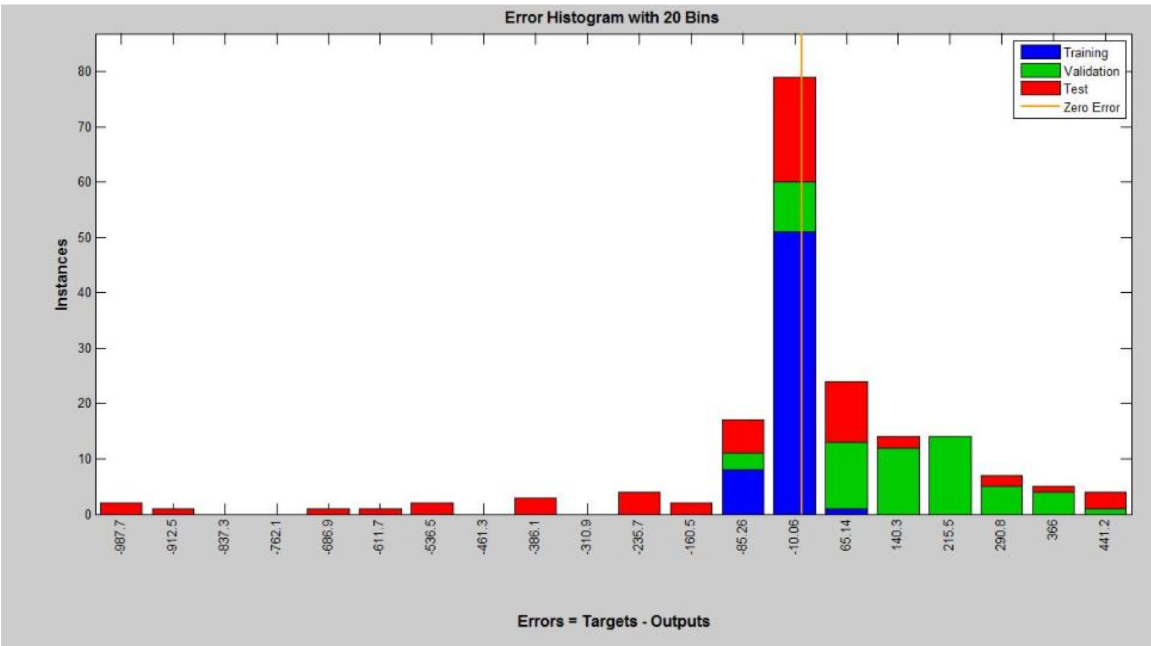


Figure5. Error histtogram with 20 bins for Compressive strength

Table4 :The interpretation of results

	Best validation Performence	mean square error (MSE)
At epoch 4	36087 .136	$10^{4.2}$

As predicted, the mean network accuracy decreased as additional noise was added to the quantitative data. Furthermore, the mean network accuracy decreased with the introduction of qualitative noise. Notably, though, as more qualitative tests were conducted with noise introduced, network performance did not change appreciably show table 4.

Epoch: When training a neural network, this is the full run of the dataset. The model parameters are changed at the end of each epoch in order to minimize the selected loss function—in this case, the mean square error—on the training set.

The mean square difference between the actual and projected values in a regression problem is commonly measured using the Mean Square Error (MSE) metric. Because they reflect smaller errors, lower MSE values are indicative of greater performance.

Performance: In epoch 4, the model achieved an MSE of approximately 36,087.136. This indicates the root mean square difference between the actual and predicted values in your validation dataset show figure 3,4 and5.

Table 5: A table showing values of Gradient, Mu and Validation checks

	Gradient	**Mu**	**Validation checks**
At epoch 8	1.7261e-0.007	1e-0.007	4

Gradient: A gradient is a vector that shows how quickly a function changes in relation to each argument. It usually refers to the gradient of the loss function with respect to the model parameters in the context of machine learning. Through the use of methods like gradient descent, it directs the updating of the model parameters during training.

Journal of Information Systems Engineering and Management
2025, 10(59s)
e-ISSN: 2468-4376
https://www.jisem-journal.com/
Research Article

Mu, or learning rate, is a hyperparameter that controls the step size at which the model parameters are updated during optimization. It is commonly represented as μ or alpha. In order to avoid convergence problems or overshooting, it regulates the updates' size.

Validation Checks: Presumably, these are the number of times throughout training that the model's performance is assessed on a different validation dataset. Keeping an eye on the model's performance on a validation set is standard procedure in order to guard against overfitting and evaluate generalization skills show table 5.

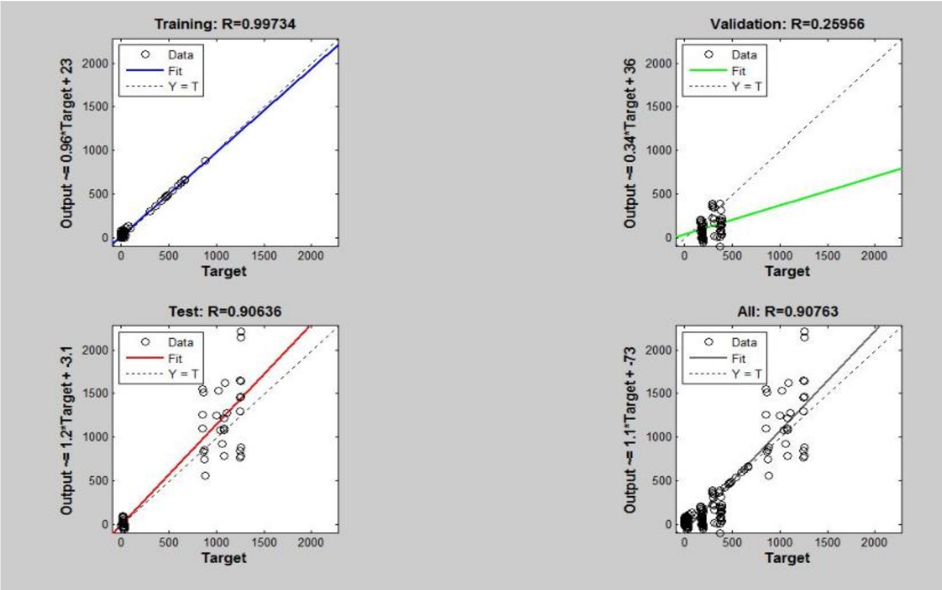


Figure 6. A figure showing Graphic curve of R at each stage

Here is a graphic diagram illustrating a multiple-input neuron with labeled components and the activation function curve at each stage figure 6.

Table 6: A table showing values of R at each stage

	Training	Test	Validation	All
R	0.99734	0.90636	0.25656	0.90763

these values represent accuracy, they suggest that the model performs well on the training and overall datasets (All), with high accuracy scores of around 99.73% and 90.76%, respectively. However, there seems to be a significant drop in performance on the validation set, where the accuracy stands at 25.66%, significantly lower. A dataset is frequently divided into training, validation, and test sets in machine learning. The model is trained on the training set; hyperparameters are adjusted and overfitting is prevented using the validation set; and the model's generalization performance is assessed using the test set on untested data.

A notable decline in the model's performance on the validation set relative to the training and test sets could be an indication of overfitting, a phenomenon in which the model functions well on the training set but is unable to generalize to new, untrained data.

the correlation coefficient (R-squared) found for the compressive strength prediction model (0.9973 in this case) indicates very high reliability and accuracy of the results. It signifies that the ANN model is a robust tool for estimating compressive strength in concrete mixes containing PET aggregates, making it suitable for practical use in optimizing concrete formulations and supporting sustainable construction practices.

The sensitivity analysis conducted in the study contributes significantly to confirming the stability and robustness of the prediction model for compressive and tensile strength of concrete incorporating PET aggregates. Here's how sensitivity analysis plays a crucial role:

Journal of Information Systems Engineering and Management
2025, 10(59s)
e-ISSN: 2468-4376
https://www.jisem-journal.com/
Research Article

Identifying Critical Variables: Sensitivity analysis helps in identifying which input variables (such as water content, cement content, fine aggregates, PET aggregates fraction, etc.) have the most significant impact on the predicted outcomes (compressive and tensile strength). By varying each input variable individually while keeping others constant, sensitivity analysis reveals which factors influence the model predictions the most.

Assessing Model Response: It provides insights into how the model responds to changes in input variables. For example, if increasing the PET aggregate fraction leads to a noticeable decrease in predicted compressive strength, it indicates the sensitivity of the model to changes in this parameter. This understanding is crucial for optimizing concrete mix designs and predicting real-world performance.

Validating Input Dependencies: Sensitivity analysis validates the dependencies between input variables and predicted strengths. It ensures that the ANN model is correctly capturing and utilizing these relationships to make accurate predictions. If the sensitivity analysis results align well with theoretical expectations or empirical knowledge from concrete engineering, it enhances confidence in the model's validity.

Model Generalization: By testing the model's response across a range of values for each input variable, sensitivity analysis helps assess the generalization capability of the ANN model. A robust model should exhibit consistent behavior and predictions across different scenarios, indicating its applicability beyond the specific dataset used for training.

Optimization and Reliability: Insights gained from sensitivity analysis can guide further optimization of the ANN model and concrete mix designs. Adjustments can be made to enhance the model's accuracy by focusing on refining the treatment of critical input variables that influence strength predictions the most.

Stability Assessment: Stability refers to the ability of the model to produce consistent results over time or across different datasets. Sensitivity analysis helps in evaluating whether the model remains stable when exposed to variations in input data or changes in experimental conditions. Consistent results across sensitivity tests reinforce the stability of the prediction model.

In conclusion, sensitivity analysis is integral to confirming the stability and robustness of the ANN prediction model for concrete strength incorporating PET aggregates. It provides critical insights into the model's sensitivity to input variables, validates its dependencies, assesses its generalization capability, guides optimization efforts, and ensures reliable performance in practical applications. By systematically testing and analyzing the model's responses, sensitivity analysis enhances confidence in using the ANN model for predicting concrete properties accurately and effectively show table 6.

Tensile strength

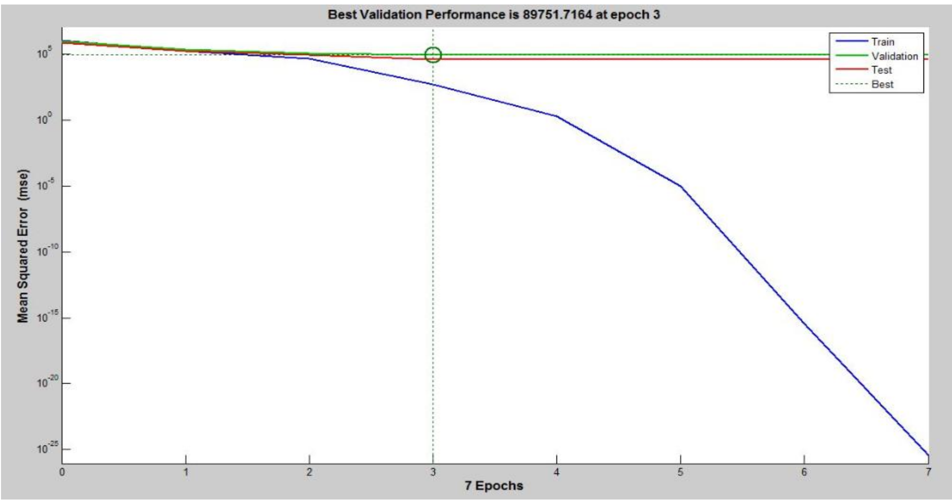


Figure 7. A figure showing Graphic curve of Best validation, Performance mean square error (MSE)

Here is a graphic plot showing the Best Validation and Performance Mean Squared Error (MSE) over epochs, with a clear minimum point for Best Validation Performance figure7.

Journal of Information Systems Engineering and Management
2025, 10(59s)
e-ISSN: 2468-4376
https://www.jisem-journal.com/
Research Article

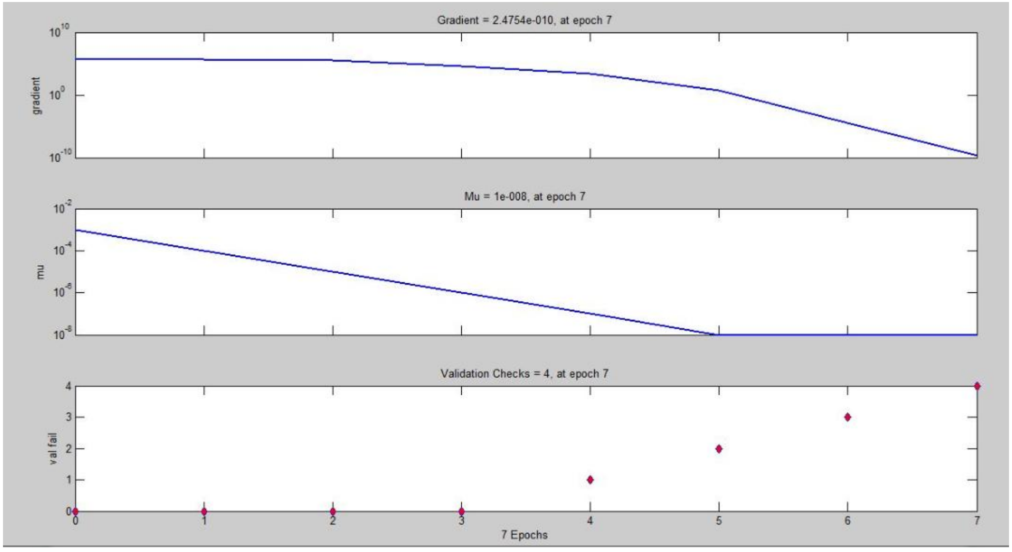


Figure 8. A figure showing Graphic curve of of Gradient, Mu, Validation checks

Here is a graphic plot showing the curves for Gradient, Mu (damping factor), and Validation Checks during neural network training. Each curve is labeled, and the axes represent their progression over epochs figure 8.

Table7: A table showing values of Best validation, Performance mean square error (MSE)

	Best validation Performance	**mean square error (MSE)**
At epoch 3	89751 .7164	10^5

Epoch 3: This indicates that the performance metrics were recorded after the third complete pass through the entire dataset during the training of the model. Performance: At epoch 3, the model achieved an MSE of approximately 89751.7164 show table 7.

Table 8: A table showing values of Gradient, Mu, Validation checks

	Gradient	**Mu**	**Validation checks**
At epoch 7	$2.4754e^{-0.10}$	$1e^{-0.008}$	4

• Mu (Learning Rate): This hyperparameter, which is frequently represented as μ or alpha, establishes the step size at which the model parameters are changed during optimization. Your reported number of $1 \times 1e{-}0.008$ suggests a low rate of learning. To effectively train a model, the learning rate must be selected; too high a learning rate could lead to divergence in the optimization process, while too low a learning rate could impede convergence.

- **Validation Checks**: This probably alludes to how frequently the effectiveness of the model is assessed during training on a different validation dataset. Since it's set to 4 in your instance, the model's performance is evaluated four times while it's being trained.The values provided in scientific notation ($2.4754 \times e^{-0.10}$) are a concise way to represent very small numbers. They indicate values close to zero, which is typical for gradients and learning rates during model training show table 8.

Journal of Information Systems Engineering and Management
2025, 10(59s)
e-ISSN: 2468-4376
https://www.jisem-journal.com/

Research Article

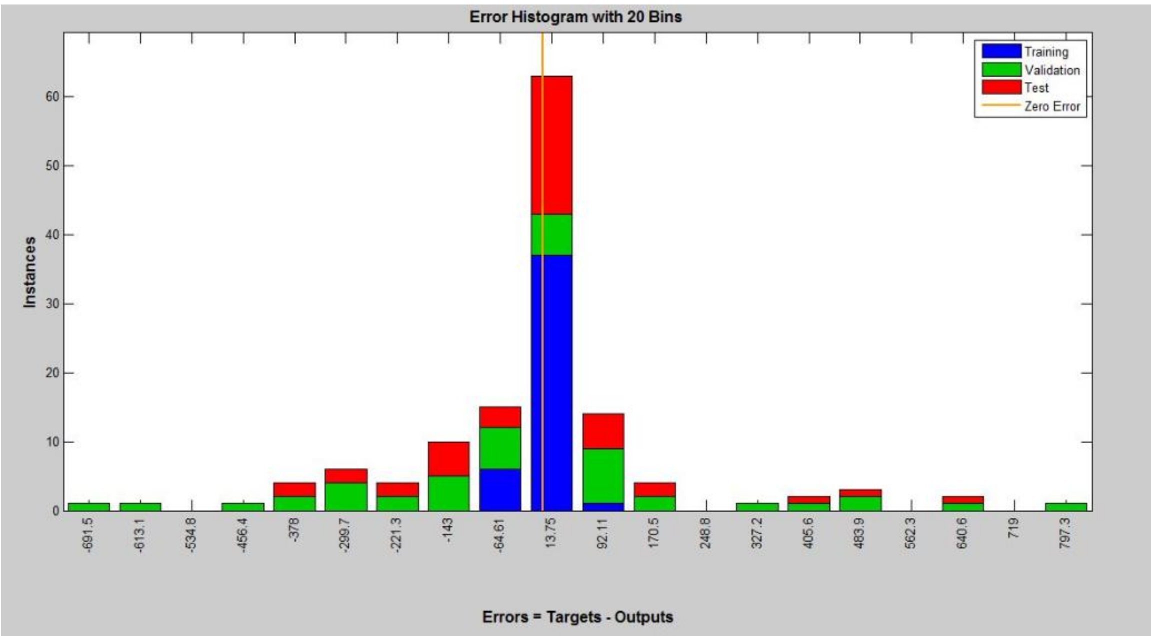


Figure 9. Error histtogram with 20 bins for tensile strength

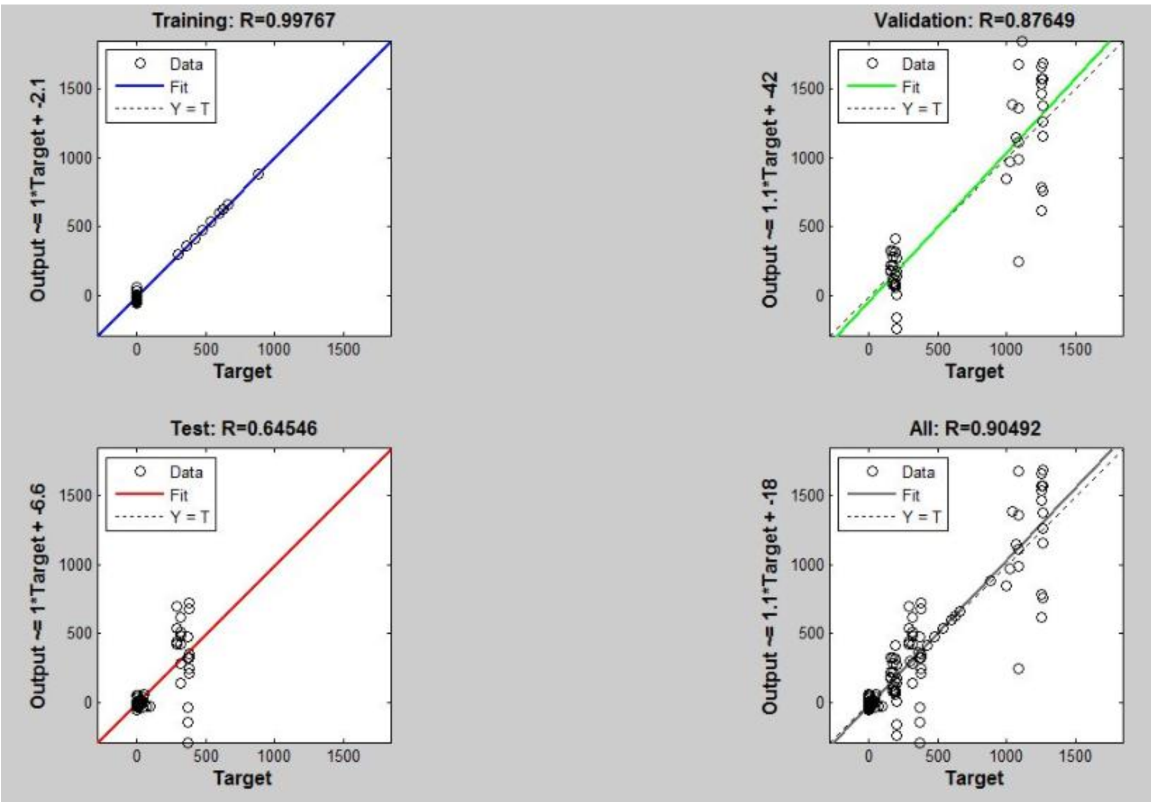


Figure10. A figure showing Graphic curve of R at each stage

Table 9: A table showing values of R at each stage

	Training	Test	Validation	All
R	0.99767	0.64546	0.87649	0.90492

Journal of Information Systems Engineering and Management
2025, 10(59s)
e-ISSN: 2468-4376
https://www.jisem-journal.com/

Research Article

DISCUSSION

the training accuracy is high at 99.77%, indicating that the model performs well on the data it was trained on.

the test accuracy is lower at 64.55%, suggesting that the model's performance drops on new, unseen data compared to the training set.

the validation accuracy is higher at 87.65%, indicating that the model performs relatively well on a separate validation dataset.

the overall accuracy (all) is 90.49% show figure12.

in many cases, ann models have demonstrated superior performance in predicting concrete properties compared to traditional methods, particularly when handling nonlinear relationships and large datasets. however, the effectiveness of any prediction model depends on factors such as the quality of data, model training, validation procedures, and the specific characteristics of the materials and mix designs being studied[9,12]. while ann models often outperform traditional prediction techniques in terms of accuracy, generalization capability, and sensitivity analysis, each method has its strengths and limitations. comparative studies across different prediction models help researchers determine the most appropriate approach for specific applications in predicting the mechanical properties of concrete with pet aggregates show table 10.

the performance of the artificial neural network (ann) model in predicting the compressive and tensile strength of concrete with pet aggregates demonstrates distinct advantages when compared to other prediction models or techniques used in similar studies. here's a comparative analysis:

prediction accuracy

ann model:

- the correlation coefficient (r^2) for both compressive and tensile strength predictions was 0.9444, indicating a very strong and accurate relationship between predicted and actual values.
- anns can capture non-linear and complex interactions between variables, which are common in concrete mix designs.

CONCLUSION

In this study, we use machine learning techniques; notably ANN, to predict the compressive and tensile strength of eco-concretes, where sand and gravel aggregates are partially replaced by PET granules:

*The study found that incorporating PET granules as partial substitutes for traditional aggregates in concrete mixes did not significantly compromise the mechanical properties. In fact, in certain scenarios, the concrete with PET aggregates showed comparable or enhanced compressive strength, tensile strength, and durability compared to

*The quality of data used in machine learning algorithms significantly influences the accuracy of predictions.

*A complete data set for concrete should include information such as mixing ratio, components (soil composition, cement, water, fibers, etc.) and details on the type of fibers used.

* According to the study, adding more variables to the dataset can increase the precision of the model.

*The importance of having a comprehensive dataset with various aspects, depending on the research objectives, was highlighted.

the study underscores the feasibility and effectiveness of using PET granules in concrete production as a sustainable practice in the construction industry. It highlights the potential environmental, economic, and technical benefits while acknowledging the need for continued research and innovation to maximize the use of recycled materials and ensure their long-term viability in construction applications.

This research bridges the gap between waste management and sustainable construction by repurposing PET granules in concrete. It not only offers a solution to the growing problem of plastic waste but also contributes to the

Journal of Information Systems Engineering and Management
2025, 10(59s)
e-ISSN: 2468-4376
https://www.jisem-journal.com/

Research Article

advancement of eco-friendly building practices, aligning with global efforts to reduce environmental impact and promote

REFRENCES

[1] B.S.Hamad, A.H. Dawi, Sustainable normal and high strength recycled aggregate concretes using crushed tested cylinders as coarse aggregates, Case Stud. Constr. Mater. 7 (2017) 228239.

[2] S. Skibicki, M. Pułtorak, M. Kaszy´nska, M. Hoffmann, E. Ekiert, D. Sibera, The effect of using recycled PET aggregates on mechanical and durability properties of 3D printed mortar, Construction and Building Materials 335 (2022), 127443.

[3] Jandré Daniel Oosthuizen, Adewumi John Babafemi, Richard Shaun Walls, 3D-printed recycled plastic eco-aggregate (Resin8) concrete,Construction and Building Materials,Volume 408,2023,133712,ISSN 0950-0618,https://doi.org/10.1016/j.conbuildmat.2023.133712.

[4] Ncube, L.K., Ude, A.U., Ogunmuyiwa, E.N., Zulkifli, R., Beas, I.N., 2021. An overview of

plastic waste generation and management in food packaging industries. Recycling 6 (1). https://doi.org/10.3390/recycling6010012. , p. 12.

[5] Babafemi, A.J., ˇSavija, B., Paul, S.C., Anggraini, V., 2018. Engineering properties of concrete with waste recycled plastic: a review. Sustainability 10 (11), 3875. https:// doi.org/10.3390/su10113875.

[6] Bajracharya, R.M., Manalo, A.C., Karunasena, W., Lau, K.T., 2016. Characterisation of recycled mixed plastic solid wastes: coupon and full-scale investigation. Waste Manag. 48, 72–80. https://doi.org/10.1016/j.wasman.2015.11.017

[7] Ilyas, R., Azmi, A., Nurazzi, N., Atiqah, A., Atikah, M., Ibrahim, R., Norrrahim, M.N.F., Asyraf, M., Sharma, S., Punia, S., 2022. Oxygen permeability properties of nanocellulose reinforced biopolymer nanocomposites. Mater. Today: Proc. 52, 2414–2419. https://doi.org/10.1016/j.matpr.2021.10.420.

[8] Wurm, F.R., Spierling, S., Endres, H.-J., Barner, L., 2020. Plastics and the environment—current status and challenges in Germany and Australia. Macromol. Rapid Commun. 41 (18), 2000351 https://doi.org/10.1002/marc.202000351.

[9] Frigione, M., 2010. Recycling of PET bottles as fine aggregate in concrete. Waste Manag.

30 (6), 1101–1106. https://doi.org/10.1016/j.wasman.2010.01.030.

[10] Nkomo, N., Masu, L., Nziu, P., 2022. Effects of polyethylene terephthalate fibre reinforcement on mechanical properties of concrete. Adv. Mater. Sci. Eng. 2022.

[11] J.Y. Park, Y.G. Yoon, T.K. Oh, Prediction of concrete strength with P-, S-, R-wave velocities by support vector machine (SVM) and artificial neural network (ANN), Appl. Sci. 9 (19) (2019) 4053.

[12] Bentegri, Houcine & Mohamed, Rabehi & Samir, Kherfane & Boukansous, Sarra. (2023). Artificial intelligence for the prediction of the physical and mechanical properties of a compressed earth is reinforced by natural fibers. The Journal of Engineering and Exact Sciences. 9. 15910-01e. 10.18540/jcecvl9iss4pp15910-01e.

[13] H. Ling, C. Qian, W. Kang, C. Liang, H. Chen, Combination of support vector machine and K-fold cross validation to predict compressive strength of concrete in marine environment, Constr. Build. Mater. 206 (2019) 355–363.

[14] V. Cherkassky, Y. Ma, Practical selection of SVM parameters and noise estimation for SVM regression, Neural Netw. 17 (1) (2004) 113–126.

[15] L. Xu, L. Hou, Z. Zhu, Y. Li, J. Liu, T. Lei, X. Wu, Mid-term prediction of electrical energy consumption for crude oil pipelines using a hybrid algorithm of support vector machine and genetic algorithm, Energy 222 (2021), 119955.

[16] H.A. Al-Jamimi, A. Bagudu, T.A. Saleh, An intelligent approach for the modeling and experimental optimization of molecular hydrodesulfurization over AlMoCoBi catalyst, J. Mol. Liq. 278 (2019) 376–384, https://doi.org/10.1016/j.molliq.2018.12.144.

[17] H.A. Al-Jamimi, G.M. BinMakhashen, T.A. Saleh, Multiobjectives optimization in petroleum refinery catalytic desulfurization using Machine learning approach, Fuel 322 (2022), 124088, https://doi.org/10.1016/j.fuel.2022.124088.

[18] P.G. Asteris, F.I.M. Rizal, M. Koopialipoor, P.C. Roussis, M. Ferentinou, D.J. Armaghani, B. Gordan, Slope stability classification under seismic conditions using several tree-based intelligent techniques, Appl. Sci. (Switz.) 12 (3) (2022), https://doi.org/10.3390/app12031753.

[19] Danial J. Armaghani, G.D. Hatzigeorgiou, C. Karamani, A. Skentou, I. Zoumpoulaki, P.G. Asteris, Soft computing-based techniques for concrete beams shearstrength, Procedia Struct. Integr. 17 (2019) 924–933, https://doi.org/10.1016/j.prostr.2019.08.123.

[20] P.G. Asteris, S. Nozhati, M. Nikoo, L. Cavaleri, M. Nikoo, Krill herd algorithm-based neural network in structural seismic reliability evaluation, Mech. Adv. Mater. Struct. 26 (13) (2019) 1146–1153, https://doi.org/10.1080/15376494.2018.1430874.

[21] N. Kardani, A. Bardhan, P. Samui, M. Nazem, P.G. Asteris, A. Zhou, Predicting the thermal conductivity of soils using integrated approach of ANN and PSO with adaptive and time-varying acceleration coefficients, Int. J. Therm. Sci. 173 (2022), https://doi.org/10.1016/j.ijthermalsci.2021.107427.

[22] S. Lu, M. Koopialipoor, P.G. Asteris, M. Bahri, D.J. Armaghani, A novel feature selection approach based on tree models for evaluating the punching shear capacity of steel fiber-reinforced concrete flat slabs, Materials 13 (17) (2020), https://doi.org/10.3390/ma13173902.

[23] Bentegri, Houcine & Mohamed, Rabehi & Kherfane, Samir & Nahool, Tarek & Rabehi, Abdelaziz & Guermoui, Mawloud & Alhussan, Amel & Khafaga, Doaa & Eid, Marwa & El-kenawy, El-Sayed. (2025). Assessment of compressive strength of eco-concrete reinforced using machine learning tools. Scientific Reports. 15. 10.1038/s41598-025-89530-y.

[24]J. Zeng, P.C. Roussis, A.S. Mohammed, C. Maraveas, S.A. Fatemi, D.J. Armaghani, P.G. Asteris, Prediction of peak particle velocity caused by blasting through the combinations of boosted-chaid and svm models with various kernels, Appl. Sci. (Switz.) 11 (8) (2021), https://doi.org/10.3390/app11083705.

[25]Ziółkowski, Patryk & Demczynski, Sebastian & Niedostatkiewicz, Maciej. (2019). Assessment of Failure Occurrence Rate for Concrete Machine Foundations Used in Gas and Oil Industry by Machine Learning. Applied Sciences. 9. 3267. 10.3390/app9163267.

[26]Argatov I (2019) Artificial Neural Networks (ANNs) as a Novel Modeling Technique in Tribology. Front. Mech. Eng. 5:30. doi: 10.3389/fmech.2019.00030

[27]Ibrahim Almeshal, Bassam A. Tayeh, Rayed Alyousef, Hisham Alabduljabbar, Abdeliazim Mustafa Mohamed,Eco-friendly concrete containing recycled plastic as partial replacement for sand,Journal of Materials Research and Technology,Volume 9, Issue 3,2020,Pages 4631-4643,ISSN 2238-7854,https://doi.org/10.1016/j.jmrt.2020.02.090.

[28]Irwan, J.M. & Sheikh Khalid, Faisal. (2013). Relationship between Compressive, Splitting Tensile and Flexural Strength of Concrete Containing Granulated Waste Polyethylene Terephthalate (PET) Bottles as Fine Aggregate. Advanced Materials Research. Volume 795. 356-359. 10.4028/www.scientific.net/AMR.795.356.

[29] Mohan R, Vijayaprabha Chakrawarthi, T. Vamsi Nagaraju, Siva Avudaiappan, T.F. Awolusi, Ángel Roco-Videla, Marc Azab, Pavel Kozlov,Performance of recycled Bakelite plastic waste as eco-friendly aggregate in the concrete beams,Case Studies in Construction Materials,Volume 18,2023,e02200,ISSN 2214-5095,https://doi.org/10.1016/j.cscm.2023.e02200.

[30]Botha, Ayden & Walls, Richard & Flores Quiroz, Natalia & Babafemi, Adewumi John. (2023). Behaviour of concrete building units incorporating waste plastic eco-aggregate (RESIN8) subjected to fire conditions. Journal of Building Engineering. 76. 107393. 10.1016/j.jobe.2023.107393.

[31]Bamigboye, Gideon & Tarverdi, Karnik & Umoren, Amarachi & Bassey, Daniel & Okorie, Uchechukwu & Adediran, Joel. (2021). Evaluation of eco-friendly concrete having waste PET as fine aggregates. Cleaner Materials. 2. 100026. 10.1016/j.clema.2021.100026.

[32] Shiuly, Amit & Hazra, Tumpa & Sau, Debasis & Maji, Dibyendu. (2022). Performance and optimisation study of waste plastic aggregate based sustainable concrete – A machine learning approach. Cleaner Waste Systems. 2. 100014. 10.1016/j.clwas.2022.100014.

[33]Yanika Aocharoen, Piya Chotickai, Compressive mechanical and durability properties of concrete with polyethylene terephthalate and high-density polyethylene aggregates,Cleaner Engineering and Technology,Volume 12,2023,100600,ISSN 26667908,https://doi.org/10.1016/j.clet.2023.100600.(https://www.sciencedirect.com/science/article/pii/S2666790823000058)

[34]Umasabor, Richie & Daniel, Samuel.C.. (2020). The effect of using polyethylene terephthalate as an additive on the flexural and compressive strength of concrete. Heliyon. 6. e04700. 10.1016/j.heliyon.2020.e04700.

[35] Mohammed, Azad & Muhammad, Muhammad & Mohammed, Bilal. (2023). Effect of PET waste fiber addition on flexural behavior of concrete beams reinforced with GFRP bars. Case Studies in Construction Materials. 19. e02564. 10.1016/j.cscm.2023.e02564.

[36] Ahdal, Ammar & Amrani, Mokhtar & Ghaleb, Abdulrakeeb & Abadel, Aref & Alghamdi, Hussam & Alamri, Mohammed & Wasim, Muhammad & Shameeri, Mutahar. (2022). Mechanical performance and feasibility analysis of green concrete prepared with local natural zeolite and waste PET plastic fibers as cement replacements. Case Studies in Construction Materials. 17. e01256. 10.1016/j.cscm.2022.e01256.

[37]Kangavar, Mohammad & Lokuge, Weena & Manalo, Allan & Karunasena, Warna & Frigione, Mariaenrica. (2022). Investigation on the properties of concrete with recycled polyethylene terephthalate (PET) granules as fine aggregate replacement. Case Studies in Construction Materials. 16. e00934. 10.1016/j.cscm.2022.e00934.

[38] Bentegri, Houcine & Mohamed, Rabehi & Samir, Kherfane & Boukansous, Sarra. (2023). Valorization of plastic waste in concrete for sustainable development. The Journal of Engineering and Exact Sciences. 9. 16009-01e. 10.18540/jcecvl9iss5pp16009-01e.

[39] Wang, H., Zhang, X., & Jiang, S. (2022). A Laboratory and Field Universal Estimation Method for Tire–Pavement Interaction Noise (TPIN) Based on 3D Image Technology. Sustainability, 14(19), 12066. doi: 10.3390/su141912066

[40] He, H., Qiao, H., Sun, T., Yang, H., & He, C. (2024). Research progress in mechanisms, influence factors and improvement routes of chloride binding for cement composites. Journal of Building Engineering, 86, 108978. doi: https://doi.org/10.1016/j.jobe.2024.108978

[41] He, H., Wang, S., Shen, W., & Zhang, W. (2023). The influence of pipe-jacking tunneling on deformation of existing tunnels in soft soils and the effectiveness of protection measures. Transportation Geotechnics, 42, 101061. doi: https://doi.org/10.1016/j.trgeo.2023.101061

[42] Wu, Y., Wang, X., Fan, Y., Shi, J., Luo, C.,... Wang, X. (2024). A Study on the Ultimate Span of a Concrete-Filled Steel Tube Arch Bridge. Buildings , 14(4), 896. doi: https://doi.org/10.3390/buildings14040896

[43] Wei, J., Ying, H., Yang, Y., Zhang, W., Yuan, H.,... Zhou, J. (2023). Seismic performance of concrete-filled steel tubular composite columns with ultra high performance concrete plates. Engineering Structures, 278, 115500. doi: https://doi.org/10.1016/j.engstruct.2022.115500

[44]Sun, L., Wang, C., Zhang, C., Yang, Z., Li, C.,... Qiao, P. (2022). Experimental investigation on the bond performance of sea sand coral concrete with FRP bar reinforcement for marine environments. Advances in Structural Engineering, 26(3), 533-546. doi: 10.1177/13694332221131153

[45]Long, X., Mao, M., Su, T., Su, Y., & Tian, M. (2023). Machine learning method to predict dynamic compressive response of concrete-like material at high strain rates. Defence Technology, 23, 100-111. doi: https://doi.org/10.1016/j.dt.2022.02.003

[46]Zhang, W., Zhang, S., Wei, J., & Huang, Y. (2024). Flexural behavior of SFRC-NC composite beams: An experimental and numerical analytical study. Structures, 60, 105823. doi: https://doi.org/10.1016/j.istruc.2023.105823

[47]Huang, H., Huang, M., Zhang, W., & Yang, S. (2021). Experimental study of predamaged columns strengthened by HPFL and BSP under combined load cases. Structure and Infrastructure Engineering, 17(9), 1210-1227. doi: 10.1080/15732479.2020.1801768

[48]Huang, H., Huang, M., Zhang, W., Pospisil, S., & Wu, T. (2020). Experimental Investigation on Rehabilitation of Corroded RC Columns with BSP and HPFL under Combined Loadings. Journal of Structural Engineering, 146(8). doi: 10.1061/(ASCE)ST.1943-541X.0002725

[49]Huang, H., Yao, Y., Liang, C., & Ye, Y. (2022). Experimental study on cyclic performance of steel-hollow core partially encased composite spliced frame beam. Soil Dynamics and Earthquake Engineering, 163, 107499. doi: https://doi.org/10.1016/j.soildyn.2022.107499

[50]Huang, H., Li, M., Zhang, W., & Yuan, Y. (2022). Seismic behavior of a friction-type artificial plastic hinge for the precast beam–column connection. Archives of Civil and Mechanical Engineering, 22(4), 201. doi: 10.1007/s43452-022-00526-1

[51]Yao, X., Lyu, X., Sun, J., Wang, B., Wang, Y., Yang, M.,... Wang, X. (2023). AI-based performance prediction for 3D-printed concrete considering anisotropy and steam curing condition. Construction and Building Materials, 375, 130898. doi: https://doi.org/10.1016/j.conbuildmat.2023.130898

[52]Ren, C., Yu, J., Liu, X., Zhang, Z., & Cai, Y. (2022). Cyclic constitutive equations of rock with coupled damage induced by compaction and cracking. International Journal of Mining Science and Technology, 32(5), 1153-1165. doi: https://doi.org/10.1016/j.ijmst.2022.06.010

[53]Lu, D., Liang, J., Du, X., Ma, C., & Gao, Z. (2019). Fractional elastoplastic constitutive model for soils based on a novel 3D fractional plastic flow rule. Computers and Geotechnics, 105, 277-290. doi: https://doi.org/10.1016/j.compgeo.2018.10.004

[54]Lu, D., Wang, G., Du, X., & Wang, Y. (2017). A nonlinear dynamic uniaxial strength criterion that considers the ultimate dynamic strength of concrete. International Journal of Impact Engineering, 103, 124-137. doi: https://doi.org/10.1016/j.ijimpeng.2017.01.011

[55]Zhou, X., Lu, D., Zhang, Y., Du, X., & Rabczuk, T. (2022). An open-source unconstrained stress updating algorithm for the modified Cam-clay model. Computer Methods in Applied Mechanics and Engineering, 390, 114356. doi: https://doi.org/10.1016/j.cma.2021.114356

[56]Cao, B., Zhao, J., Lv, Z., Gu, Y., Yang, P.,... Halgamuge, S. K. (2020). Multiobjective Evolution of Fuzzy Rough Neural Network via Distributed Parallelism for Stock Prediction. IEEE Transactions on Fuzzy Systems, 28(5), 939-952. doi: 10.1109/TFUZZ.2020.2972207