Bulletin of Computational Intelligence
https://www.sciltp.com/journals/bci

*Article*

# Predicting the Compressive Strength of Fly Ash Composite Foam Concrete Using Artificial Neural Networks and Soft Computing Techniques

Aidn Maqsud Muhammed [1], Mohamed Amin Idrees Omer [1], Rahand Shaho Haider [1], Namarq Tareq Abd [1] and Ahmed Salih Mohammed [2,3,*]

1 Civil Engineering Department, The American University of Iraq, Sulaimani 46001, Iraq
2 Civil Engineering Department, College of Engineering, University of Sulaimani, Sulaimani 460013, Iraq
3 The American University of Iraq, Sulaimani (AUIS), Sulaimani 46001, Iraq
* Correspondence: ahmed.mohammed@univsul.edu.iq

**How To Cite:** Muhammed, A.M.; Omer, M.A.I.; Haider, R.S.; et al. Predicting the Compressive Strength of Fly Ash Composite Foam Concrete Using Artificial Neural Networks and Soft Computing Techniques. *Bulletin of Computational Intelligence* **2026**, *2*(1), 83–102. https://doi.org/10.53941/bci.2026.100005

Received: 30 October 2025
Revised: 9 November 2025
Accepted: 21 November 2025
Published: 20 January 2026

**Abstract:** This study develops soft-computing models to predict the compressive strength of Fly Ash Composite Foam Concrete (FFC), a lightweight, sustainable cementitious material. A database of 302 experimental records was compiled from previous studies, including wet density, cement content, fly ash content, sand content, water–binder ratio, foam content, and curing age. Five predictive models were evaluated, with the Artificial Neural Network (ANN) achieving the best performance, yielding an accuracy of 98% and the lowest prediction error. Sensitivity analysis identified wet density, cement content, and foam content as the most influential variables. The results demonstrate that soft computing approaches can significantly reduce experimental effort, lower costs, and support the sustainable design of FFC mix ratios for diverse applications.

**Keywords:** FFC (fly ash composite foam concrete); compressive strength; soft computing; mix design optimization; artificial neural network (ANN); sustainability

## 1. Introduction

Approximately 8% of global $CO_2$ emissions are from cement production, making it a significant contributor to climate change [1,2]. Cement, the second-most widely used product on Earth after water, underscores the urgent need for sustainable alternatives. This study presents Fly Ash Composite Foam Concrete (FFC) as a feasible alternative, in which a fraction of cement is substituted with fly ash, a byproduct of coal combustion. Compared to traditional concrete, FFC reduces density and carbon footprint, and improves thermal insulation qualities [3,4]. FFC provides significant technical advantages in addition to environmental benefits. Its porous microstructure increases durability, resists cracking, and improves acoustic insulation [5,6]. The lightweight nature of FFC makes it suitable for both structural and non-structural applications by reducing dead load. The chemical interactions among foam components produce a strong microstructure that balances mechanical strength with reduced weight [4]. Furthermore, by using recycled materials and minimizing embodied energy, FFC contributes to the circular economy [6]. Traditional evaluation requires a 28-day curing period and substantial effort, resulting in increased costs and building duration [1]. As a result, there is an increased demand for quicker, non-destructive prediction approaches. Soft computing models have demonstrated significant potential in this field, offering data-driven models that can capture complex nonlinear interactions and yield accurate strength estimates with reduced reliance on physical testing [1,6]. Predictive models, such as Artificial Neural Networks (ANNs) and Interaction Models (INs), have proven effective for estimating the compressive strength of complex concrete mixes. These methods excel at processing large datasets, identifying patterns, and modeling behaviors that are difficult to detect with traditional statistical techniques. In this study, 302 mix design datasets (filtered from an initial 320 samples after outlier removal) were used to build predictive models for FFC compressive strength.

The dataset was divided into 66% for training, 17% for testing, and 17% for validation. To assess the model's performance and accuracy, several statistical metrics were used, including $R^2$, Root Mean Square Error (RMSE), Mean Absolute Error (MAE), and Scatter Index. This study employs multiple soft computing models, including Linear Regression (LR), Multilinear Regression (MLR), Full Quadratic Model (FQ), Interaction Model (IN), and Artificial Neural Network (ANN), and compares them. The results of this study indicate that the ANN performed exceptionally well, achieving higher accuracy in predicting compressive strength and outperforming all other techniques. This study presents an analytical approach to predict and optimize FFC mix design, thereby supporting the broader adoption of sustainable building materials. The application of soft computing promotes economical, ecologically friendly building processes while increasing efficiency by reducing dependency on conventional laboratory techniques. This study further explores the sustainability potential of FFC, emphasizing its energy-saving, environmental, and practical benefits. The partial replacement of cement with fly ash significantly reduces $CO_2$ emissions, aligning with ecological goals [2,3]. This substitution also limits construction waste and supports the reuse of industrial byproducts [4,5]. By minimizing resource extraction, FFC contributes to long-term environmental conservation [6]. In addition, soft computing models facilitate the rapid and precise optimization of mix designs [1,7], improving performance while lowering material and energy demands [8]. These models can incorporate real-time data to enable dynamic, on-site adjustments [9,10]. Such features enhance construction efficiency and reduce the need for repeated laboratory testing [11]. Overall, these innovations position FFC as a scalable, sustainable material aligned with global development goals [6,12].

Fly Ash Composite Foam Concrete (FFC) comprises fly ash, cement, sand, foam, and a specific water-binder ratio. Fly ash, derived from the burning of coal, can replace cement, making it a recycled, eco-friendly material that is also more cost-effective. Adding foam to FFC reduces the concrete's weight by incorporating air bubbles and providing additional thermal insulation. The water-binder mix affects the concrete's strength and workability. Decreasing the water content results in stronger concrete; however, it reduces workability [13]. FFC must be significantly lighter than regular concrete, requiring less structural support [1]. Its air pockets will make it soundproof and more temperature-controlled [5].

Due to FFC's lightweight properties, it simplifies application on construction sites. Additionally, FFC can be used to fill gaps due to its lightweight nature, strength, and insulating properties. With FFC's heat-retention prowess, it can maintain lower interior temperatures in summer while keeping them higher in winter, allowing houses to use less electricity and making the environment cleaner. FFC can also work as a waterproof shield, making walls more energy-efficient [6]. FFC could effectively minimize external noise. Furthermore, FFC requires a lower water-binder ratio, which makes it easier to work with by reducing the needed curing time.

FFC is eco-friendly because it uses fly ash, a waste material [5]. Additionally, cement production can produce more $CO_2$ than FFC, making it less environmentally sustainable [5]. Cement is not a reliable insulator, which makes it less eco-friendly because it requires more electricity to maintain a consistent temperature difference between the inside and outside. In contrast, FFC offers better insulation and sustainability. Additionally, Soft computing models will help the industry by conserving resources, eliminating material waste, and enabling tests to be conducted as frequently as needed. This will help the global industry become more efficient with its resource expenditure. The combination of different soft computing models can aid faster, more error-free mix design optimization, thereby enhancing their applicability in real-life construction.

The waste-derived and nano-enhanced materials were studied to evaluate their effect on the residual compressive strength (RCS) of concrete exposed to high temperatures. Granite and marble waste powders (1–9% cement replacement) were initially tested for their impact on compressive strength, followed by the creation of hybrid mixes incorporating nano carbon tubes (NCTs) and nano alumina (NAl). A total of 288 and 156 experimental data points were used to train several machine learning (ML) and metaheuristic models, including the Water Cycle Algorithm (WCA), Genetic Algorithm (GA), Artificial Neural Networks (ANN), Fuzzy Logic (FL), and Multiple Linear Regression (MLR). The WCA model consistently showed the highest predictive accuracy, closely followed by ANN and FL, with mean absolute errors below 4 $kg/cm^2$. The best mixture included 9% waste granite powder (WGP) and 5% waste marble powder (WMP), which retained 59.6% more RCS after exposure to 800 °C for 2 h. The nonlinear RCS prediction equations derived from WCA and GA exhibited excellent regression performance. Sensitivity analyses (using ANN weights and SHAP interpretation) indicated that temperature and exposure duration were the most influential factors, followed by the proportions of NAl, NCTs, WGP, and WMP, respectively [14,15].

*Research Objectives*

In this study, 302 mix design datasets (filtered from an initial 320 samples after outlier removal) were used to develop predictive models for the compressive strength of FFC. The dataset was divided into 66% for training, 17% for testing, and 17% for validation. Model performance was evaluated using statistical error metrics, including $R^2$, Root Mean Square Error (RMSE), Mean Absolute Error (MAE), and Scatter Index (SI). Multiple soft computing models were employed, namely Linear Regression (LR), Multilinear Regression (MLR), Full Quadratic Model (FQ), Interaction Model (IN), and Artificial Neural Network (ANN). Among these, the ANN model demonstrated the best performance, achieving the highest predictive accuracy for compressive strength. This analytical approach provides a framework for optimizing FFC mix design and supports the broader adoption of sustainable building materials.

## 2. Methodology

The methodology of this study is illustrated in Figure 1, which outlines the steps undertaken. The dataset used for this research was compiled from prior FFC-based research, comprising 302 datasets. The summary of the data used in this research, including averages for the seven inputs, the strength result, units, and ranges, is shown in Table 1. The data was split into training, testing, and validation sets to ensure more accurate models. The initial set, comprising 202 datasets, was designated as the training dataset. The second group was defined as the test set, and the third as the validation dataset. The dataset was divided into 66% for training, 17% for testing, and 17% for validation. After analyzing the data, the overall $R^2$ increased to a very suitable number. The parameters that are selected as input variables are wet density (WD), cement content (CC), fly ash content (FAC), sand content (SC), water/binder ratio (WBD), foam content (FC), curing age (CA), and compressive strength (CS). The training, testing, and validating dataset groups were applied to multiple models to determine the coefficient of determination ($R^2$), root mean squared error (RMSE), mean absolute error (MAE), scatter Index (SI), and objective (OBJ). These numbers indicate how well the model aligns with the data. The predictive models used in this study are linear regression (LR), complete multilinear regression (MLR), full quadratic model (FQ), interaction model (IN), and artificial neural networks (ANN).

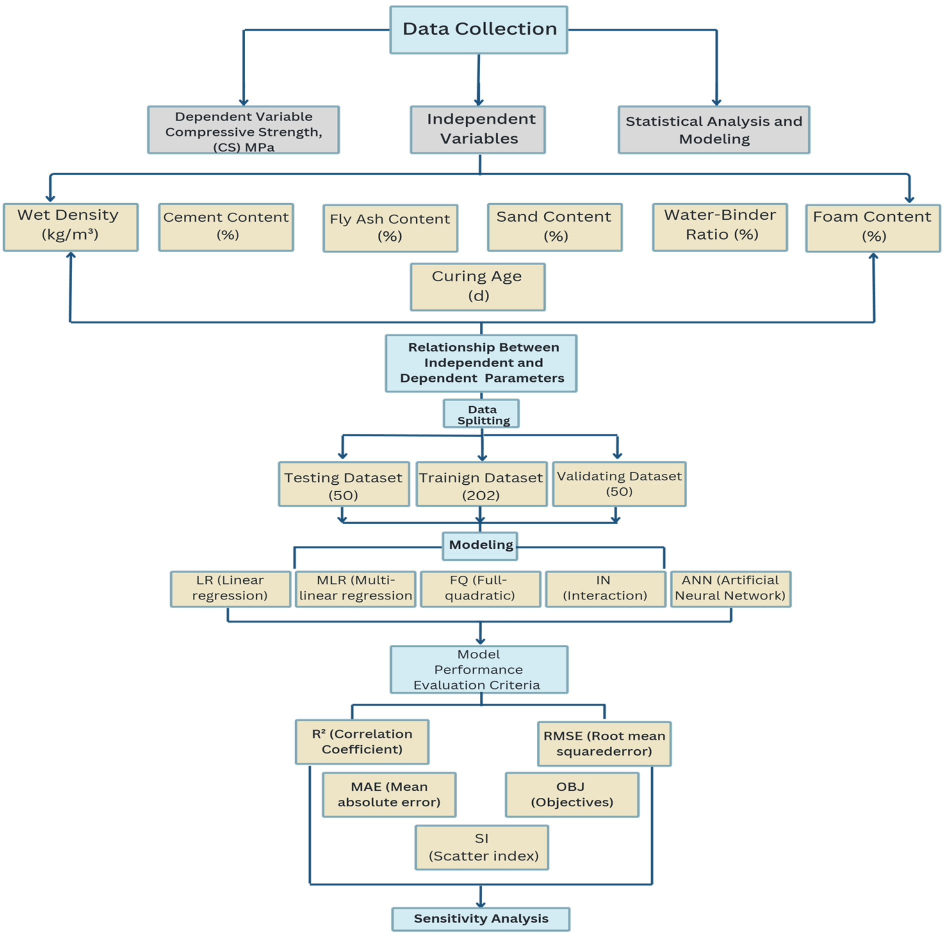



**Figure 1.** The flowchart diagram for the study.

**Table 1.** Dataset information.

| Sources | Numbers | Proportion (%) | Sources | Numbers | Proportion (%) |
|---|---|---|---|---|---|
| [16] | 36 | 11 | [17] | 17 | 5 |
| [18] | 35 | 11 | [19] | 16 | 5 |
| [20] | 24 | 8 | [21] | 16 | 5 |
| [20] | 24 | 8 | [22] | 15 | 5 |
| [23] | 18 | 6 | [24] | 15 | 5 |
| [25] | 18 | 6 | [26] | 14 | 4 |
| [27] | 18 | 6 | [16] | 7 | 2 |
| [28] | 18 | 6 | [26] | 6 | 2 |
| [29] | 18 | 6 | [30] | 5 | 2 |

### *2.1. Overview of Applied Models*

#### 2.1.1. Linear Regression Model

Linear regression (LR) modeling is a statistical approach used to predict the relationship between independent and dependent variables by fitting a linear equation to observed data, thereby predicting the compressive strength of FFC. This model demonstrates that soft computing models, particularly linear regression, can enhance the efficiency of concrete mix design by reducing the need for extensive laboratory testing. Training, testing, and validating the LR model ensures its predictive accuracy and reliability, making it a viable alternative for preliminary strength assessments. The linear model uses Equation (1) to determine the optimal compressive strength. LR model's compressive strength is based on input parameters, as shown in Equation (1).

$$CS\ (MPa) = A + B(WD) + C(CC) + D(FAC) + E(SC) + F(WBR) + G(FC) \ + H(CA) \tag{1}$$

The independent parameters are wet density ($WD$), cement content ($CC$), fly ash content ($FAC$), sand content ($SC$), water/binder ratio ($WBR$), foam content ($FC$), and curing age ($CA$). The dependent parameter is compressive strength ($CS$). The A to H are the model parameters.

#### 2.1.2. Multi-Linear Regression Model

The third model employed in this study was a statistical soft-computing technique, specifically the multiple linear regression (MLR) model. It was used to analyze the Fly Ash Composite Foam Concrete (FCC) and its compressive strength. The MLR model is the relationship between various independent variables, including wet density, cement content, fly ash content, sand content, water-binder ratio, foam content, and curing age. To ensure that only the most significant independent variables have a meaningful effect on the dependent variable, each relationship was assessed by estimating a regression coefficient for each independent variable. The general formula for the multi-linear regression model is:

$$\begin{aligned} CS\ (MPa) = A &\times (B \times (WD)^{B_1}) \times (C \times (CC)^{B_2}) \times (D \times (FAC)^{B_3}) \times (E \times (SC)^{B_4}) \times (F \times (WBR)^{B_5}) \\ &\times (G \times (FC)^{B_6}) \times (H \times (CA)^{B_7}) \end{aligned} \tag{2}$$

where $B_1$ to $B_7$ represent the model parameters.

#### 2.1.3. Full Quadratic Model

The Full quadratic model (FQ) was the third model used; a higher-order statistical technique employed to achieve complex nonlinear relationships among variables. This model was applied to predict the compressive strength of FFC concrete. The FQ model captures the linear relationship between input and output variables, including their interactions and squared terms, providing a more comprehensive analysis than simpler regression methods. Including quadratic terms helps the model capture the complex patterns in concrete mixes containing recycled materials, such as fly ash. The general form of the Full Quadratic regression model is expressed as:

$$\begin{aligned} CS\ (MPa) = A &+ B(WD) + C(CC) + D(FAC) + E(SC) + F(WBR) + G(FC) \ + H(CA) + \big(P(WD) \times (CC)\big) + \big(Q(WD) \times (FAC)\big) \\ &+ \big(R(WD) \times (SC)\big) + \big(S(WD) \times (WBR)\big) + \big(T(WD) \times (FC)\big) + \big(U(WD) \times (CA)\big) \ + \big(V(CC) \times (FAC)\big) \\ &+ \big(W(CC) \times (SC)\big) + \big(X(CC) \times (WBR)\big) + \big(Y(CC) \times (FC)\big) + \big(Z(CC) \times (CA)\big) + \big(AA(FAC) \times (SC)\big) \\ &+ \big(AB(FAC) \times (WBR)\big) + \big(AC(FAC) \times (FC)\big) + \big(AD(FAC) \times +(CA)\big) + \big(AE(SC) \times (WBR)\big) \\ &+ \big(AF(SC) \times (FC)\big) + \big(AG(SC) \times (CA)\big) + \big(AH(WBR) \times (FC)\big) + \big(AI(WBR) \times (CA)\big) \\ &+ \big(AJ(FC) \times (CA)\big) + I(WD)^2 + J(CC)^2 + K(FAC)^2 + L(SC)^2 + M(WBR)^2 + N(FC)^2 + O(CA)^2 \end{aligned} \tag{3}$$

where $A$ to $AJ$ are representing the model parameters.

2.1.4. Interaction Model

The fourth model used in this study is the multiplicative interaction regression model, which is employed to examine the influence of one independent variable on changes in the dependent variable in relation to another variable. This structure enables the modeling of conditional relationships and mitigates bias associated with key components. Particularly useful for capturing moderation effects, the model explains that coefficients on constitutive terms represent effects only when the interacting variable is zero. This approach is crucial for analyzing systems where relationships among variables are not uniform across conditions. The general form of the interaction model is expressed as:

$$\begin{aligned} CS\ (MPa) = {} & A + B(WD) + C(CC) + D(FAC) + E(SC) + F(WBR) + G(FC) \ + H(CA) \\ & + \big(I(WD) \times (CC)\big) + \big(J(WD) \times (FAC)\big) + \big(K(WD) \times (SC)\big) + \big(L(WD) \times (WBR)\big) \\ & + \big(M(WD) \times (FC)\big) + \big(N(WD) \times (CA)\big) \ + \big(O(CC) \times (FAC)\big) + \big(P(CC) \times (SC)\big) \\ & + \big(Q(CC) \times (WBR)\big) + \big(R(CC) \times (FC)\big) + \big(S(CC) \times (CA)\big) + \big(T(FAC) \times (SC)\big) \\ & + \big(U(FAC) \times (WBR)\big) + \big(V(FAC) \times (FC)\big) + \big(W(FAC) \times +(CA)\big) \\ & + \big(X(SC) \times (WBR)\big) + \big(Y(SC) \times (FC)\big) + \big(Z(SC) \times (CA)\big) + \big(AA(WBR) \times (FC)\big) \\ & + \big(AB(WBR) \times (CA)\big) + \big(AC(FC) \times (CA)\big) \end{aligned} \tag{4}$$

where $A$ to $AC$ are representing the model parameters.

2.1.5. Artificial Neural Network Model

Artificial Neural Networks (ANNs) help predict the strength of Fly Ash Composite Foam Concrete (FFC), indicating its ability to withstand heavy loads without breaking. In this study, an artificial neural network (ANN) was employed to analyze factors such as the material mix, curing time, and fly ash quality to examine the impact and strength of FFC. The model was highly accurate, with a score of 0.99, indicating that it could predict the strength almost perfectly. It helps analyze the data more effectively to determine the ideal compressive strength. This is beneficial because it is more time- and cost-efficient than conducting multiple lab tests. ANN also helps determine the optimal material combination to enhance FFC strength, which is particularly useful for building projects [31]. It can handle large amounts of data and identify patterns that older methods might neglect, making it ideal for FFC, where success depends on many factors working together. Once trained, the ANN can make more accurate predictions, assisting engineers in making decisions. The ANN model predicts compressive strength by directing input variables through a network of hidden nodes (Node 1, Node 2, Node n) to an output node (Node 0). The model computes its output from weighted inputs and a bias term. The bias allows the activation level of each node to be shifted, thereby improving the model's fit to the data by altering the response curve of the activation function.

## 3. Performance Evaluation of ML Models

Coefficient of determination ($R^2$), Root Mean Squared Error (RMSE), Mean Absolute Error (MAE), Objective function (OBJ), and Scatter Index (SI) were used to assess the models' dependence on the collected database. These correlations are visualized in Figure 2. These measures help evaluate the work efficiency of the soft computing methods. Several tests were conducted to determine the optimal settings for the key factors. Equations (5)–(9) represent the statistical parameters used to determine each of the mentioned criteria.

$$R^2 = 1 + \left( \frac{\sum_i (Yp - Yi)^2}{\sum_i (Yi - mean\ Yi)^2} \right)^2 \tag{5}$$

$$RMSE = \sqrt{\frac{\sum_i (Yp - Yi)^2}{N}} \tag{6}$$

$$MAE = \frac{\sum_i (|Yp - Yi|)^2}{n} \tag{7}$$

$$OBJ = \left( \frac{n_{tr}}{n_{all}} \times \frac{RMSE_{tr} + \ MAE_{tr}}{R_{tr}^2 + 1} \right) + \left( \frac{n_{tst}}{n_{all}} \times \frac{RMSE_{tst} + \ MAE_{tst}}{R_{tst}^2 + 1} \right) + \left( \frac{n_{vdt}}{n_{all}} \times \frac{RMSE_{vdt} + \ MAE_{vdt}}{R_{vdt}^2 + 1} \right) \tag{8}$$

$$SI = \frac{RMSE}{mean\ Yi} \tag{9}$$

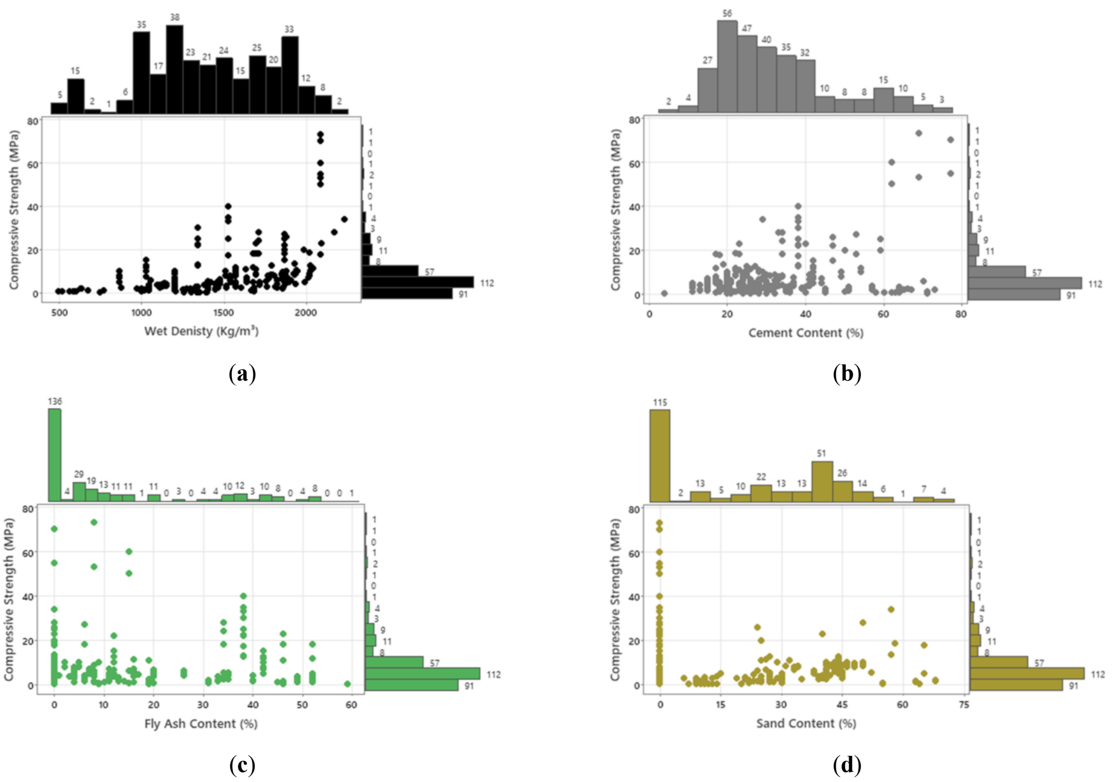
- $Yp$ denotes the predicted value of CS,
- $Yi$ represents the tested value of CS,
- $mean\ Yi$ is the average of the tested data,
- $n_{all}$ refers to the total number of datasets used (all training, testing, and validating),
- $n_{tr}$ is a value representing the number of training datasets,
- $n_{tst}$ is a value representing the number of testing datasets,
- $n_{vdt}$ is a value representing the number of validating datasets,
- $N$ is the total number of datasets in the dataset.

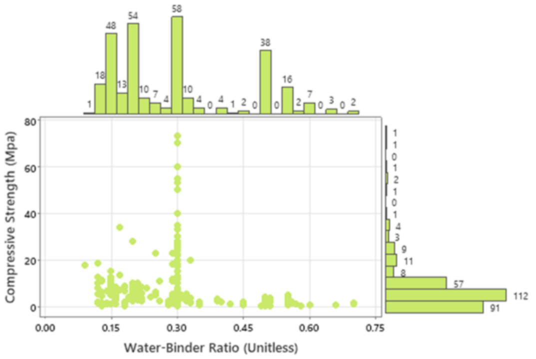
The coefficient of determination ($R^2$) ranges between 0 and 1, where 1 indicates a perfect model fit. For RMSE (Root Mean Square Error), MAE (Mean Absolute Error), and OBJ (Objective Function) values, the range extends from 0 to infinity. As the value decreases, it will be shown. As the value decreases, it indicates superior model performance, with zero being the ideal case. Figure 3 illustrates marginal plots of the distributions of these variables. The Scatter Index (SI) is a key metric for evaluating model accuracy. An SI value below 0.1 is generally considered acceptable. The results showed that the Artificial Neural Network (ANN) performed best in predicting compressive strength values. The comparative RMSE and MAE values for each model are summarized in Table 2. Figure 4 shows the frequency distribution of compressive strength, highlighting the most frequent values.

| | WD | CC | FAC | SC | WBR | FC | CA | CS |
|---|---|---|---|---|---|---|---|---|
| WD | 1 | | | | | | | |
| CC | -0.335 | 1 | | | | | | |
| FAC | -0.168 | -0.271 | 1 | | | | | |
| SC | 0.372 | -0.514 | -0.455 | 1 | | | | |
| WBR | -0.515 | 0.324 | 0.101 | -0.686 | 1 | | | |
| FC | 0.333 | -0.257 | -0.363 | -0.034 | 0.075 | 1 | | |
| CA | -0.136 | 0.002 | 0.180 | -0.177 | 0.140 | -0.033 | 1 | |
| CS | 0.474 | 0.302 | 0.097 | -0.149 | -0.190 | -0.194 | 0.092 | 1 |

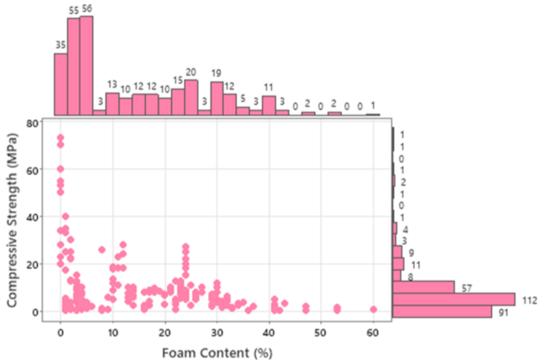
1
0.67
0.33
0
-0.33
-0.67
-1

**Figure 2.** Correlation matrix for the coefficient of determination between dependent and independent variables.

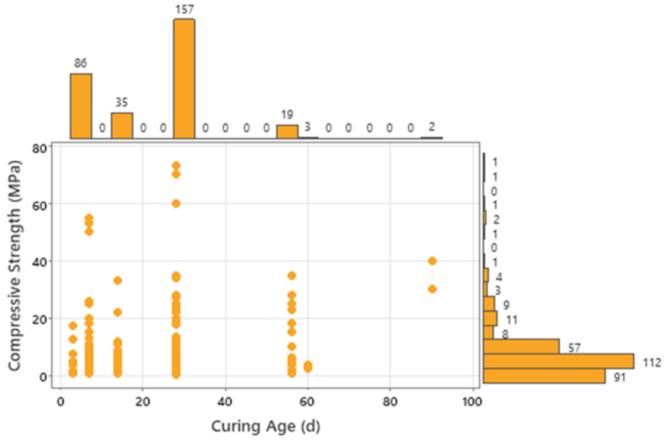





**(e)**




**(f)**




**(g)**

**Figure 3.** Marginal plot between compressive strength of fly ash composite foam concrete and (**a**) Wet density WD (Kg/m$^3$); (**b**) Cement Content CC (%); (**c**) Fly Ash Content FAC (%); (**d**) Sand Content SC (%); (**e**) Water-binder ratio WBR (Unitless); (**f**) Foam Content FC (%); (**g**) Curing age CA.

**Table 2.** Root mean squared error (RMSE) and mean absolute error (MAE) for the developed models in different compressive strengths.

| Models | Training | | Testing | | Validation | |
|---|---|---|---|---|---|---|
| | No. of Datasets = 202 | | No. of Datasets = 50 | | No. of Datasets = 50 | |
| | RMSE | MAE | RMSE | MAE | RMSE | MAE |
| LR | 6.07 | 4.48 | 5.73 | 3.76 | 4.37 | 4.37 |
| MLR | 4.30 | 3.10 | 5.31 | 3.43 | 4.22 | 3.1 |
| FQ | 3.2 | 2.57 | 3.86 | 2.74 | 2.81 | 2.20 |
| IN | 3.08 | 2.34 | 3.10 | 2.86 | 2.67 | 2.13 |
| ANN | 2.16 | 1.35 | 0.95 | 2.63 | 0.54 | 1.40 |

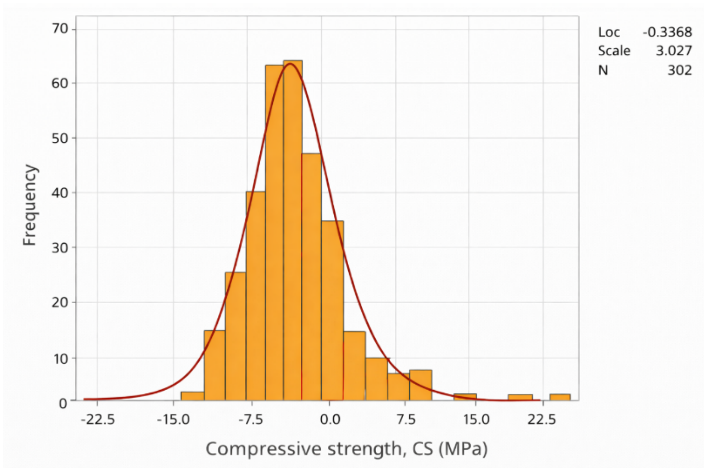



**Figure 4.** Frequency plot for geopolymer concrete's compressive strength, CS (MPa).

3.2.1. LR Model

The linear regression model (LM) has been tested using three separate datasets: training, testing, and validation. A high $R^2$ value, such as 0.8, indicates that the model can explain approximately 80% of the variation in compressive strength. In other words, 80% of the variation in the strength can be predicted by your model [32]. The training set yielded an $R^2$ of 0.65, indicating that the model explained 65% of the variation in the data. After testing and validation, different datasets were used for each of the 50 datasets. Other sets of data yielded R-squared values of 0.74 for testing and 0.77 for validation. Figure 5 shows the LR model's prediction accuracy. After using different data, we can see that the model's accuracy has changed. The next step was the root mean squared error (RMSE). The three datasets were used for training, with a value of 6.1; however, this value was dropped for the other datasets, which tested 5.72 and validated at 4.37. RMSE measures the average difference between predicted and actual values, as shown in Equation (10). That means the lower the RMSE is, the better. The drop in RMSE from training to testing indicates that the model performs adequately on new data. However, the slight increase in RMSE during validation suggests that the model may struggle with some unseen datasets. In the combined training, testing, and validation dataset, the error envelope spans −40% to 60%, indicating that 60% of all datasets fall within the range 0.60 to 1.60 for the ratio of predicted to measured compressive strength.

$$CS\ (MPa) = -159.4 + 0.02(WD) + 1.8(CC) - 1.5(FAC) + 1.3(SC) + 59.2(WBR) + 0.84(FC) + 0.09(CA) \quad (10)$$

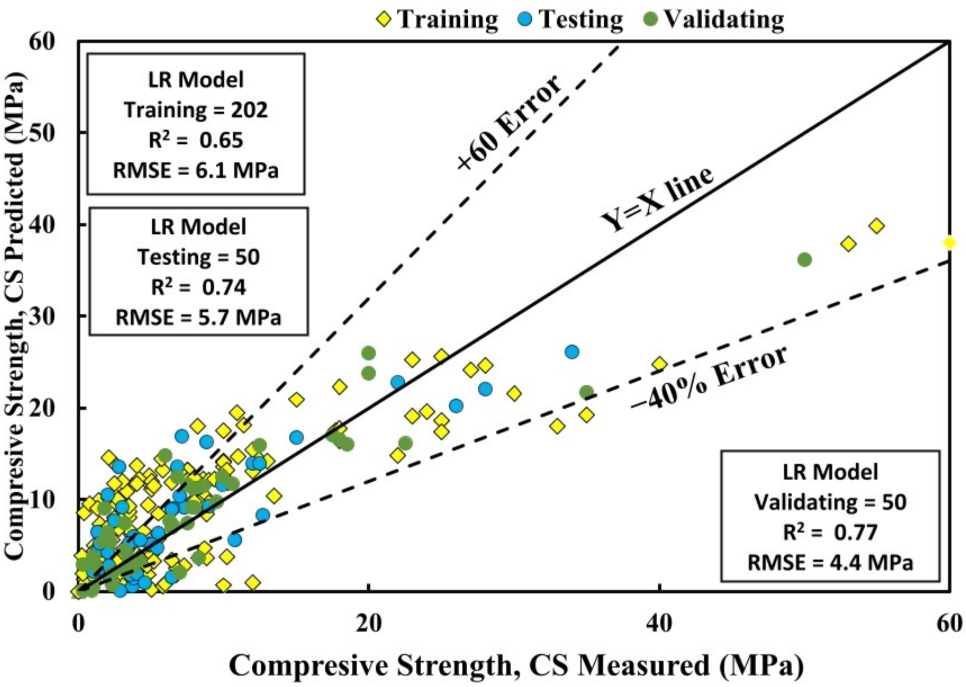



**Figure 5.** Comparison of measured and predicted Compressive strength using the LR model for training, testing, and validating datasets.

3.2.2. MLR Model

The data for the MLR model is split similarly to the LR model's data. Starting with the training, the $R^2$ was 0.82, indicating that the model explained 82% of the variation in compressive strength. Moving to the testing, the $R^2$ decreased to 0.77 and then increased to 0.78 in the validating dataset. Both testing and training have 50 datasets each, and 202 training samples. Moving towards the Root Mean Square Error (RMSE) for the same three datasets, training, testing, and validation coincided with values of 4.3, 5.30, and 4.22, respectively, indicating a decline. Figure 6 shows the MLR model's prediction results. The Root Mean Square Error (RMSE) indicates the average difference between the actual and the predicted values, as shown in Equation (11). Therefore, the lower the RMSE, the more accurate the model is. The decline in RMSE across the three datasets from training to validation indicates that the model performs well on new datasets when predicting compressive strength.

$$CS\ (MPa) = 0.12 \times (0.05 \times (WD)^{2.1}) \times (0.01 \times (CC)^{0.5}) \times (0.2 \times (FAC)^{0.01}) \times (0.12 \times (SC)^{-0.04}) \times (0.21 \times (WBR)^{-0.7}) \times (0.7 \times (FC)^{-0.02}) \times (0.14 \times (CA)^{0.3}) \quad (11)$$

https://doi.org/10.53941/bci.2026.100005 

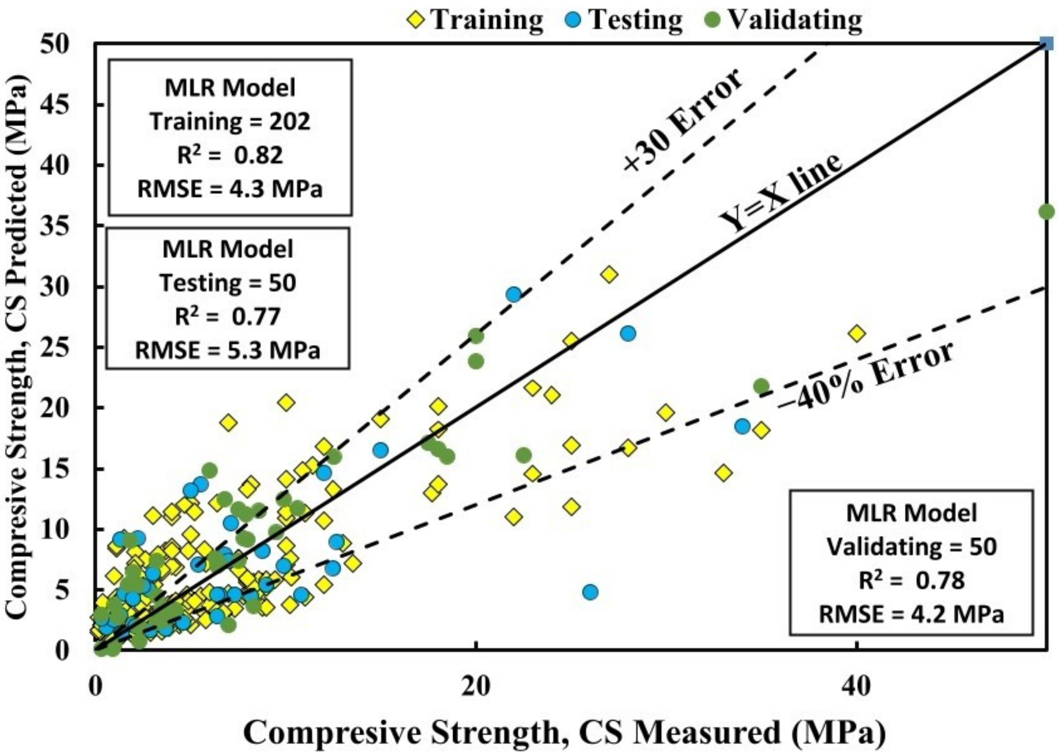



**Figure 6.** Comparison of measured and predicted Compressive strength using the MLR model for training, testing, and validating datasets.

3.2.3. FQ Model

Another tested model was the full quadratic model (FQ), which was separated into three parts: training, testing, and validation. The $R^2$ for each of them is a fair point to mention in this model, which, during training, was 0.90, explaining 90% of the variability in the data. Then, the testing $R^2$ is 0.88, which is lower than that of the pure quadratic model. After that, the validating data rose to 0.90, making it less reliable. Tables 3 and 4 compare model performance measures and ranks. Then they tested the root-mean-square error for each dataset. The Root Mean Squared Error (RMSE) is a measure of that the well a prediction model performs. It indicates the average difference between the predicted and actual values. A smaller RMSE suggests that the model makes more accurate predictions [31]. After that, it squares those differences, averages them, and takes the square root. The RMSE values were 3.2 for training, 3.9 for testing, and 2.8 for validation. The predicted versus actual compressive strength using the FQ model is shown in Figure 7. The lower the error, the better the data predicts. It performs well on training data but struggles somewhat with new information.

$$\begin{aligned} CS\ (MPa) = {} & 0.98 - 0.02(WD) + 0.4(CC) + 0.67(FAC) + 1.12(SC) + 0.97(WBR) + 1.1(FC) \\ & + 0.43(CA) + CS\ (MPa) + \big(0{,}001(WD) \times (CC)\big) + \big(0.0003(WD) \times (FAC)\big) \\ & + \big(0.0002(WD) \times (SC)\big) - \big(0.1(WD) \times (WBR)\big) - \big(0.001(WD) \times (FC)\big) \\ & + \big(0.0002(WD) \times (CA)\big) - \big(0.02(CC) \times (FAC)\big) - \big(0.03(CC) \times (SC)\big) \\ & + \big(0.03(CC) \times (WBR)\big) - \big(0.02(CC) \times (FC)\big) - \big(0.01(CC) \times (CA)\big) \\ & - \big(0.02(FAC) \times (SC)\big) + \big(0.5(FAC) \times (WBR)\big) - \big(0.02(FAC) \times (FC)\big) \\ & - \big(0.005(FAC) \times +(CA)\big) + \big(1.3(SC) \times (WBR)\big) - \big(0.002(SC) \times (FC)\big) \\ & - \big(0.01(SC) \times (CA)\big) + \big(1.24(WBR) \times (FC)\big) + \big(0.1(WBR) \times (CA)\big) \\ & - \big(0.01(FC) \times (CA)\big) + 1.2(WD)^2 - 0.01CC)^2 - 0.03(FAC)^2 - 0.01(SC)^2 \\ & - 0.9(WBR)^2 - 0.002(FC)^2 - 0.001(CA)^2 \end{aligned} \tag{12}$$

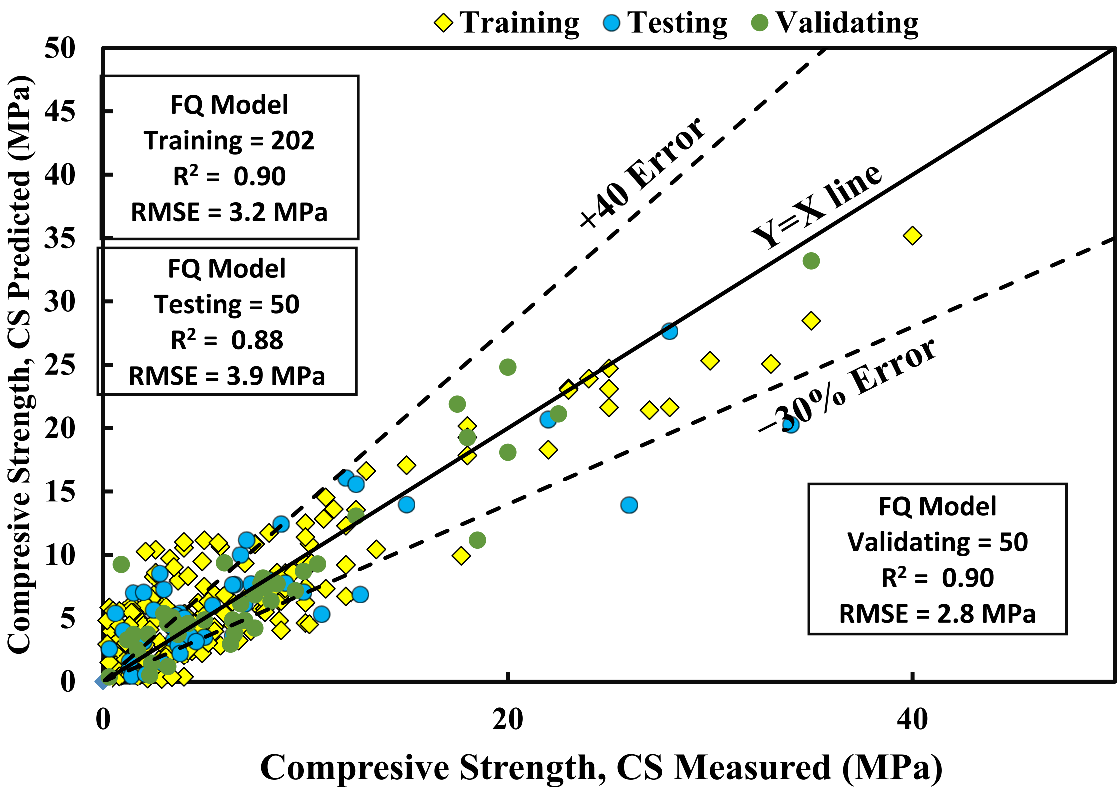



**Figure 7.** Comparison of measured and predicted Compressive strength using the FQ for training, testing, and validating data.

**Table 3.** Summary of the parameters used to evaluate the performance of the produced models.

| Database | Models | $R^2$ | RMSE (MPa) | MAE(MPa) | Ranking |
|---|---|---|---|---|---|
| Training | LR | 0.65 | 6.07 | 4.48 | 5 |
| | MLR | 0.82 | 4.30 | 3.10 | 4 |
| | FQ | 0.90 | 3.2 | 2.57 | 3 |
| | IN | 0.91 | 3.08 | 2.34 | 2 |
| | ANN | 0.96 | 2.16 | 1.35 | 1 |
| Testing | LR | 0.74 | 5.73 | 3.76 | 5 |
| | MLR | 0.77 | 5.31 | 3.43 | 4 |
| | FQ | 0.88 | 3.86 | 2.74 | 3 |
| | IN | 0.88 | 3.10 | 2.86 | 2 |
| | ANN | 0.99 | 0.95 | 2.63 | 1 |
| Validating | LR | 0.77 | 4.37 | 4.37 | 5 |
| | MLR | 0.78 | 4.22 | 3.1 | 4 |
| | FQ | 0.90 | 2.81 | 2.20 | 3 |
| | IN | 0.91 | 2.67 | 2.13 | 2 |
| | ANN | 0.96 | 0.54 | 1.40 | 1 |

**Table 4.** Summary of statistical analysis of the FFC mixtures.

| Variables | WD | CC | FAC | SC | WBR | FC | CA | CS |
|---|---|---|---|---|---|---|---|---|
| Mean | 1406.2 | 32.7 | 12.2 | 22.6 | 0.1 | 14.2 | 22.7 | 7.6 |
| Median | 1400 | 29 | 4 | 24.5 | 0.27 | 9.5 | 28 | 4.2 |
| Mode | 1199 | 21 | $1 \times 10^{-10}$ | $1 \times 10^{-10}$ | 0.3 | 4 | 28 | 0.8 |
| SD | 400.1 | 15.1 | 16.4 | 20.9 | 0.2 | 13.4 | 14.7 | 10.3 |
| Var | 160,063.1 | 227.4 | 267.4 | 434.1 | 0.02 | 178.9 | 214.9 | 105.9 |
| Kurt | −0.6 | 0.2 | 0.03 | −1.3 | −0.5 | −0.23 | 2.6 | 14.7 |
| Skew | −0.2 | 0.9 | 1.2 | 0.23 | 0.84 | 0.9 | 1.15 | 3.5 |
| Min | 496 | 4 | 0 | 0 | 0.09 | $1 \times 10^{-23}$ | 3 | 0.2 |
| Max | 2227 | 77 | 59 | 68 | 0.7 | 60 | 90 | 73 |

### 3.2.4. IN Model

The dataset used in this study was divided into three subsets: training, testing, and validation, to further evaluate the performance of the interaction model. A high $R^2$ value, such as 0.9 or higher, indicates that the model can explain variation in compressive strength with high accuracy [32]. Figure 8 presents the prediction outcomes for this interaction model. Regarding the training set, the $R^2$ value was 0.91, indicating a positive correlation. The testing stage showed a decrease in the $R^2$ value to 0.88, which subsequently increased to 0.91 throughout the validation stage. Both the testing and validation stages include 50 samples each, for a total of 100 samples per stage. The Root Mean Square Error (RMSE) indicates the average difference between the actual values and the predicted ones, as shown in Equation (6). The RMSEs for the three subsets, training, testing, and validation, are 3.1, 3.9, and 2.7, respectively. Therefore, the value of the RSME is inversely proportional to the quality of the results obtained with this model. Table 4 presents simple statistics for all input and output variables in the FFC dataset. The decline in RSME values across the three datasets indicates that the model's predictive accuracy is maintained with new data.

$$\begin{aligned} CS\ (MPa) = {} & 268 - 0.1(WD) - 3.6(CC) - 3.3(FAC) - 2.6(SC) - 45(WBR) - 1.6(FC) - 3.4(CA) \\ & + \big(0.01(WD) \times (CC)\big) + \big(0.001(WD) \times (FAC)\big) + \big(0.001(WD) \times (SC)\big) \\ & - \big(0.03(WD) \times (WBR)\big) + \big(0.0002(WD) \times (FC)\big) + \big(0.0002(WD) \times (CA)\big) \\ & + \big(0.001(CC) \times (FAC)\big) - \big(0.012(CC) \times (SC)\big) - \big(0.5(CC) \times (WBR)\big) \\ & - \big(0.012(CC) \times (FC)\big) + \big(0.04(CC) \times (CA)\big) - \big(0.01(FAC) \times (SC)\big) \\ & - \big(0.4(FAC) \times (WBR)\big) - \big(0.001(FAC) \times (FC)\big) + \big(0.04(FAC) \times +(CA)\big) \\ & + \big(0.9(SC) \times (WBR)\big) + \big(0.004(SC) \times (FC)\big) + \big(0.03(SC) \times (CA)\big) \\ & + \big(0.6(WBR) \times (FC)\big) + \big(1.5(WBR) \times (CA)\big) + \big(0.02(FC) \times (CA)\big) \end{aligned} \tag{13}$$

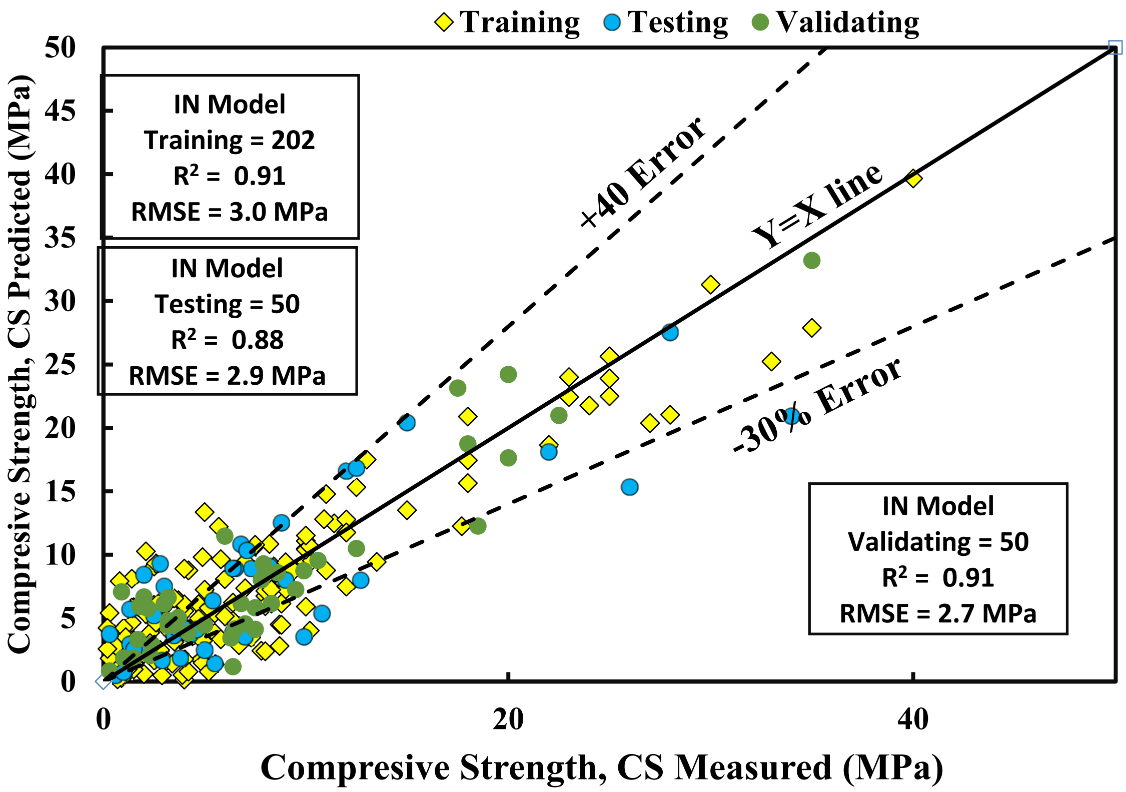



**Figure 8.** Comparison of measured and predicted Compressive strength using the IN for training, testing, and validating data.

### 3.2.5. ANN Model

An artificial neural network was employed for the research, and the data were separated into three categories: training, testing, and validation. Then, $R^2$ values are calculated for each dataset. The Artificial Neural Network (ANN) predictor model for the compressive strength of Fly Ash Composite Foam Concrete (FFC) utilizes each input parameter via linked nodes, resulting in an output node (Node 0) as shown in Equations (14)–(20). Each node's operation is to weigh inputs and add a bias component. The bias term allows the activation function to change its response. This modification enhances the model's capacity to fit complex patterns in data by allowing greater flexibility when the model is active. It shows the rate at which the model captures data variance. $R^2$ ranges from 0 to 1 [31]. A value close to 1 indicates that the model accurately predicts the target. For training, the $R^2$ was 0.96, which is a very reliable number for the fly ash data. Then, the testing $R^2$ increased to 0.99, which remains an excellent value. Ultimately, the validation with the best data was raised to 0.96. Then, for each dataset, the Root Mean Square Error (RMSE) was calculated, with a training RMSE of 2.16, indicating a low root error, and it decreased further to 0.95 for testing. The RMSE value decreased to 0.54 for the validation set. This shows that the ANN data are very reliable for predicting the compressive strength of FFC. The ANN's predicted and actual values are shown in Figure 9.

$$Node\ 1 = -0.60 + 2.02(WD) + 0.41(CC) - 1.17(FAC) - 0.06(SC) - 0.20(WBR) + 2.13(FC) + 0.81(CA) \quad (14)$$

$$Node\ 2 = -1.24 + 1.15(WD) + 2.01(CC) + 2.54(FAC) + 0.02(SC) - 1.28(WBR) - 2.60(FC) + 1.42(CA) \quad (15)$$

$$Node\ 3 = 0.47 + 0.80(WD) + 2.54(CC) - 2.26(FAC) - 2.10(SC) - 0.57(WBR) + 0.30(FC) - 0.64(CA) \quad (16)$$

$$Node\ 4 = 0.67 + 2.10(WD) + 2.65(CC) - 0.69(FAC) - 3.83(SC) + 0.61(WBR) + 0.59(FC) - 0.01(CA) \quad (17)$$

$$Node\ 5 = -2.01 + 1.38(WD) + 1.76(CC) + 0.91(FAC) + 0.58(SC) - 0.41(WBR) - 0.24(FC) + 0.90(CA) \quad (18)$$

$$Node\ 6 = -1.50 + 4.36(WD) + 3.00(CC) + 1.62(FAC) - 2.02(SC) + 0.82(WBR) - 0.20(FC) + 0.15(CA) \quad (19)$$

$$Node\ 7 = 5.01 - 1.90(Node\ 1) - 3.20(Node\ 2) - 2.80(Node\ 3) + 3.10(Node\ 4) - 1.14(Node\ 5) - 2.50(Node\ 6) \quad (20)$$

$$Node\ 0 = 1.30 - 2.32(Node\ 7)$$

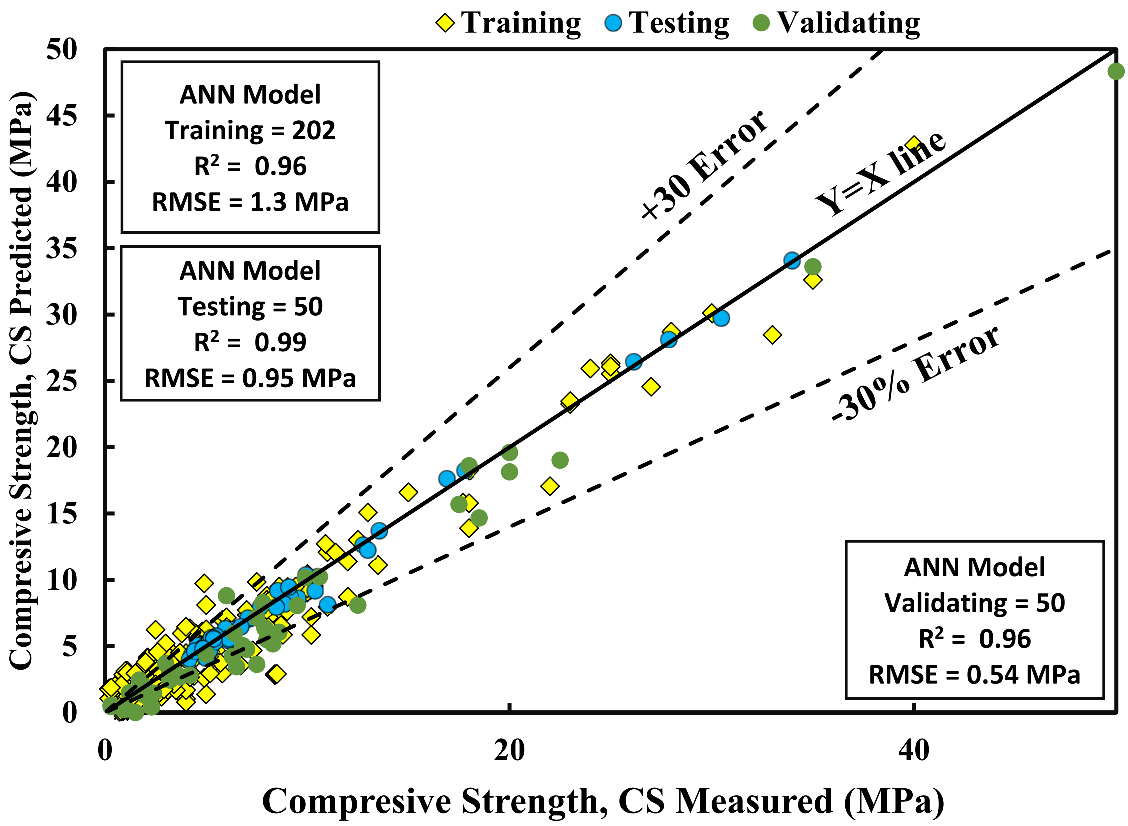



**Figure 9.** Comparison of measured and predicted Compressive strength using the ANN for training, testing, and validating data.

*3.2. Advantages and Limitations of Soft Computing Models*

Soft computing models can be advantageous for laboratory testing due to their improved predictive accuracy. Artificial Neural Networks (ANNs) achieve a superior $R^2$ and lower root mean squared error (RMSE) than laboratory regression techniques. This is because they can comprehend complex relationships [7]. A summary of the comparison of model metrics across ANN and traditional models is shown in Figure 10. This includes the cost of resources and the time consumed. ANNs handle non-linear interactions among input variables, which are beyond the capabilities of traditional regression models. For example, the impact of curing age on compressive strength and sustainability is further enhanced by soft computing models, which enable dynamic adjustment of mix ratios while allowing continuous tracking of material properties. Figure 11 shows that the ANN model outperforms the other models in terms of the OBJ, SI, and MAE metrics for both the training and testing datasets.

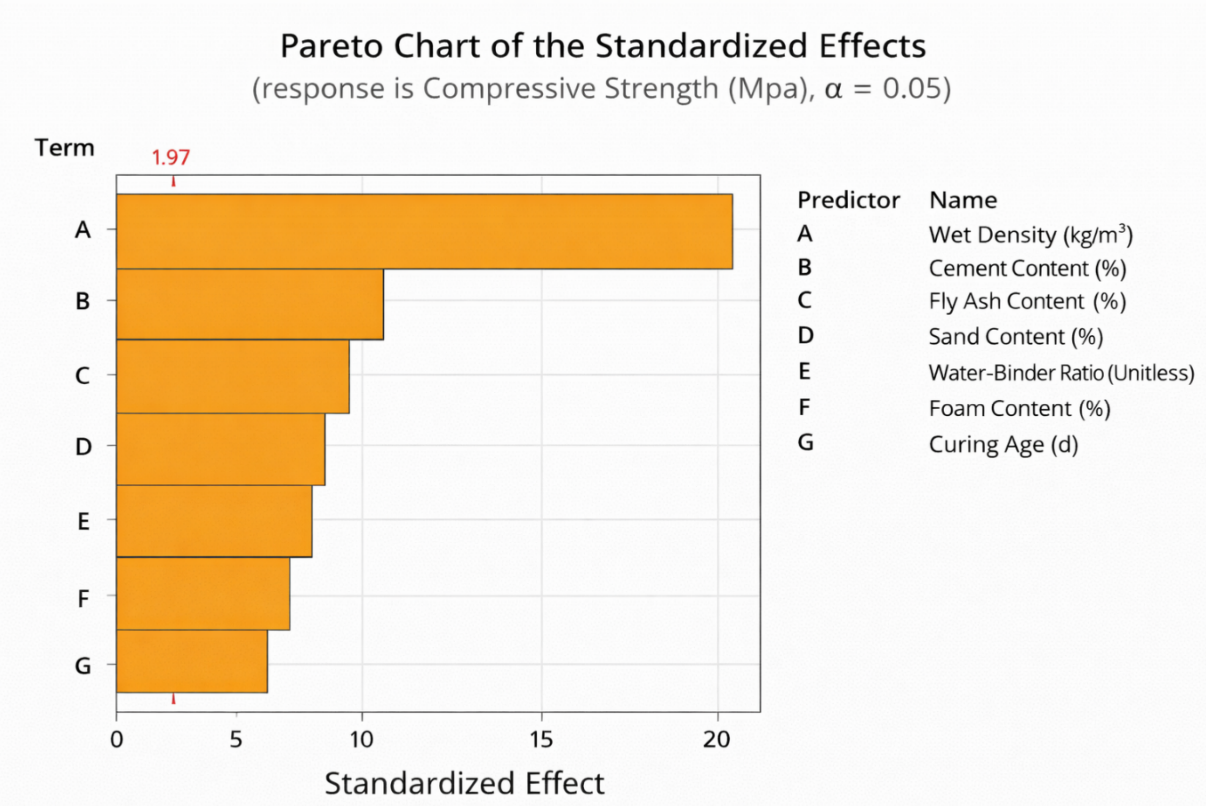
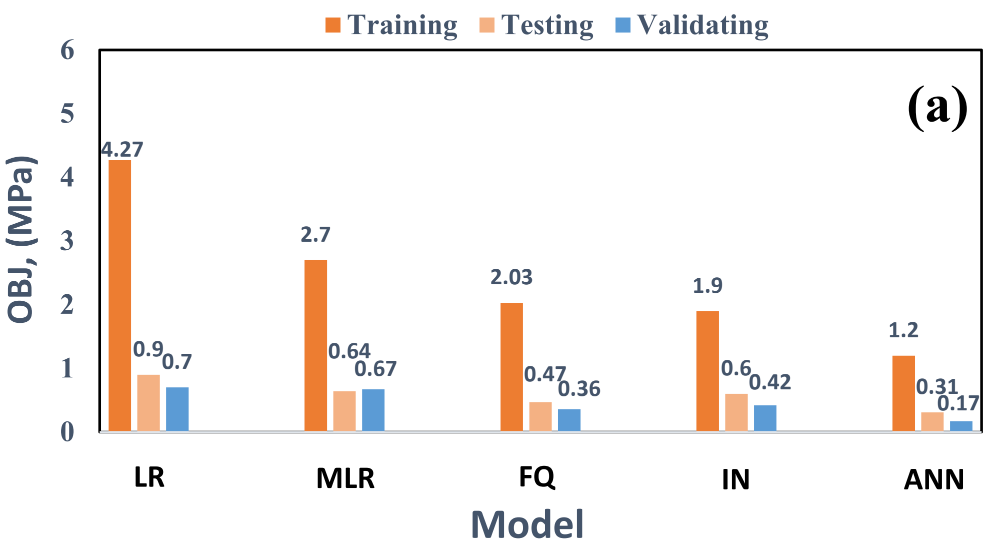
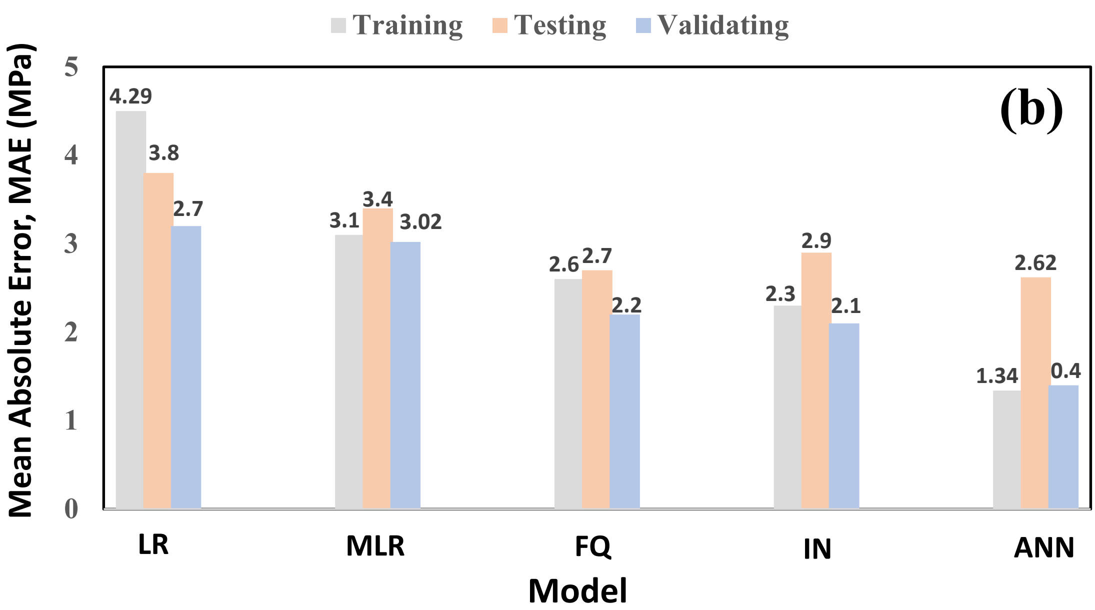



**Figure 10.** Pareto chart of the standardized effects of each independent variable on CS.





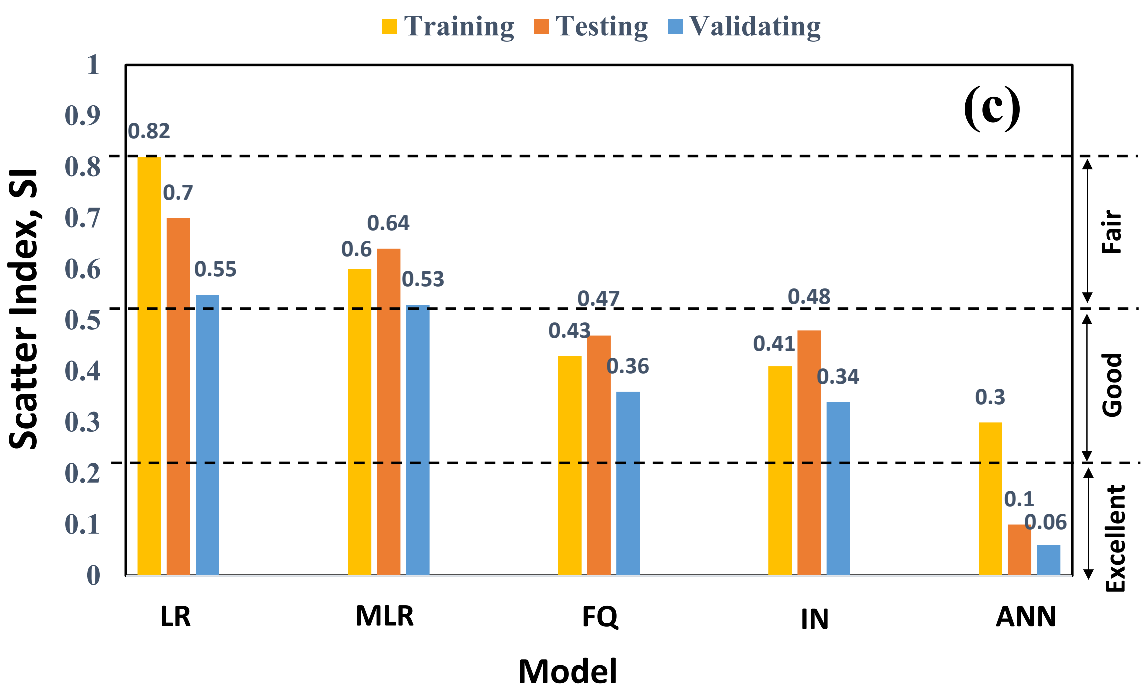




**Figure 11.** Comparison of (**a**) OBJ, (b) SI, and (**c**) MAE performance metrics across the five employed models using the training and testing datasets.

*3.3. Limitations of Soft Computing Models*

Various limitations accompany soft computing algorithms. First is the complexity of computation. More advanced models require more computational resources. Additionally, handling large datasets is impossible for applications with limited resources. However, soft computing models require large, high-quality datasets to enable effective training. Otherwise, predictions can be inaccurate [7]. Another potential limitation is overfitting. Models such as artificial neural networks (ANNs) can fail to generalize well on unseen data due to overfitting the training data. Residual error comparisons between models are presented in Figure 12.

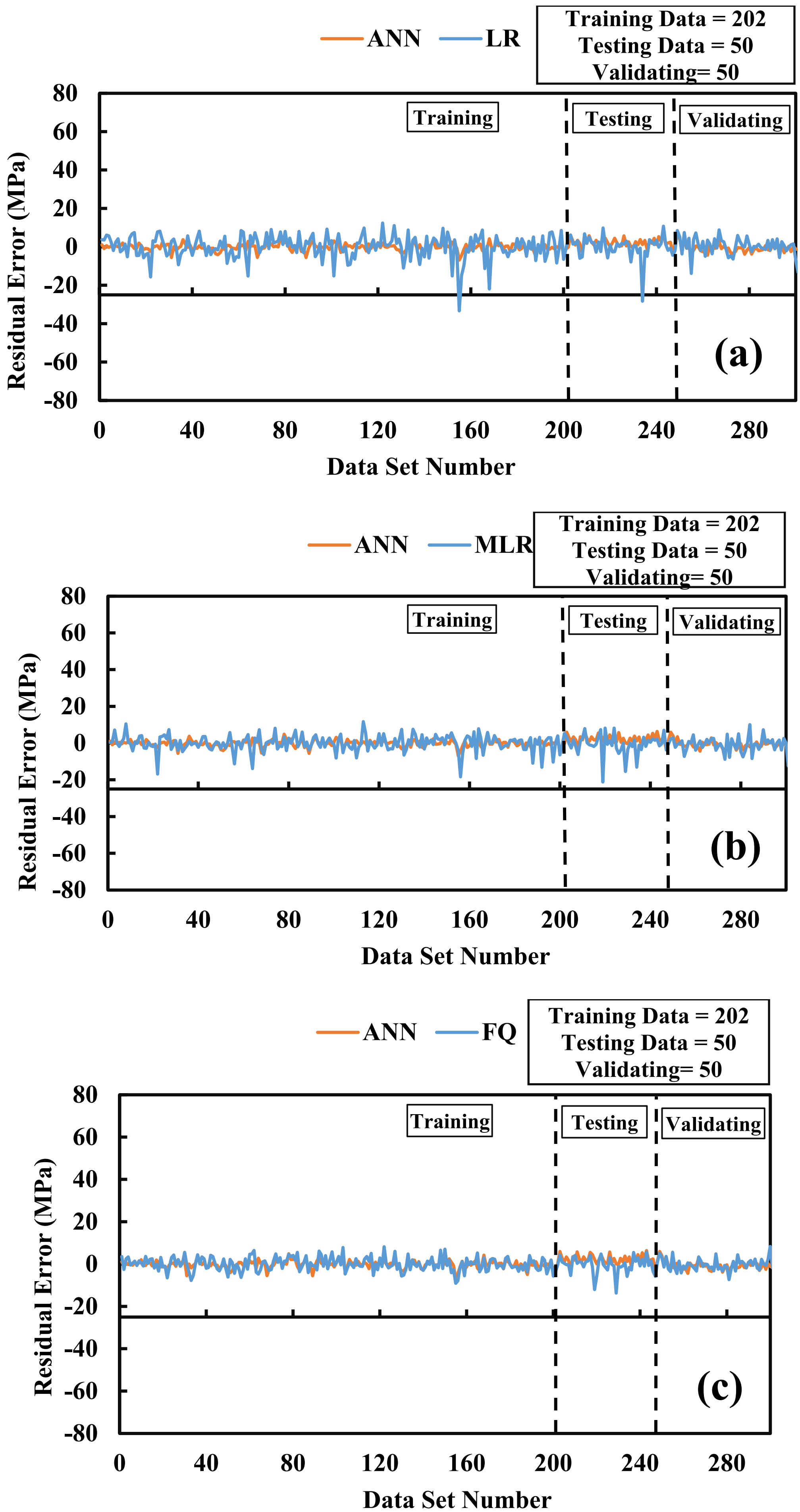

ANN
LR
Training Data = 202
Testing Data = 50
Validating= 50
Training
Testing
Validating
(a)
Residual Error (MPa)
Data Set Number
ANN
MLR
Training Data = 202
Testing Data = 50
Validating= 50
Training
Testing
Validating
(b)
Residual Error (MPa)
Data Set Number
ANN
FQ
Training Data = 202
Testing Data = 50
Validating= 50
Training
Testing
Validating
(c)
Residual Error (MPa)
Data Set Number


**Figure 12**. Comparison between developed models for shear strength based on residual error (**a**) ANN and LR; (**b**) ANN and NL; (**c**) ANN and ML; and (**d**) ANN and FQ.

## 4. Sensitivity Analysis of Input Variables

### *4.1. Wet Density (kg/m$^3$)*

Wet density has been used as an input to determine the optimal compressive strength for FFC, with units kg/m$^3$. Wet density is the weight of wet concrete per unit volume. It is a method for measuring the degree of compaction of a concrete mixture while it is still fresh and damp [33]. The distribution of compressive strength across the dataset is shown in Figure 4. A higher density means the concrete has fewer air bubbles and less vacuum. A denser mixture results in stronger, more reliable concrete. Due to the close-packed arrangement of particles, such as sand and aggregates, the bonding between them strengthens the concrete. The highest wet density in the data is 2227 kg/m$^3$, which results in higher compressive strength. The lowest, 496 kg/m$^3$, means the compressive strength will still be acceptable, but not as high as that of the highest wet density. The reason for choosing a low wet density is to reduce the concrete's weight, making it more suitable for FFC.

### *4.2. Cement Content (%)*

The cement content (%) is another key input for the FFC concrete mixture, resulting in high compressive strength. The higher the cement content, the higher the concrete's compressive strength. In cement-treated mixtures, curing times range from 7 to 28 days, indicating that longer curing times result in stronger concrete [34] due to the mixture's hydration. Additionally, the FFC plays a crucial role in concrete, adding strength and providing reinforcement. Furthermore, fly ash will reduce the concrete's weight. However, the cement content will also play a significant role in determining the concrete's weight while providing higher compressive strength. Using soft-computing algorithms to predict compressive strength reduces the need for extensive laboratory testing. This approach optimizes cement content and other variables to produce sustainable, efficient construction materials.

### *4.3. Sand Content (%)*

Sand content is a crucial ingredient that affects the compressive strength, weight, and durability of concrete. The effectiveness of sand in the mixture depends on the materials with which it is mixed. Suppose the mix is contaminated, resulting in reduced mechanical strength. The sand particle structure similarly affects the mix; the sand's properties, such as grain size, shape, and grading, either enhance or detract from the mix's properties. If the sand particles have a more textured surface, they will bond more effectively with the cement, leading to higher-strength concrete and a better, stronger FFC [35]. In this study, using soft computing models to predict sand types is significantly easier than relying on laboratory data, making it faster and less expensive. The sand should be cleaned before use in the mixture [13]. Adding sand quality will enhance the accuracy and reliability of the predictions for the data. Using soft computing algorithms, the FFC will be more eco-friendly and stronger, as the projections require less time than the laboratory method.

### *4.4. Foam Content (%)*

Foam content (%) is a key parameter in the FFC mix, primarily influencing the material's density. Foam is generated by mixing a foaming agent with water [1], introducing air voids into the concrete. As foam content increases, the number of entrained air bubbles rises, resulting in a lighter concrete with lower density. However, excessive foam content can reduce the mechanical strength of FFC, as the increased void ratio diminishes the material's load-bearing capacity. Using soft computing models, the optimal foam content can be efficiently determined. However, a foam content of around 25% strikes a decent balance between strength and lightweight concrete [1].

### *4.5. Water-Binder Ratio*

The water-binder (w/b) ratio is the ratio of particles, such as cement and fly ash, in FFC. An increase in the water-binder ratio indicates a decrease in the amount of binder. A lower w/b ratio means more strength because it is denser and has fewer holes [4]; the greater the w/b ratio, the weaker the concrete. However, workability at the low w/b ratio will be more difficult because it will be more solid. Therefore, maintaining an optimal water-to-binder (w/b) ratio is crucial for balancing strength and workability in concrete. For instance, concrete with a w/b ratio of 0.50 exhibits greater strength than that with a w/b ratio of 0.65 [4]. In addition to durability, a reduced water-to-binder ratio enhances it by preventing the entry of harmful chemicals into the mixture.

## 5. Sensitivity Analysis

The effect of each variable on the expected compressive strength of fly ash composite foam concrete (FFC) was examined in the sensitivity analysis. Figure 11 shows the relative importance of the input variables using a Pareto chart. A satisfactory artificial neural network (ANN) model, determined to be suitable for predicting compressive strength (CS), was used for this analysis. Wet density, cement content, and foam content were found to be the most significant factors affecting concrete properties. Compressive strength was most significantly affected by wet density, cement content, and foam content. These three variables were crucial in defining the structural behavior of FFC, as shown by their most notable contributions to the model's output. The fly ash content, curing age, sand content, and water-binder ratio all showed minor but visible impacts. As shown in Table 5, the suggested mix design values are based on the sensitivity analysis results, which indicate that these factors have the greatest effect on the compressive strength of Fly Ash Composite Foam Concrete (FFC). Higher compressive strength results from a more compact, denser internal structure in the composite, which is correlated with increased density. Cement content also promotes constant hydration and metallic reactions, which gradually increase strength, as shown in Figure 11. Although foam content is essential for reducing the weight of FFC, its increased porosity at higher values reduces compressive strength. Balanced proportions of fly ash and sand, along with appropriate curing times, enhance workability and mechanical performance. Additionally, lower water--binder ratios increase paste matrix density, thus improving structural integrity. This analysis highlights the significance of all mix components and preparation steps, demonstrating that even minor variations, similar to those in pre-processing conditions of other material systems, can significantly influence concrete properties. Overall, the sensitivity analysis confirmed that wet density and cement content were the most influential parameters affecting compressive strength, followed by foam content and fly ash content. These results emphasize the importance of optimizing mix design to achieve both high structural performance and enhanced environmental sustainability in FFC applications.

**Table 5.** Optimized mix design parameters for enhancing compressive strength in fly ash composite foam concrete (FFC) based on sensitivity analysis.

| Design Variable | Optimized Range/Observed Performance Impact |
|---|---|
| Wet Density | ~1800–1900 kg/m$^3$—Higher density improved compressive strength without compromising workability. |
| Cement Content | ~35–45% of binder mix—Contributed significantly to early and peak strength development. |
| Fly Ash | ~10–15%—Balanced mechanical strength and sustainability by partially replacing cement. |
| Water/Binder Ratio | ~0.25–0.30—Optimized range for achieving desirable strength and mix consistency. |
| Foam Content | ~20–25%—Controlled density and insulation properties while maintaining strength. |
| Curing Age | ≥28 days—Strength reached peak after standard curing duration. |

## 6. Limitations

- The study is based on a specific dataset size and composition, which may not fully capture the variability of concrete produced under different mix proportions, curing conditions, and material sources.
- Some AI model implementation details (e.g., hyperparameter tuning strategies) were constrained due to computational limitations.
- The current work focused primarily on compressive and tensile strength prediction; other mechanical and durability properties (e.g., shrinkage, permeability, resistance to ASR) were not included.

## 7. Future Research Directions

- Expanding the dataset to cover a broader range of concrete mixtures, including sustainable binders (e.g., glass powder, rice husk ash, slag), to enhance generalizability.
- Conducting sensitivity and uncertainty analyses is better to understand the influence of input parameters on predictive performance.
- Comparing additional advanced AI methods (e.g., Gradient Boosting, XGBoost, Deep Learning) with the models used in this study.
- Validating the models through experimental testing and benchmarking against international standards.

## 8. Conclusions

This study analyzed 302 FFC mix design datasets using soft computing models to predict compressive strength based on six key input variables. This approach reduces reliance on traditional laboratory testing, which can be time-consuming, resource-intensive, and less scalable. The study successfully developed and evaluated the following multiple soft computing models: Linear Regression (LR), Multi-Linear Regression (MLR), Full Quadratic Model (FQ), Interaction Model (IN), and Artificial Neural Network (ANN) for predicting the compressive strength of Fly Ash Composite Foam Concrete (FFC). The most critical factors affecting compressive strength, as determined by the sensitivity analysis, were wet density, cement content, and fly ash content. These results highlight the investigation of vital mix design components to achieve optimal FFC performance. The ANN model outperformed the other models in terms of predictive power and durability across performance indicators. Based on the compiled dataset and detailed statistical evaluations, the following conclusions can be drawn:

I. The dataset included several input parameters, including Wet Density, fly ash content, foam content, water-to-binder ratio, curing time, cement content, and sand content. Higher wet density and optimized cement content primarily contributed to increased compressive strength, confirming the efficacy of wet density as a sustainable binder in FFC mixtures.

II. The optimized mix design results indicate that wet density in the range of 1800–1900 kg/m$^3$ had the most significant influence on compressive strength, with higher density contributing to improved mechanical performance. A cement content of between 35–45% significantly enhanced strength development, particularly during the early stages of curing. A foam content of around 20–25% effectively balances weight reduction and thermal insulation without excessively compromising structural integrity. Fly ash replacement at 10–15% provided a sustainable alternative to cement while maintaining acceptable strength.

III. The Artificial Neural Network (ANN) model also ranked highest based on Objective Function (OBJ) and Scatter Index (SI) metrics. For the training, testing, and validation datasets, the SI values were 0.30, 0.12, and 0.70, respectively, while the corresponding OBJ values were 1.2 MPa, 0.3 MPa, and 0.16 MPa.

IV. Sensitivity analysis confirmed that wet density and cement content were the most influential parameters, followed by foam content and fly ash content. These findings highlight the critical role of mix design optimization in producing high-performance, environmentally sustainable FFC.

## Author Contributions

A.M.M., N.T.A., and M.A.I.O.: conceptualization, methodology, software; A.S.M.: data curation, writing—original draft preparation; A.S.M., A.M.M., and R.S.H.: Writing. All authors have read and agreed to the published version of the manuscript.

## Funding

This research received no external funding.

### Institutional Review Board Statement

Not applicable.

### Informed Consent Statement

Not applicable.

### Data Availability Statement

The data supporting the conclusions of this article are included with the article.

### Conflicts of Interest

The authors declare no conflict of interest. As an Editorial Board Member, Ahmed Salih Mohammed had no involvement in the peer review of this paper and no access to information about its peer-review process. Full responsibility for the editorial process of this paper was delegated to another editor of the journal.

### Use of AI and AI-Assisted Technologies

The authors utilized OpenAI ChatGPT-4o to enhance readability during the preparation of this work. They thoroughly reviewed and edited all content generated by these tools and take full responsibility for the final version of the published article.

### Abbreviations

| | |
|---|---|
| FFC | Fly Ash Composite Foam Concrete |
| LR | Linear Regression |
| MLR | Multi-linear Regression |
| FQ | Full Quadratic |
| IN | Interaction Model |
| ANN | Artificial Neural Network |
| $R^2$ | Coefficient of Determination |
| MAE | Mean Absolute Error, MPa |
| SI | Scatter Index, MPa |
| RMSE | Root Mean Square Error, MPa |
| OBJ | The objective function, MPa |

### References


1. Ahmad, S.A.; Bashir, M.F.; Rehman, S.K.U.; et al. Machine learning approach for predicting compressive strength in foam concrete under varying mix designs and curing periods. *Smart Constr. Sustain. Cities* **2023**, *1*, 16. https://doi.org/10.1007/s44268-023-00021-3.
2. Andrew, R.M. Global $CO_2$ emissions from cement production. *Earth Syst. Sci. Data* **2019**, *11*, 1675–1710. https://doi.org/10.5194/essd-11-1675-2019.
3. Ahmad, H.; Wahid, N.; Rahman, M.F.A.; et al. Influence of Fly Ash on the Compressive Strength of Foamed Concrete at Elevated Temperature. In Proceedings of the MATEC Web of Conferences, Perak, Malaysia, 27 August 2014. https://doi.org/10.1051/matecconf/20141501003.
4. Song, H.; Xu, L.; Xu, J.; et al. Preparation of ultrafine fly ash-based superhydrophobic composite coating and its application to foam concrete. *Polymers* **2020**, *12*, 2187. https://doi.org/10.3390/polym12102187.
5. Li, S.; Yan, C.; Ding, Y.; et al. Investigating the mechanical and durability characteristics of fly ash foam concrete. *Materials* **2022**, *15*, 6077. https://doi.org/10.3390/ma15176077.
6. Suhendro, B. Toward green concrete for better sustainable environment. *Procedia Eng.* **2014**, *95*, 305–320. https://doi.org/10.1016/j.proeng.2014.12.190.
7. DeRousseau, M.A.; Kasprzyk, J.R.; Srubar, W.V. Computational design optimization of concrete mixtures: A review. *Cem. Concr. Res.* **2018**, *109*, 42–53. https://doi.org/10.1016/j.cemconres.2018.03.015.
8. Kapil, A.; Jadda, K.; Jee, A.A. Developing machine learning models to predict the fly ash concrete compressive strength. *Asian J. Civ. Eng.* **2024**, *25*, 5505–5523. https://doi.org/10.1007/s42107-024-01125-6.
9. Wattanapanich, C.; Kanchanomai, C.; Rodsin, K. Optimizing recycled aggregate concrete for severe conditions through machine learning techniques: A review. *Eng. Sci.* **2024**, *31*, 1191. https://doi.org/10.48048/wjst.2024.187318.

10. Cook, T.R.; Gupton, G.; Modig, Z.; et al. *Explaining Machine Learning by Bootstrapping Partial Dependence Functions and Shapley Values*; Federal Reserve Bank of Kansas City: Kansas City, MO, USA, 2021. https://doi.org/10.18651/RWP2021-12.
11. Hurtado-Alonso, N.; Baena-Moreno, F.M.; Espuelas, S. Optimization of cementitious mixes through response surface method: A systematic review. *Arch. Civ. Mech. Eng.* **2025**, *25*, 54. https://doi.org/10.1007/s43452-024-01112-3.
12. Zhao, J.; Song, Y.; Ahmad, A.; et al. Prediction of compressive strength of fly ash-based concrete using ensemble and non-ensemble supervised machine learning approaches. *Constr. Build.* **2021**, *308*, 125021. https://doi.org/10.1016/j.conbuildmat.2021.125021.
13. Torabian Isfahani, F.; Redaelli, E.; Bassani, M.; et al. Effects of nanosilica on compressive strength and durability properties of concrete with different water to binder ratios. *J. Mater.* **2016**, *2016*, 8453567. https://doi.org/10.1155/2016/8453567.
14. Mahmoud, A.A.; El-Sayed, A.A.; Aboraya, A.M.; et al. Synergizing machine learning and experimental analysis to predict post-heating compressive strength in waste concrete. *Struct. Concr.* **2025**, *26*, 2916–2950.
15. Zeyad, A.M.; Mahmoud, A.A.; El-Sayed, A.A.; et al. Compressive strength of nano concrete materials under elevated temperatures using machine learning. *Sci. Rep.* **2024**, *14*, 24246.
16. Tikalsky, P.J.; Pospisil, J.; MacDonald, W. A method for assessment of the freeze–thaw resistance of preformed foam cellular concrete. *Cem. Concr. Res.* **2004**, *34*, 889–893. https://doi.org/10.1016/j.cemconres.2003.11.005.
17. Zhang, C.; Zhu, Z.; Zhang, Y.; et al. Engineering properties and optimal design of foam lightweight soil composite fly ash: An eco-friendly subgrade material. *J. Clean. Prod.* **2023**, *429*, 139631. https://doi.org/10.1016/j.jclepro.2023.139631.
18. Abd, A.M.; Abd, S.M. Modelling the strength of lightweight foamed concrete using support vector machine (SVM). *Case Stud. Constr. Mater.* **2017**, *6*, 8–15. https://doi.org/10.1016/j.cscm.2016.11.002.
19. Jitchaiyaphum, K.; Sinsiri, T.; Jaturapitakkul, C.; et al. Cellular lightweight concrete containing high-calcium fly ash and natural zeolite. *Int. J. Miner. Metall. Mater.* **2013**, *20*, 462–471. https://doi.org/10.1007/s12613-013-0752-1.
20. Gopalakrishnan, R.; Sounthararajan, V.M.; Mohan, A.; et al. The strength and durability of fly ash and quarry dust lightweight foam concrete. *Mater. Today Proc.* **2020**, *22*, 1117–1124. https://doi.org/10.1016/j.matpr.2019.11.317.
21. Kearsley, E.P.; Wainwright, P.J. The effect of high fly ash content on the compressive strength of foamed concrete. *Cem. Concr. Res.* **2001**, *31*, 105–112. https://doi.org/10.1016/S0008-8846(00)00430-0.
22. Asadzadeh, S.; Khoshbayan, S. Multi-objective optimization of influential factors on production process of foamed concrete using Box–Behnken approach. *Constr. Build. Mater.* **2018**, *170*, 101–110. https://doi.org/10.1016/j.conbuildmat.2018.02.189.
23. Bing, C.; Zhen, W.; Ning, L. Experimental research on properties of high-strength foamed concrete. *J. Mater. Civ. Eng.* **2012**, *24*, 113–118. https://doi.org/10.1061/(ASCE)MT.1943-5533.0000353.
24. Richard, A.O.; Ramli, M. Experimental production of sustainable lightweight foamed concrete. *Br. J. Appl. Sci. Technol.* **2013**, *3*, 994–1005. https://doi.org/10.9734/BJAST/2013/4242.
25. Gökçe, H.S.; Hatungimana, D.; Ramyar, K. Effect of fly ash and silica fume on hardened properties of foam concrete. *Constr. Build. Mater.* **2019**, *194*, 1–11. https://doi.org/10.1016/j.conbuildmat.2018.11.036.
26. Falliano, D.; De Domenico, D.; Ricciardi, G.; et al. Experimental investigation on the compressive strength of foamed concrete: Effect of curing conditions, cement type, foaming agent and dry density. *Constr. Build. Mater.* **2018**, *165*, 735–749. https://doi.org/10.1016/j.conbuildmat.2017.12.241.
27. Chen, Y.G.; Guan, L.L.; Zhu, S.Y.; et al. Foamed concrete containing fly ash: Properties and application to backfilling. *Constr. Build. Mater.* **2021**, *273*, 121685. https://doi.org/10.1016/j.conbuildmat.2020.121685.
28. Othman, R.; Jaya, R.P.; Muthusamy, K.; et al. Relation between density and compressive strength of foamed concrete. *Materials* **2021**, *14*, 2967. https://doi.org/10.3390/ma14112967.
29. Pan, Z.; Hiromi, F.; Wee, T. Preparation of high performance foamed concrete from cement, sand and mineral admixtures. *J. Wuhan Univ. Technol. Mater. Sci. Ed.* **2007**, *22*, 295–298. https://doi.org/10.1007/s11595-005-2295-4.
30. Ghorbani, S.; Ghorbani, S.; Tao, Z.; et al. Effect of magnetized water on foam stability and compressive strength of foam concrete. *Constr. Build. Mater.* **2019**, *197*, 280–290. https://doi.org/10.1016/j.conbuildmat.2018.11.160.
31. Wang, M.; Guo, R.; Liu, J.; et al. Research on prediction of compressive strength of fly ash and slag mixed concrete based on machine learning. *PLoS ONE* **2022**, *17*, e0279293. https://doi.org/10.1371/journal.pone.0279293.
32. Chicco, D.; Warrens, M.J.; Jurman, G. The coefficient of determination R-squared is more informative than SMAPE, MAE, MAPE, MSE and RMSE in regression analysis evaluation. *PeerJ Comput. Sci.* **2021**, *7*, e623. https://doi.org/10.7717/peerj-cs.623.
33. Nimat, A.J.; Mohammed, A.A.; Mohammed, A.S. Evaluation of fracture mechanics parameters of light-weight concrete by implementing natural pumice stone as coarse aggregate. *Sulaimani J. Eng. Sci.* **2023**, *9*, 61–74.
34. Fang, S.; Lam, E.S.S.; Li, B.; et al. Effect of alkali contents, moduli and curing time on engineering properties of alkali activated slag. *Constr. Build. Mater.* **2020**, *249*, 118799. https://doi.org/10.1016/j.conbuildmat.2020.118799.
35. Ngugi, H.N.; Mutuku, R.N.; Gariy, Z.A. Effects of sand quality on compressive strength of concrete: A case of Nairobi County and its environs, Kenya. *Open J. Civ. Eng.* **2014**, *4*, 255–273.