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Research Paper

Predicting the Compressive Strength of UHPFRC Using Machine Learning and Soft Computing Models: Optimization of Fiber Content and Additives

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ABSTRACT

Ultra-high-performance fiber-reinforced concrete (UHPFRC) is a relatively new material known for its superior mechanical properties, particularly its compressive strength (CS), making it suitable for advanced structural applications. Traditional experimental methods for predicting CS are time-consuming and costly. In this study, a dataset of 276 samples with 12 input parameters was compiled from existing literature to develop predictive analytical models. The input variables include cement, sand, water, superplasticizer, silica fume, fiber content, water–binder ratio, water–cement ratio, curing age, fiber aspect ratio, temperature, and fiber volume. The reported CS values range from 90 to 186 MPa. Five modeling techniques—Linear Regression (LR), Log Base Regression (LBR), Nonlinear Regression (NLR), M5P-tree, and Artificial Neural Network (ANN)—were employed to predict the compressive strength of UHPFRC. Among these models, ANN demonstrated the highest prediction accuracy across all evaluation criteria, followed by the M5P-tree model. Residual error analysis confirmed that the ANN produced the lowest prediction error. Sensitivity analysis revealed that temperature, curing age, and superplasticizer content significantly influence CS. Optimization results indicated that a fiber content between 2.05% and 2.09% yields maximum compressive strength. These findings provide valuable insights for optimizing UHPFRC mix design using machine learning approaches.

1 Introduction

Ultra-high-performance fiber-reinforced concrete (UHPFRC) is a new type of concrete that emerged in the 1990s [1].

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Utilizing Ultra-High-Performance Fiber-Reinforced Concrete (UHPFRC) offers substantial benefits, including reduced construction time and enhanced serviceability and durability, enabling the structure to reach its intended design life with minimal maintenance [2]. Compressive strength is a material or structure's ability to endure loads that typically decrease in size. Concrete refers to the maximum stress the material can bear before collapsing under a crushing load [3]. UHPFRC's extremely high strength characteristics result in a significant reduction in structural weight, i.e., the weight of UHPFRC structures is approximately one-third (or half) that of ordinary reinforced concrete (RC) structures with identical external loads [4]. The compressive strength of UHPFRC exceeds 150 MPa, and a design value of tensile strength is 8 MPa [5]. The fiber content of UHPFRC has a considerable impact on its compressive strength, impact resistance, and overall performance. Rong and Sun (2012) and Yunsheng et al. (2008) found that increasing fiber volume improves tensile strength by bridging cracks and inhibiting their propagation, especially at high strain rates [6, 7]. Pyo and El-Tawil (2015) have also supported this statement [8]. However, research suggests that returns decrease beyond a particular fiber concentration. Mao et al. (2015) found that UHPFRC panels enhanced blast resistance with fiber content up to 6%, but further increases had no significant effect on penetration depth or crater diameter [9]. Furthermore, increasing fiber volume can cause decreased workability, increased porosity, and fiber balling, resulting in a non-linear rise in post-cracking flexural strength, as observed by Yoo et al. (2017) and Millard et al. (2010). The ideal fiber content must be determined to compromise impact resistance and workability [10, 11]. Wu et al. (2019) indicate that the optimal fiber content in Ultra-High-Performance Fiber-Reinforced Concrete for enhancing compressive strength typically ranges from 2% to 3% by volume [12]. According to Yoo et al. (2016), excessive fiber content can lead to poor flowability and uneven fiber distribution [13]. Finally, while enhancing UHPFRC performance, using excessive amounts may cause issues; therefore, finding the optimal mix is essential. Superplasticizer (SP) is a crucial component in modern concrete formulations, enhancing workability and strength. It accomplishes this by lowering the water-to-binder (W/B) ratio while maintaining flowability, resulting in a denser and more durable concrete matrix [14]. SP has a considerable impact on the workability and compressive strength of UHPFRC at a constant W/B ratio. Furthermore, the improved fiber efficiency significantly reduced the likelihood of fiber settlement, which in turn influenced strength development. The SP concentration should be 3.5% to achieve the high-fiber reinforcing effect and appropriate operating performance parameters [15]. Superplasticizer (SP) is crucial in enhancing the particle packing structure in UHPFRC, which is vital for increasing its strength and durability [16]. The additional SP in UHPFRC reduces the water-to-binder (W/B) ratio. It helps maintain fluidity, which is crucial for achieving high compressive strength, especially when coarse aggregates are excluded from this type of concrete. However, the dosage of SP must be carefully regulated, as excessive levels might cause fiber settling, which affects the distribution and orientation of the fibers and eventually compromises the material's mechanical properties [17]. Temperature is considered a critical variable in measuring compressive strength, and numerous researchers have investigated its significance in this context. Tahawia (2017) discovered that specimens of UHPFRC with steel fibers spalled at oven temperatures ranging from 400°C to 500°C, whereas compressive strength increased from 20°C to 200°C before declining [18]. According to Tai et al. (2020), concrete exhibits significant spalling above 500 °C, making it unsuitable for mechanical testing. However, the dispersion of steel fibers remains uniform even after failure [19]. One of the primary fields of artificial intelligence is machine learning, which focuses on creating algorithms that can recognize complex trends in experimental data without relying on a pre-existing equation as a model, thereby enabling intelligent decision-making [20]. ML applications are anticipated to grow in the concrete area, enabling direct data analysis and facilitating scientific discovery as ML models become more widely available to users [21]. There are six steps in a standard ML study: defining the problem, gathering data, pre-processing (or cleaning) data, developing a model, evaluating the model, and deploying the model [21]. Artificial intelligence has demonstrated significant potential to reduce material, labor, and experimental test costs, as well as time-consuming research procedures [22]. One of ML application that has been used in this research is ANN (Artificial Neural Network), Garrett (1994) gave an engineering description of an artificial neural network (ANN) as a computational system capable of obtaining, representing, and computing mappings from one multivariate information space to another, using a given set of data that means that mapping [23]. One of the most essential properties of artificial neural networks (ANNs) is their ability to learn from experience, generalize from examples, and adapt to changing conditions. ANNs may conduct causal mapping, which establishes links between cause and effect for estimation and prediction, and inverse mapping, which infers probable causes from observed effects [23]. These networks represent real-world problems by linking input patterns with related target outcomes. AI and ANN are handy when the rules are unknown or difficult to discover [24]. The M5P algorithm, a sophisticated and efficient application, is handy for analyzing complex systems with high dimensionality and many properties. Quinlan [25] introduced it as the M5 algorithm, which was designed to solve classification and regression problems. Later, Wang and Witten [26] improved the M5 algorithm, leading to the development of the well-known M5P

method [27].

1.1 Research Objectives

This research aims to investigate the impact of fiber content on compressive strength across varying temperatures, superplasticizer dosages, and curing ages in ultra-high-performance fiber-reinforced concrete (UHPFRC), drawing on previous literature. Another study goal is to identify the modulus that most strongly influences compressive strength. Unlike prior studies that employed multiple statistical models, this study focuses on models specifically designed to investigate correlations between variables. The following are the study's specific objectives:

- Conduct a thorough sensitivity analysis to identify the critical variables influencing the compressive strength of UHPFRC.
- Determine the optimum fiber content that results in the highest compressive strength of UHPFRC, beyond which strength begins to drop.
- Develop credible soft computing and ML models to estimate the compressive strength of 278 various UHPFRC mixtures.

1.2 Dataset Description

To numerically estimate the CS of UHPFRC, a dataset of 276 samples across various mix ratios was used, each with 12 input variables and 1 output variable (Table 1). These data sets were gathered from prior studies on the topic, and Table 2 shows statistical data for the classification features of the dataset's 12 input characteristics. The normalizing procedure was employed to increase the reliability of the original data. The fundamental characteristic before employing soft computing and ML models for data analysis is to use a data normalization equation to normalize the values. After applying the equation, the results are normalized to a range of 0 to 1. Equation 1 is used in this study to pre-normalize each result to a range of 0 to 1.

$$X_{norm} = \frac{X - X_{min}}{X_{max} - X_{min}} \quad (1)$$

Where X_{norm} , X_{max} , and X_{min} stand for the original value, maximum value, and minimum value, respectively, in each feature.

2 Methodology

Fig. 1 illustrates the processes required to conduct the research. Studies on ultra-high-performance fiber-reinforced concrete are crucial, and 276 samples and mixes of this type of concrete have been gathered [28-51]. The database was divided into training and testing datasets to generate accurate and dependable models. A total of 194 samples were used for training (70%), while the remaining 80 samples were used for testing (30%). The variables include the following: water-to-binder ratio, water-to-cement ratio, cement, water, sand, superplasticizers, silica fume, age, fiber, fiber aspect ratio, temperature, and fiber content. The primary purpose of this study is to predict the value of CS and to develop reliable models. The primary predictive models employed were linear regression (LR), non-linear regression (NLR), log base regression (LBR), artificial neural network (ANN), and M5P Tree. The impact of different moduli on forecasting CS, including superplasticizers and silica fume, is being intensively researched.

2.1 Data Statistics

The obtained datasets underwent statistical analysis to determine the relationship between each independent variable (input variable) and the dependent variable (output variable). Fig. 2 shows a marginal plot of the compressive strength of ultra-high-performance fiber-reinforced concrete for each independent parameter. Fig. 3 shows the measured compressive strength data using a frequency histogram. Fig. 4 presents a graph of the relationship between the independent and dependent variables. Each parameter in this study was analysed for its mode, mean, standard deviation, minimum, and maximum. The mean is the average of all the values in a dataset, whereas the median is the central value when the data is ordered. The mode indicates the value that occurs most often. Deviation indicates how far individual data points deviate from the mean, revealing the range of values around the average. Meanwhile, variance measures the total dispersion of the dataset, indicating the degree of variability. Table 2 summarizes statistics for all variables.

Table 1. Collected database of variables for UHPFRC: ranges and references

Ref	W/B (%)	W/C (%)	C (kg/m ³)	W (kg/m ³)	Sand (kg/m ³)	SP (kg/m ³)	SF (kg/m ³)	Age (Days)	Fiber (kg/m ³)	Fiber AR	T(°C)	FL (mm)	FD (mm)	F cont. (%)	No. of Data
[29]	0.24	0.28	657	185	1051	40	119	7-180	157	65	10-90	13	0.20	2	25
[31]	0.20	0.25	1280	273-320	292-647	30.26-77.22	273-320	28	0-468	63.5	60	12.70	0.20	0-6	11
[32]	0.15	0.18	657	116.46	1050	1.05	119.40	7-56	156	65	20-90	13	0.20	2	14
[37]	0.19-0.26	0.24-0.32	960	277-306	960	24	240	7-28	192	72	20	13	0.18	2.50	7
[39]	0.24	0.26	700	180	1104	30	50	28	0-78	65	20	13	0.20	0-1	5
[40]	0.22	0.25	1500	372.50	650	40	175	7-28	0-188.40	60-120	28	12-21	0.2-0.35	0-2.42	24
[43]	0.16	0.22	784-809.9	171-177	1045-1079	20.9-21.6	261-270	7-90	0-234	65	20	13	0.20	0-3	13
[46]	0.16	0.20	850	170	850	76.5	226	28	78-157	65	20	13	0.20	1-2	2
[47]	0.24	0.28	657	185	1051	40	119	7-28	157	65	90	13	0.20	2	3
[48]	0.22-0.31	0.23-0.33	612.40-874.90	202.10	1273.40	45.9	43.70	7-28	39-195	65	21	13	0.20	0.5-2.5	26
[50]	0.12	0.15	712	109	1020	30.7	231	3-58	156	62.5	60-90	12.50	0.20	2	10
[52]	0.16	0.21	1050	224	678	42	350	5	39-117	60	80	12	0.20	0.5-1.5	3
[53]	0.14	0.18	750-800	135-144	1250	75-80	225-240	7-28	40	16.25	25	13	0.80	0.51	4
[54]	0.22	0.35	413	143	1593-1827	9.75	32.5	28	0-234	50	20	30	0.6	0-2	4
[55]	0.16-0.18	0.2-0.23	788	157.6-181.24	795.88	14.77	197	28	157	81	25-200	13	0.16	2	3
[1]	0.33	0.35-0.36	641-648	228	943-952	34.2-45.6	40.8-41.3	28	312-390	65	23	13	0.20	4-5	2
[5]	0.14	0.19	720	136	1025	30	240	28	0-157	63.5	22	12.70	0.20	0-2	4
[6]	0.18	0.22	800	176	896-976	39	200	28	160-240	59	21	132-3	0.22	2-3	2
[7]	0.20	0.25	900	225	826	36	225	56	0-78.91	60	200	12	0.20	0-1.01	2
[8]	0.14-0.17	0.18	900	162	764-1055	40	44-220	28	157	85	22	12.7	0.15	2	19
[9]	0.13-0.16	0.16-0.22	703-950	155	690	24.5-28.5	285	28	0-117	0-1014.29	21-125	0-50	0-0.60	1.5	20
[10]	0.18-0.20	0.24	900	216	1125	27	180-270	7	0-154.8	380.79	25	12-13	0.038-0.2	0-3	11
[11]	0.12-0.14	0.14-0.16	998.8	141-164.5	898.7-1013.9	49.4-88.2	176.25	7-28	0-78	722-722.23	21	13	0.018	0-3	39
[14]	0.2	0.20	1163-1543	233.7-312.6	607-1923	39.41-89.7	5.5-20	28	0-468	0-63.5	60	0-12.7	0-0.2	0-4	23

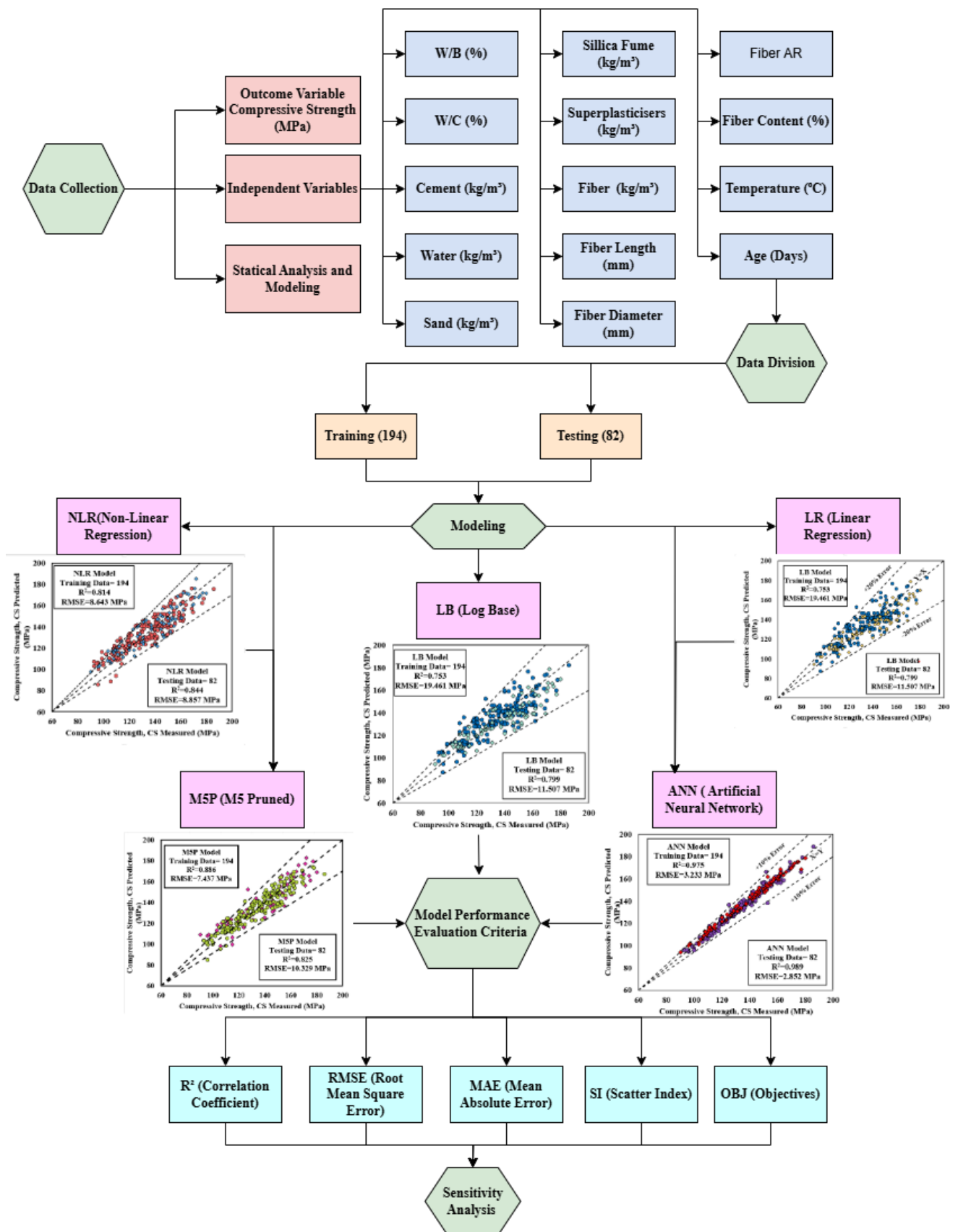


Fig. 1 - Flowchart diagram for the performed study

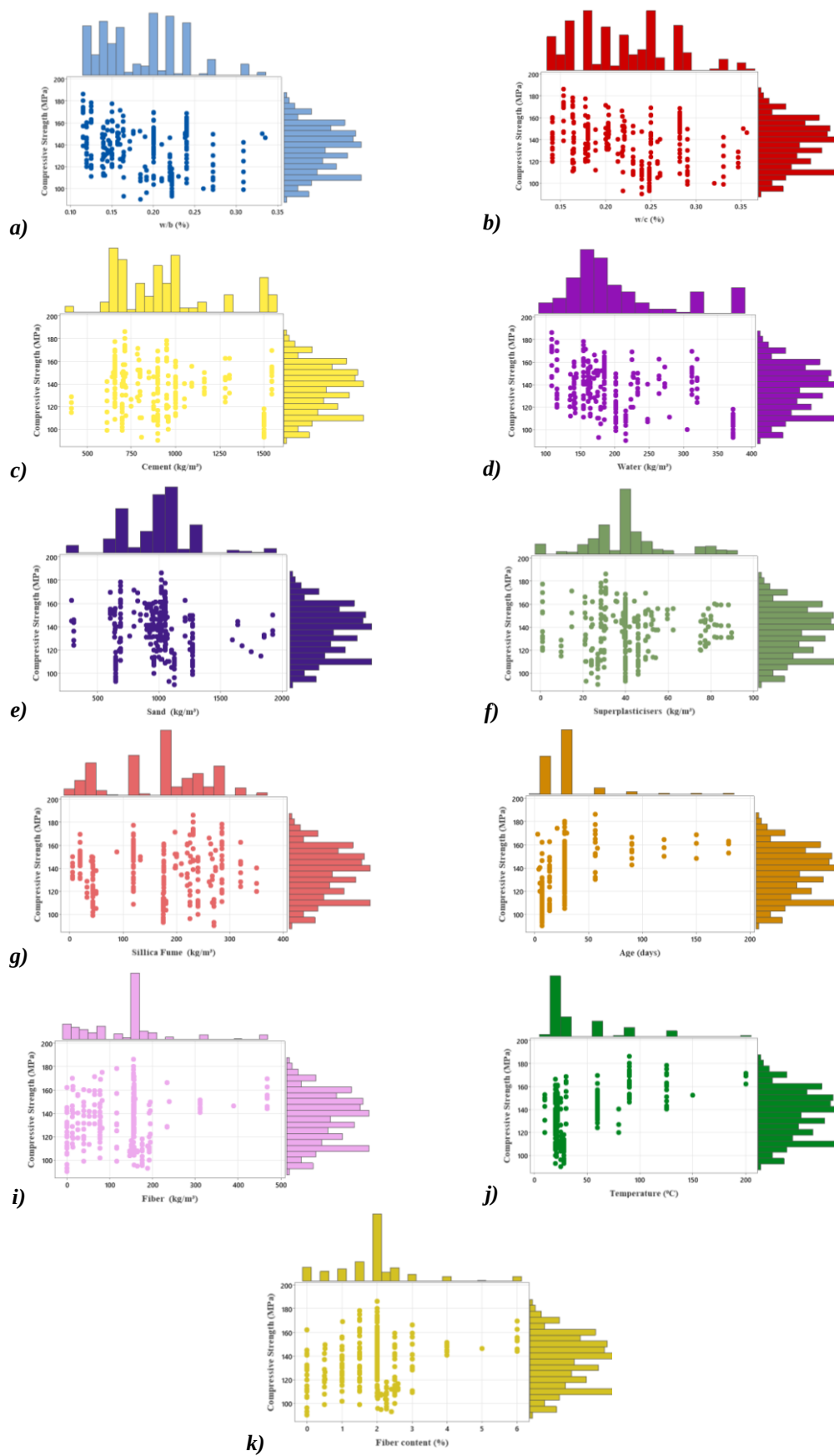
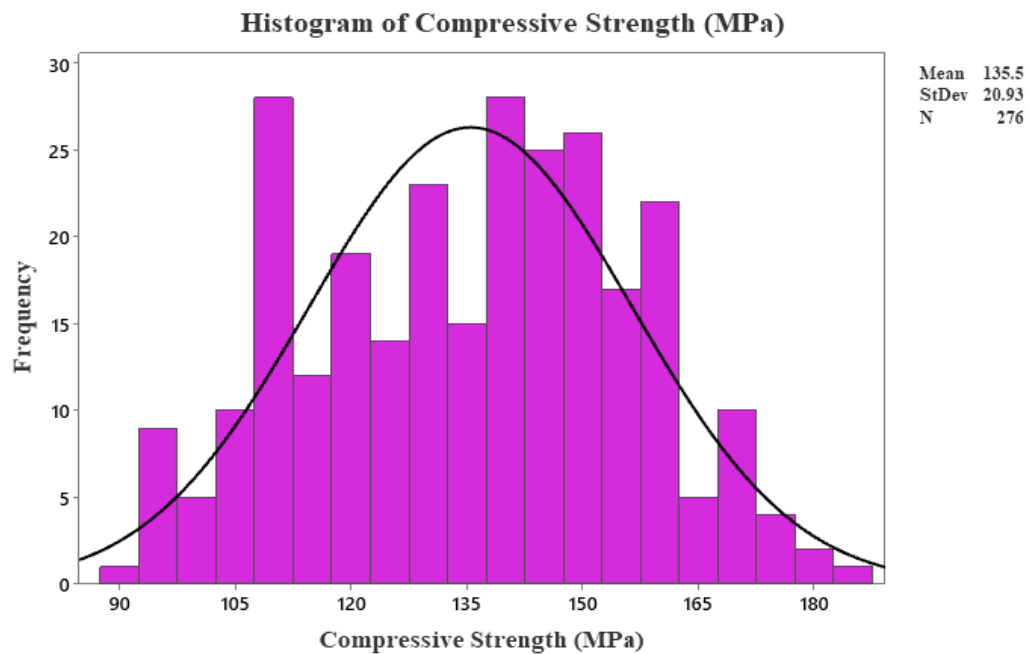


Fig. 2 - Marginal plot between compressive strength of UHPFRC and (a) W/B (%); (b) W/C (%); (c) Cement (kg/m³); (d) Water(kg/m³); (e) Sand(kg/m³); (f) Superplasticizer (kg/m³); (g)Silica Fume (kg/m³) ; (h) Age (Days) ; (i) Fiber (kg/m³); (j) Temperature (°C); (k) Fiber Content(%).

Table 2. Statistical information for input and output variables

variables	Units	Subscript	Min	Max	Mode	Mean	Standard deviation
Water/Binder	-	w/b	0.12	0.33	0.20	0.19	0.05
Water/Cement	-	w/c	0.14	0.36	0.28	0.22	0.05
Cement	kg/m ³	C	413.00	1543.00	657.00	937.05	281.66
Water	kg/m ³	W	109.00	372.50	185.00	202.14	72.89
Sand	kg/m ³	S	292.00	1923.00	1051.00	972.26	275.88
Superplasticizers	kg/m ³	SP	1.05	89.70	40.00	40.45	19.03
Sillica Fume	kg/m ³	SF	5.50	350.00	176.25	164.07	88.92
Age	Days	Age	3.00	180.00	28.00	28.80	27.80
Fiber	kg/m ³	F	0.00	468.00	157.00	129.51	94.12
Fiber AR	-	FAR	0.00	1014.29	65.00	201.31	257.52
Temperature	C ^o	T	10.00	200.00	21.00	40.82	34.58
Fiber length	mm	Fl	0.00	50.00	13.00	13.62	5.69
Fiber diameter	mm	Fd	0.00	0.80	0.20	0.18	0.13
Fiber content	%	Fc	0.00	6.00	2.00	1.88	1.12
sand size	mm	Ss	0.08	0.60	0.27	0.41	0.17
Compressive Strength	Mpa	FC	90.18	186.00	140.00	135.49	20.90

**Fig. 3 - Frequency plot for UHPFRC's compressive strength, CS (MPa).**

	W/B	W/C	C	W	S	SP	SF	Age	F	FAR	T	Fc	CS
W/B	1												1
W/C	0.93	1											0.8
C	-0.03	-0.19	1										0.6
W	0.51	0.41	0.81	1									0.4
S	0.19	0.17	-0.54	-0.43	1								0.2
SP	-0.09	-0.24	0.34	0.11	-0.13	1							0
SF	-0.54	-0.32	0.02	-0.10	-0.54	-0.11	1						-0.2
Age	0.15	0.19	-0.26	-0.13	0.05	-0.13	-0.10	1					-0.4
F	0.34	0.30	0.22	0.39	-0.16	-0.16	-0.17	0.11	1				-0.6
FAR	-0.50	-0.51	0.07	-0.28	-0.11	0.41	0.23	-0.21	-0.46	1			-0.8
T	-0.17	-0.12	0.00	-0.05	-0.24	-0.23	0.19	0.02	0.05	-0.06	1		-1
Fc	0.17	0.14	0.25	0.30	-0.24	-0.03	-0.07	0.05	0.91	-0.16	0.07	1	
CS	-0.32	-0.31	-0.23	-0.41	-0.06	0.01	0.04	0.45	0.23	0.00	0.50	0.27	1

Fig. 4 - Correlation matrix for the correlation between all the variables

2.2 Modelling techniques

This study employs modeling techniques to determine the relationship between the independent and dependent variables. This was accomplished by separating the acquired data into two subsets: a training dataset and a testing dataset. The model was developed using the training dataset, while the testing dataset was utilized to assess its reliability. Analysis of the correlation matrix revealed that the relationship between compressive strength and temperature, age, and fiber content exhibited acceptable correlation coefficients of approximately 0.50, 0.45, and 0.27, respectively. However, it revealed a low relationship between compressive strength and all other independent variables, as shown in Fig. 4. The computed correlation coefficients were -0.32 for W/B ratio, -0.31 for W/C ratio, -0.23 for cement, -0.41 for water, -0.06 for sand, 0.01 for superplasticizers, 0.04 for silica fume, 0.23 for fiber, and 0 for fiber aspect ratio. The five models were developed to estimate the CS of ultra-high-performance fiber-reinforced concrete. Prediction accuracy and reliability were evaluated using R^2 , RMSE, MAE, SI, and OBJ for training and testing datasets. R^2 is a metric used in regression analysis to describe the degree of fit for bias in independent data errors. The root mean squared error (RMSE) is the average of the squared differences between the expected and observed values. MAE, which stands for Mean Absolute Error, compares the differences between paired observations of the same phenomenon. SI is a statistical error metric that examines the difference between observed and simulated values. It can be estimated using various formulae, including RMSE/range and RMSE/mean. OBJ is an objective function, a linear function with two decision variables that is maximized or minimized according to the constraints specified.

2.2.1 Linear-Regression Model (LR)

Linear regression is a soft computing algorithm that fits a linear equation to the data to establish a linear relationship between the dependent variable (compressive strength) and any additional independent variables. There are four LR models, two based on the number of independent variables. When there is just one independent variable, the technique is known as simple linear regression; when there are numerous independent variables, the technique is known as multiple linear regression [27]. In this study, a multiple linear regression model was used. The other two forms rely on the dependent variables; univariate linear regression is used when there is only one dependent variable, while multivariate linear regression is used when there are several dependent variables. Univariate linear regression was applied in this research. Although the linear regression model is expected to have the lowest accuracy among all models, it is not the least reliable in this research. Equation 2 is the linear regression model representing the relationship between UHPFRC parameters.

$$CS (MPa) = \beta_1(W/B) + \beta_2(W/C) + \beta_3(C) + \beta_4(W) + \beta_5(S) + \beta_6(SP) + \beta_7(SF) + \beta_8(Age) + \beta_9(F) + \beta_{10}(FAR) + \beta_{11}(T) + \beta_{12}(Fc)^2 \quad (2)$$

the independents variables are water to binder ratio(W/B), water to cement ratio (W/C), cement (C), water (W), sand (S), Superplasticizers (SP), silica fume (SF), age (Age), fiber (F), fiber aspect ratio (FAR), temperature (T), fiber content (Fc). Also, β_1 until β_{12} are the parameters.

2.2.2 Non-Linear Regression Model (NLR)

This study also utilized a nonlinear regression model to estimate compressive strength. The distinction between nonlinear and linear regression models is that linear regression models define the relationship using a straight line. However, the nonlinear regression model establishes the relationship using a curve, resulting in less error and a more precise answer [55]. Nonlinear regression encompasses polynomial, exponential, logarithmic, power, and piecewise linear regression models. This research used power-equation regression, as represented in Equation 3.

$$CS (MPa) = \beta_0 \times (W/B)^{\beta_1} + (W/C)^{\beta_2} + (C)^{\beta_3} + (W)^{\beta_4} + (S)^{\beta_5} + (SP)^{\beta_6} + (SF)^{\beta_7} + (Age)^{\beta_8} + (F)^{\beta_9} + (FAR)^{\beta_{10}} + (T)^{\beta_{11}} + (FC)^{\beta_{12}} \quad (3)$$

Whereas β_1 until β_{12} are the parameters.

2.2.3 Log Base Regression Model

The study also employs a novel type of nonlinear model, the log-based regression model, to estimate the compressive strength of UHPFRC. This model uses a logarithmic relationship between the independent variables and the critical parameters to compute compressive strength accurately and to analyse errors relative to experimental data. The logarithmic equation is shown by Equation 4:

$$CS (MPa) = \beta_0 + \beta_1 \ln(W/B) + \beta_2 \ln(W/C) + \beta_3 \ln(C) + \beta_4 \ln(W) + \beta_5 \ln(S) + \beta_6 \ln(SP) + \beta_7 \ln(SF) + \beta_8 \ln(Age) + \beta_9 \ln(F) + \beta_{10} \ln(FAR) + \beta_{11} \ln(T) + \beta_{12} \ln(FC) \quad (4)$$

Whereas β_1 until β_{12} are the parameters.

2.2.4 M5P-tree Model

The M5P-tree model was another model used in research. The predicted outcome of the UHPFRC using the M5P-tree model proved quite effective. This method was introduced in a paper and is used in WEKA, a genetic algorithm platform for regression analysis. WEKA relies on various models, including this one, an M5P-tree model that excels in regression issues. WEKA's M5P-tree model focuses on numerical prediction and builds upon the fundamental decision tree technique. The leaf nodes are linear regression models that reflect the linearity and non-linearity of the relationship between the data points. This enables the model to predict compressive strength [56]. The M5P-tree method, like typical decision trees, splits the data based on attribute values to reduce variability in the output variable, specifically compressive strength. In contrast to typical decision trees, which use discrete class labels at leaf nodes, the M5P model employs linear regression at each leaf node, making it more suited to regression tasks [57].

2.2.5 Artificial Neural Network Model

UHPFRC compressive strength may also be predicted using the artificial neural network (ANN) model. This model utilizes an application embedded within the WEKA software and operates on a network of interconnected nodes trained on data [4]. Neural networks can learn from data by processing input through multiple layers, allowing them to identify patterns, categorize data, and predict future occurrences. This learning capacity was utilized in this study. It can be taught through training datasets, and its behavior is defined by the connections between its parts and their respective strengths. During training, these relationships are automatically modified by a given learning rule in a predetermined manner. Therefore, the ANN can be utilized to estimate the compressive strength of UHPFRC using the input data [58]. The ANN model achieves the highest R^2 and the most accurate results when applied to this database with a 70/30 split, and it can generate code specifying the number of hidden layers and the learning process.

2.3 Performance evaluation criteria

The reliability of the models with the obtained database was evaluated using the correlation coefficient (R^2), root mean squared error (RMSE), mean absolute error (MAE), objective function (OBJ), and scatter index (SI). They are used as performance evaluation metrics to test and validate the usefulness of machine learning techniques. Several experiments were conducted to determine the optimal values of the independent parameters. Equations (10-14) represent the statistical parameters needed to determine each criterion [52-54, 60].

$$R^2 = \left(\frac{\sum_i (xi - \bar{x}) \times (yi - \bar{y})}{\sqrt{\sum_i (xi - \bar{x})^2 \times \sum_i (yi - \bar{y})^2}} \right)^2 \quad (5)$$

$$MAE = \frac{\sum_{i=1}^n (|yi - xi|)}{n} \quad (6)$$

$$RMSE = \sqrt{\frac{\sum_{i=1}^n (yi - xi)^2}{N}} \quad (7)$$

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

$$SI = \frac{RMSE}{yi} \quad (9)$$

1. xi represents the predicted value of CS,
2. yi denotes the tested value of CS,
3. $\bar{x}$ stands for the average of the predicted values,
4. $\bar{y}$ stands for the average of the tested data,
5. n_{all} refers to the total number of datasets used (including training and testing),
6. n_{tr} is a value representing the number of training datasets,
7. n_{tst} is a value representing the number of testing datasets,
8. N represents the total number of data points in the dataset.

R^2 ranges from 0 to 1, with 1 being the best fit. RMSE, MAE, and range from 0 to infinity, with lower values indicating better model performance, and zero representing the optimal value. The Scatter Index (SI) value is used to evaluate model performance. The model is regarded as high-performing if the SI value is less than 0.1. The SI value is classified into performance levels: less than 0.03 signifies excellent performance, between 0.03 and 0.06 indicates satisfactory performance, between 0.06 and 0.09 reflects fair performance, and greater than 0.09 indicates poor outcomes [55, 61].

3 Results and discussion

3.1 Linear Regression Model

The compressive strength of UHPFRC was determined using a linear regression model with various mix ratios. This method produces inaccurate results because its mathematical parameters are derived from constant terms and a linear relationship between recycled aggregate concrete properties. Fig. 5 shows the predicted and measured compressive strength UHPFRC as shown in the graph, the R^2 value is 0.80 and RMSE of 8.970 MPa for training datasets, and for testing, the model has given R^2 of 0.830 and RMSE of 9.243 MPa the graph shows that the error line is between -15% and 15%, implying that 85% of the data points are within a ratio of 0.85 to 1.15 between the predicted and real compressive strength. Equation 10 is used on the training datasets and then applied to the test datasets.

$$CS (MPa) = 107 - 58.4 \left(\frac{W}{B} \right) - 0.0375 \left(\frac{W}{C} \right) + 0.291(C) - 0.006(W) - 0.270(S) - 0.064(SP) + 0.269(SF) + 0.130(Age) + 0.0007(F) + 0.297(T) - 3.01(Fc) \quad (10)$$

3.2 Non-Linear Regression Model (NLR)

The nonlinear regression model (NLR) is another model employed in this study to estimate the CS of UHPFRC. As previously stated, nonlinear has several varieties; the one used in this study is power regression. The equation for the NLR model was developed using training datasets and validated on test datasets to ensure the model's correctness. NLR is the most accurate and reliable regression model, with the highest R^2 and the lowest RMSE. As shown in Fig. 6, the R^2 value for the training datasets is 0.814. The RMSE value is 8.643 MPa. For testing, the model yielded an R^2 of 0.844 and an RMSE of 8.857 MPa. Equation 11 is the NLR model equation derived to predict the most accurate answer for the compressive strength

of UHPFRC. The margin of error in this model is between -15% and 15%, meaning that 85% of data points stay between 0.85 and 1.15. That small range concludes that the error is minor compared to other regression models.

$$CS \text{ (MPa)} = 95.7 + (W/C)^{0.50} + (C)^{0.749} + (S)^{0.714} + (SP)^{0.121} + (SF)^{0.757} + (Age)^{0.555} + (FAR)^{0.766} + (T)^{1.383} + (FC)^{0.01} \quad (11)$$

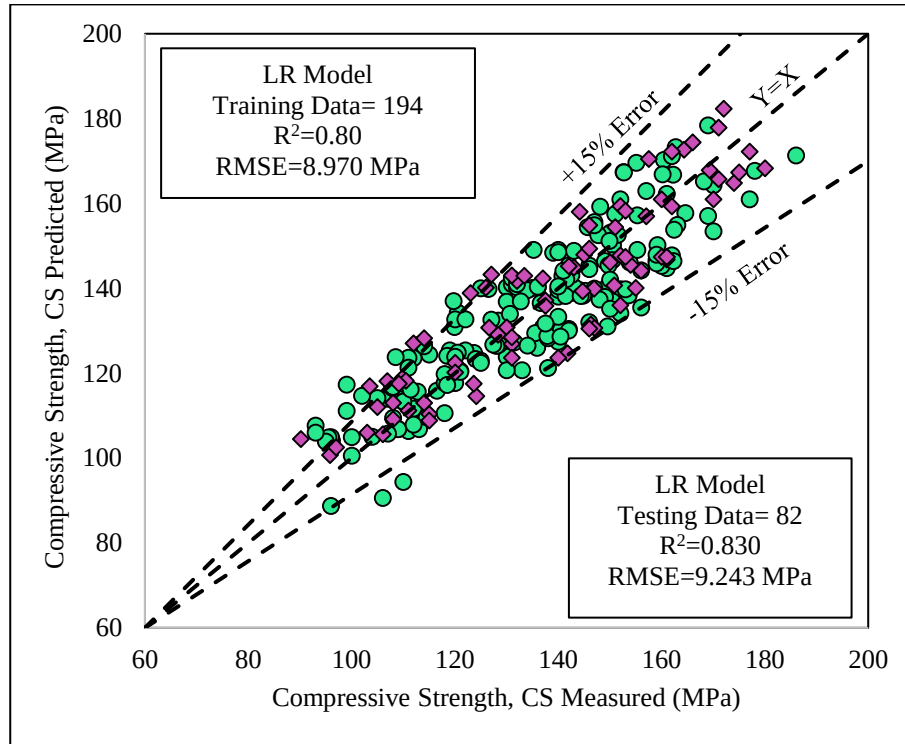


Fig.5 - Comparison between compressive strength predictions and measurements using the LR model for training and testing datasets.

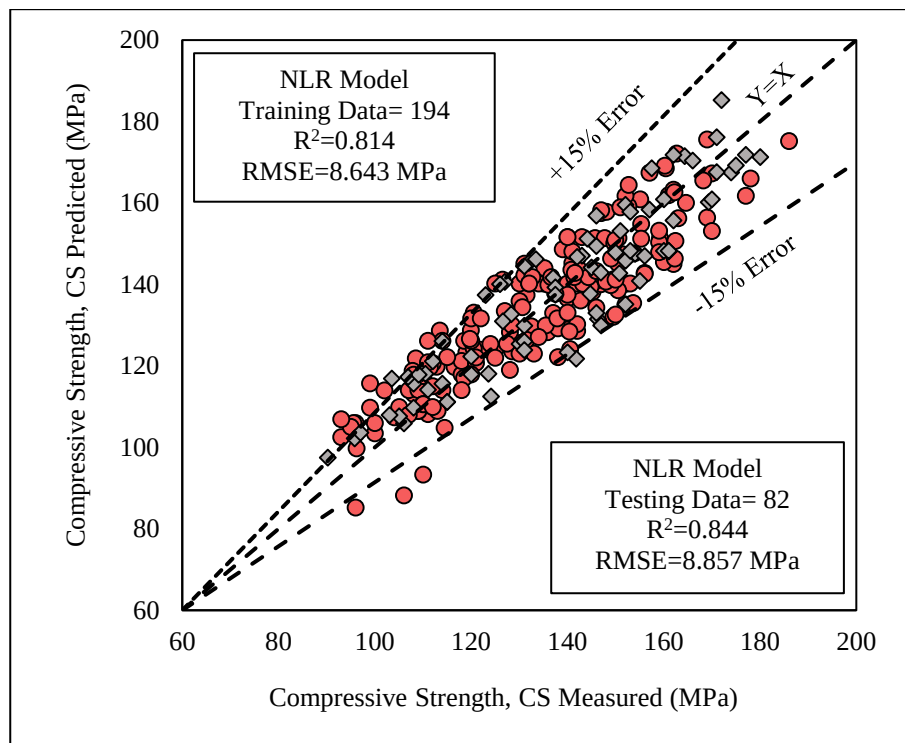


Fig. 6 Comparison between compressive strength predictions and measurements using the NLR model for training and testing datasets.

3.3 Log Base Regression Model

The plot of real compressive strength versus predicted compressive strength by the LB model is shown in Fig. 7. The R^2 and RMSE values for the training dataset are 0.753 and 19.461 MPa, and for the testing dataset, 0.799 and 11.507 MPa, respectively. Also, the error margin is within the range of -20% to 20%, indicating that 80% of the data points fall within the ratio 0.850 to 1.1520. Equation 12 is the equation of the LB model. The equation was extracted from the training datasets and subsequently applied to the testing datasets to verify its accuracy.

$$CS \text{ (MPa)} = 120.7 - 12.6 \ln\left(\frac{W}{B}\right) - 1.80 \ln\left(\frac{W}{C}\right) - 21.08 \ln(C) - 0.004 \ln(W) + 5.63 \ln(S) + 0.40 \ln(SP) + 13.25 \ln(SF) + 2.084 \ln(Age) - 0.93 \ln(F) + 15.21 \ln(FAR) - 1.47 \ln(T) + 2.94 \ln(FC) \quad (12)$$

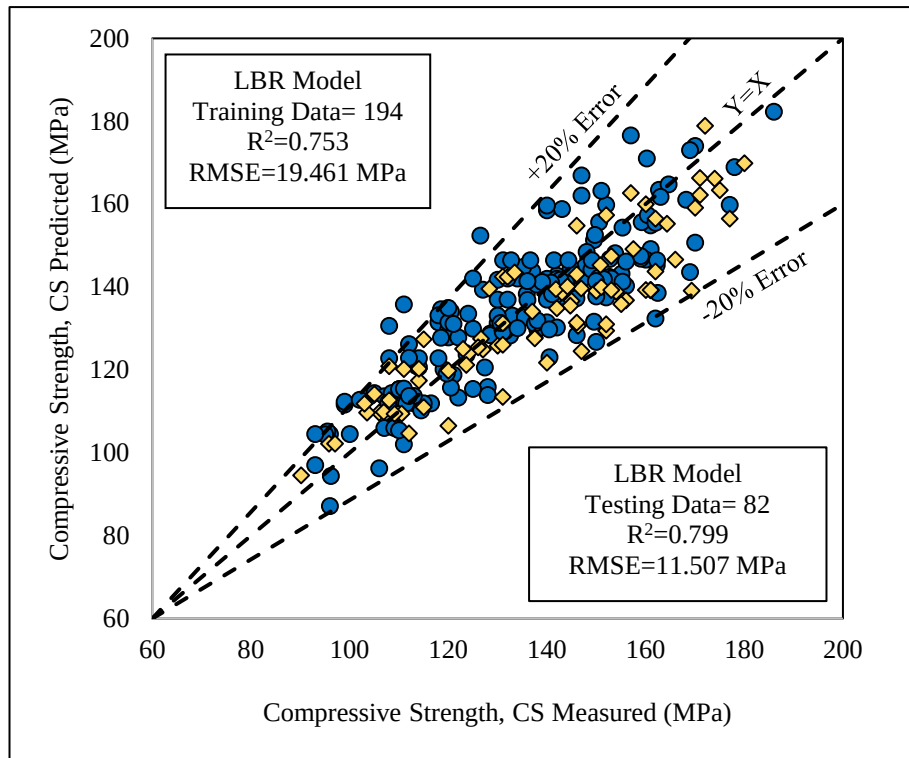


Fig.7 - Comparison between compressive strength predictions and measurements using the LBR model for training and testing datasets.

3.4 M5P-tree Model

The compressive strength of UHPFRC was evaluated using the M5P-tree model. It is not written as a linear equation since it was created using the WEKA program. WEKA is a machine learning program used to train the model on the training dataset and then test it on the testing dataset to ensure its reliability and effectiveness. Fig 8. Depicts the disparity between predicted and measured compressive strength values. The M5P-tree model achieved an R^2 of 0.886 and an RMSE of 7.437 MPa on the training dataset. The testing dataset yielded an R^2 of 0.825, with an RMSE of 10.329 MPa. The graph also shows the error margin from 5% to 5%, with 95% of data points falling between 0.85 and 1.15 for predicted vs. measured compressive strength. The M5P tree classifier with a batch size of 400 was utilized, and the minimum number of occurrences was set at 5. The model used 70% of the dataset for training and 30% for testing.

3.5 Artificial Neural Network Model

The compressive strength of UHPFRC was determined using the ANN model, which varies from a typical linear equation in that it was produced with the WEKA program. WEKA, a machine learning tool, was used to train the model on a training dataset and then test it on a test dataset to ensure its correctness and efficacy. Since ANN provided the highest R^2 and the lowest RMSE, it has, as anticipated, been the most accurate and dependable model. The R^2 value for the training datasets is 0.975, with an RMSE of 3.233 MPa, as shown in Fig. 9. For testing, the model yielded $R^2 = 0.989$ and RMSE = 2.852 MPa.

90% of the data points in this model fall between 0.90 and 1.10, with a margin of error of $\pm 10\%$. This narrow range indicates that the inaccuracy is lower than in other models.

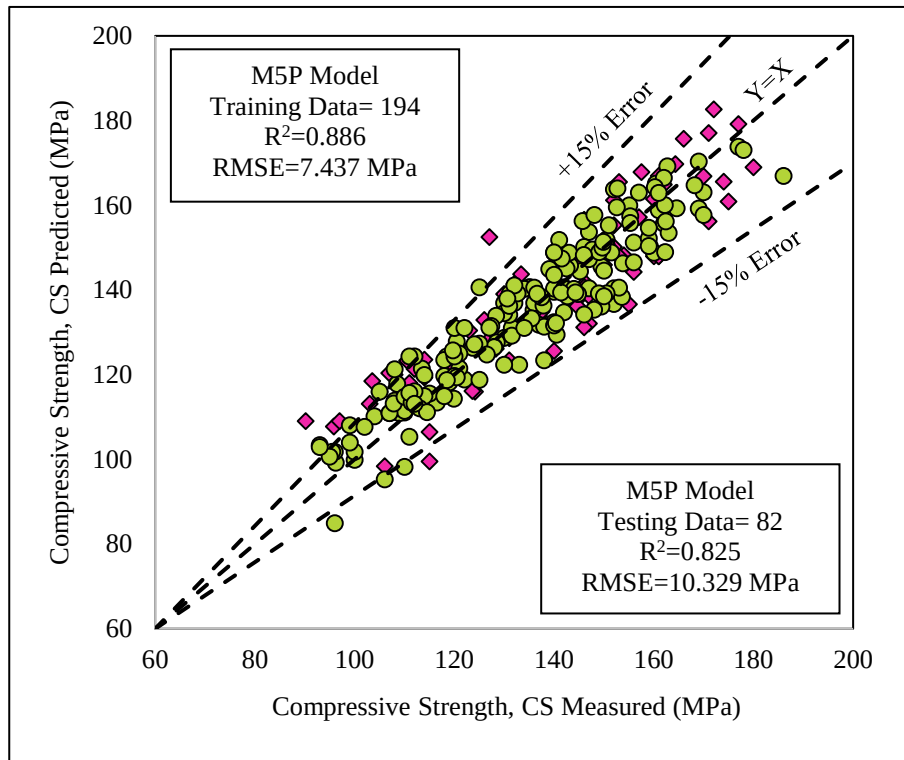


Fig.8 - Comparison of compressive strength predictions and measurements using the M5P-tree model for training and testing datasets.

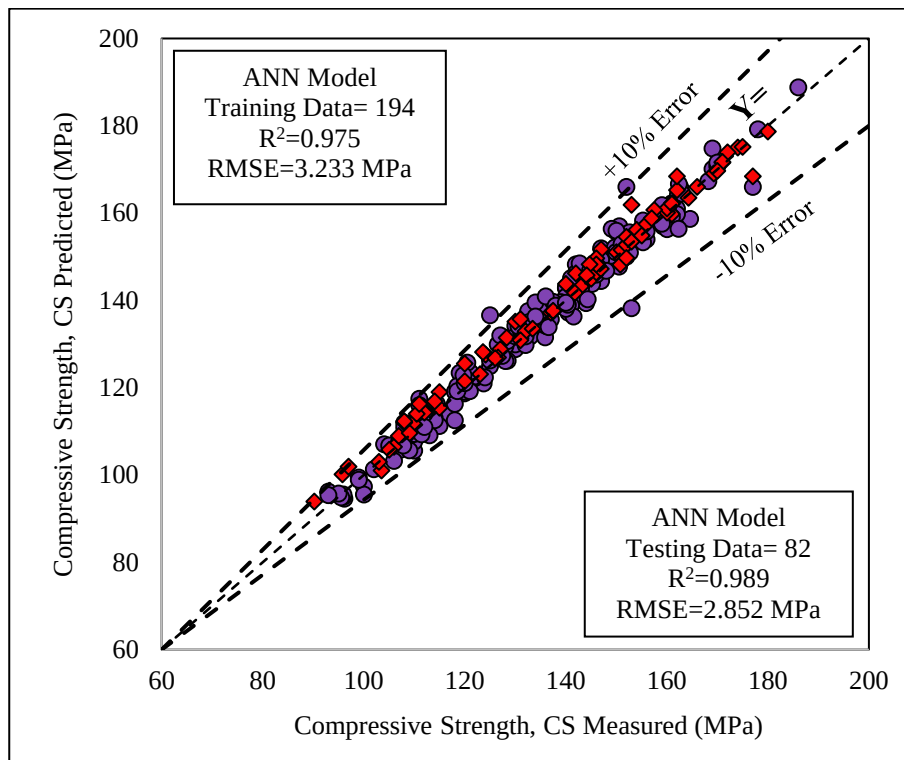


Fig. 9 - Comparison of compressive strength predictions and measurements using the ANN model for training and testing datasets.

4 Model comparison

This study examined the computed moduli to determine their impact on the compressive strength of ultra-high-performance fiber-reinforced concrete and used five distinct models to make predictions. The Artificial Neural Network (ANN) model demonstrated the highest reliability and accuracy, with 90% of data points within $\pm 10\%$ error lines for the training dataset.

The ANN revealed the following results: R^2 : 0.975, RMSE: 3.23 MPa, MAE: 2.36 MPa, SI: 0.024, and OBJ: 70.08 MPa.

The M5P tree model showed satisfactory performance, ranking second most accurate, with 85% of data points falling within $\pm 15\%$ of the error lines on the training dataset. The M5P tree model revealed the following results: R^2 : 0.886, RMSE: 7.43 MPa, MAE: 2.36 MPa, SI: 0.055, and OBJ: 76.01 MPa.

On the other hand, Linear Regression, Non-linear Regression, and Log-base Regression exhibit poorer performance. Their predictions all fall within $\pm 15\%$ to $\pm 20\%$ error lines, implying that these models are less accurate than the ANN and M5P models. The evaluation of RMSE and MAE values on the test dataset shows that they were generally lower than those on the training dataset; thus, the model's performance diminishes on new data. The OBJ value was the smallest in the ANN model, indicating that the predictions were the most accurate. Furthermore, the ANN model's SI values are the highest, indicating higher performance. When the R^2 value is higher on the test dataset than on the training dataset, the model generalizes well and makes accurate predictions on new data. Residual error analysis revealed that the ANN model's residual error ranged from -14.79 to +14.02 MPa. The M5P-tree model had a wider range, from -19.07 to +25.47 MPa. The LR, NLR, and LBR models had even broader ranges: -20.57 to +18.25 MPa, -20.0 to +16.73 MPa, -30.17 to +25.90 MPa, respectively.

Fig. 10 illustrates the performance metrics of the five models employed, comparing the OBJ, SI, and MAE values across the training and testing datasets. Fig. 11 compares residual errors in ultra-high-performance fiber concrete models, contrasting the ANN model with LR, NLR, LBR, and M5P-tree, and evaluating all employed models.

5 Sensitivity Investigation and Optimum Compressive Strength Investigation

5.1 Sensitivity investigation

The sensitivity study examined the impact of each variable on UHPFRC's predicted compressive strength. A Pareto sensitivity chart was used to forecast the sensitivity indexes of each parameter in the generated model. This analysis was conducted using the acceptable ANN model, which was found to be suitable for predicting CS. The Pareto chart of standardized effects indicates that temperature and age (H) are the most significant variables influencing concrete compressive strength, with temperature (K) having the most significant impact.

Temperature had a standardized value of 14.92, and age had a standardized value of 12.96. Superplasticizers (F) also have an essential function, possibly improving workability and strength. Water (D), fiber (J), and cement (C) have a moderate influence, demonstrating their importance in mix formulation. Meanwhile, sand (E), fiber AR (M), and water-to-binder ratio (A) have minor but detectable effects. The least influential parameters are water-to-cement ratio (B), silica fume (G), and fiber content (L), as their standardized effects are less than the statistical significance standards of 1.97, as shown in Fig.12 and Fig.13.

The sensitivity investigation discovered that temperature has the most significant impact on the compressive strength of ultra-high-performance fiber-reinforced concrete. A non-linear model with the highest coefficient of determination (R^2) was used to validate the relationship among soft computing models. In this analysis, all variables except temperature were held constant at their maximum values within the dataset. The temperature was then gradually increased by 1°C from 10°C to 200°C , with compressive strength measured at 7, 14, 28, and 180 days. The results show an upward trend in compressive strength with increasing temperature across all curing times. These findings are consistent with those of Tahawia (2017) and support the concept that the compressive strength of UHPFRC increases with temperature up to 200°C , as shown in Fig. 14.

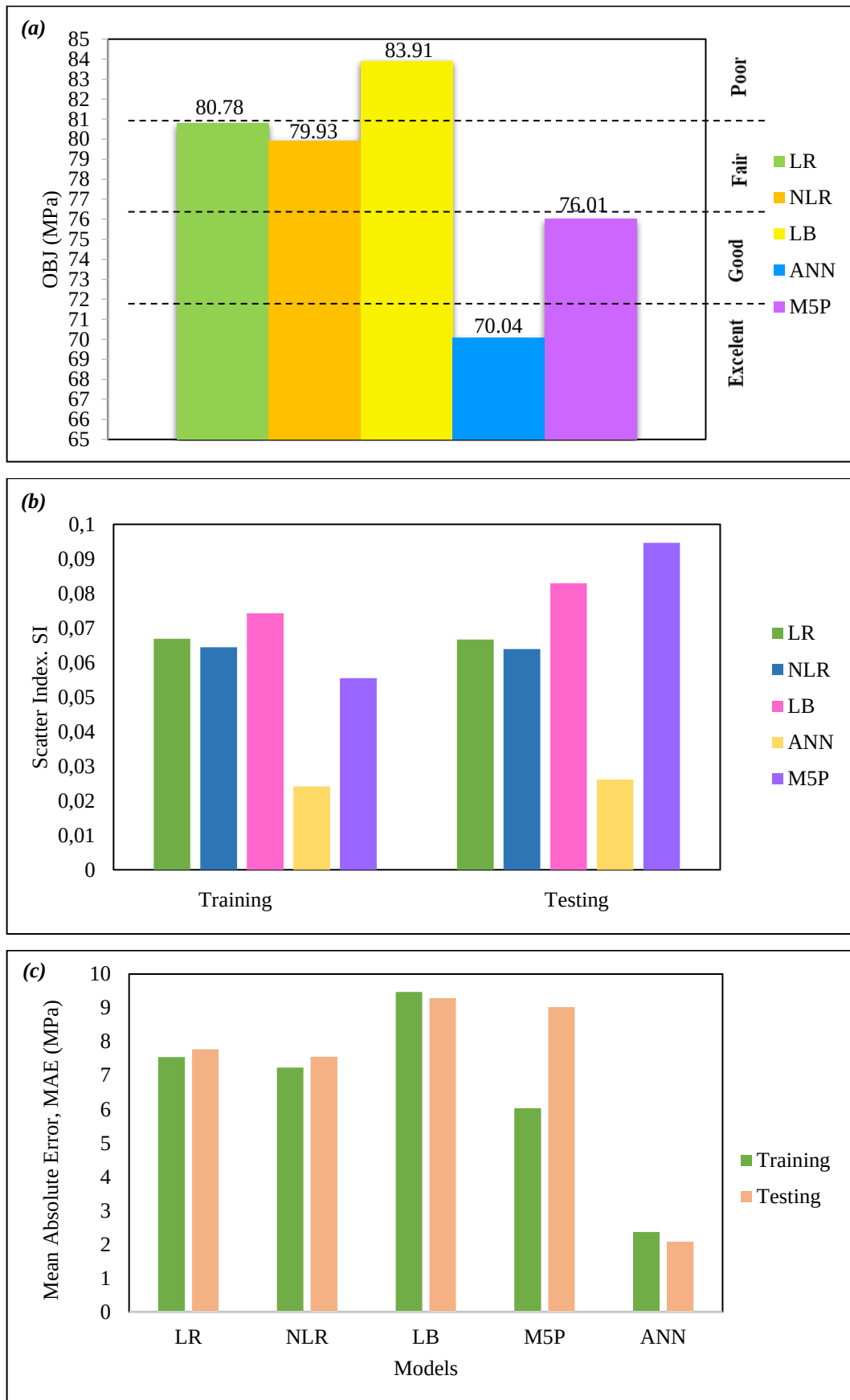


Fig. 10 - Comparison of (a) OBJ, (b) SI, and (c) MAE performance metrics across the five employed models using the training and testing datasets.

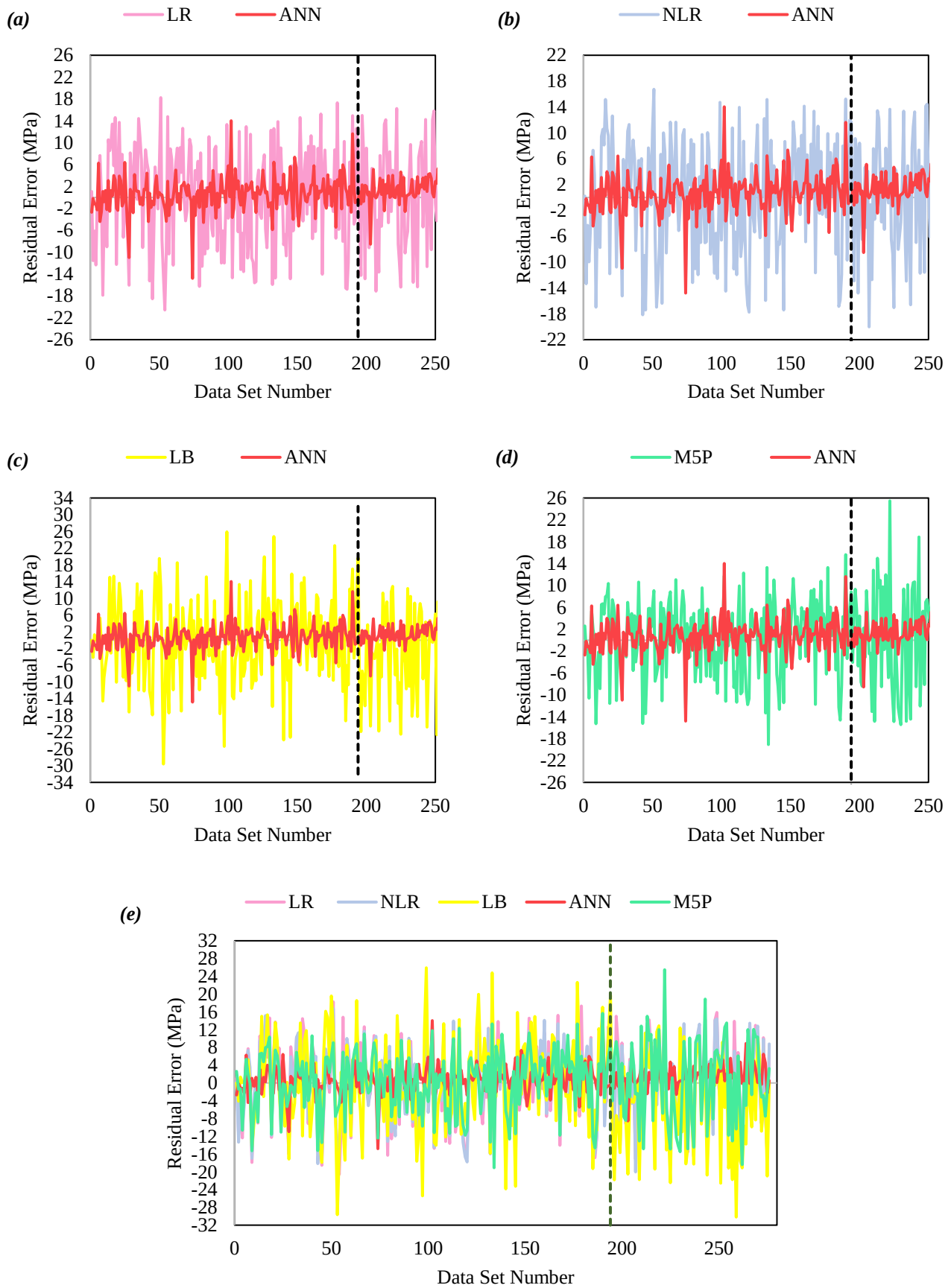


Fig. 11 - Comparison of residual errors in ultra-high performance fiber concrete models: (a) ANN vs. LR, (b) ANN vs. NLR, (c) ANN vs. LBR, (d) ANN vs. M5P-tree, (e) all employed models.

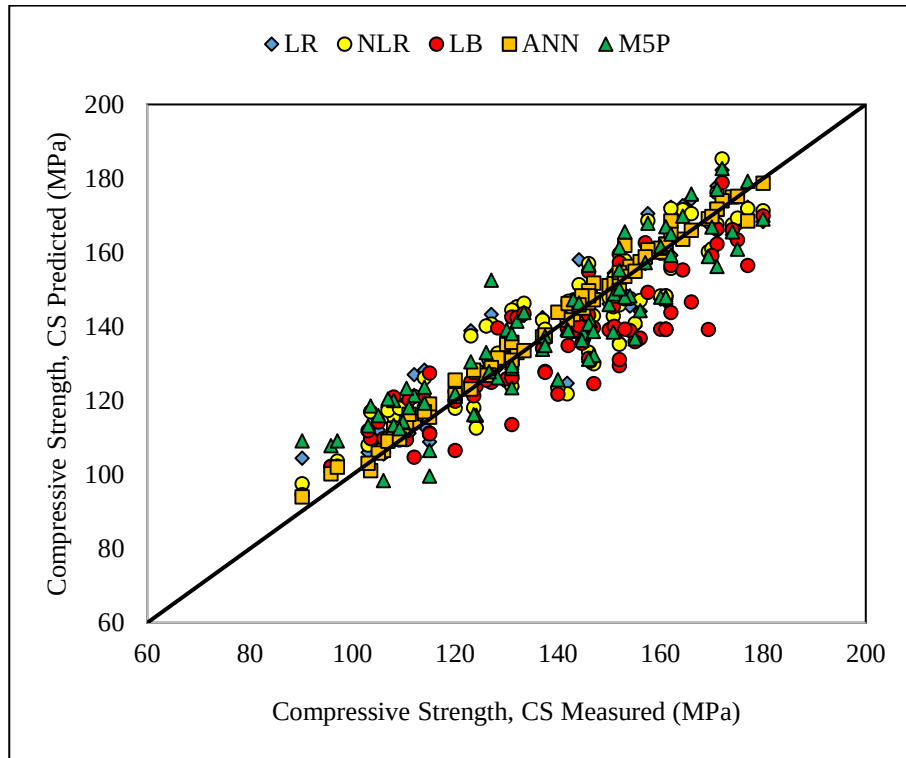


Fig. 12 - Model Prediction Testing for Datasets

Pareto Chart of the Standardized Effects
(response is Compressive Strength (MPa), $\alpha = 0.05$)

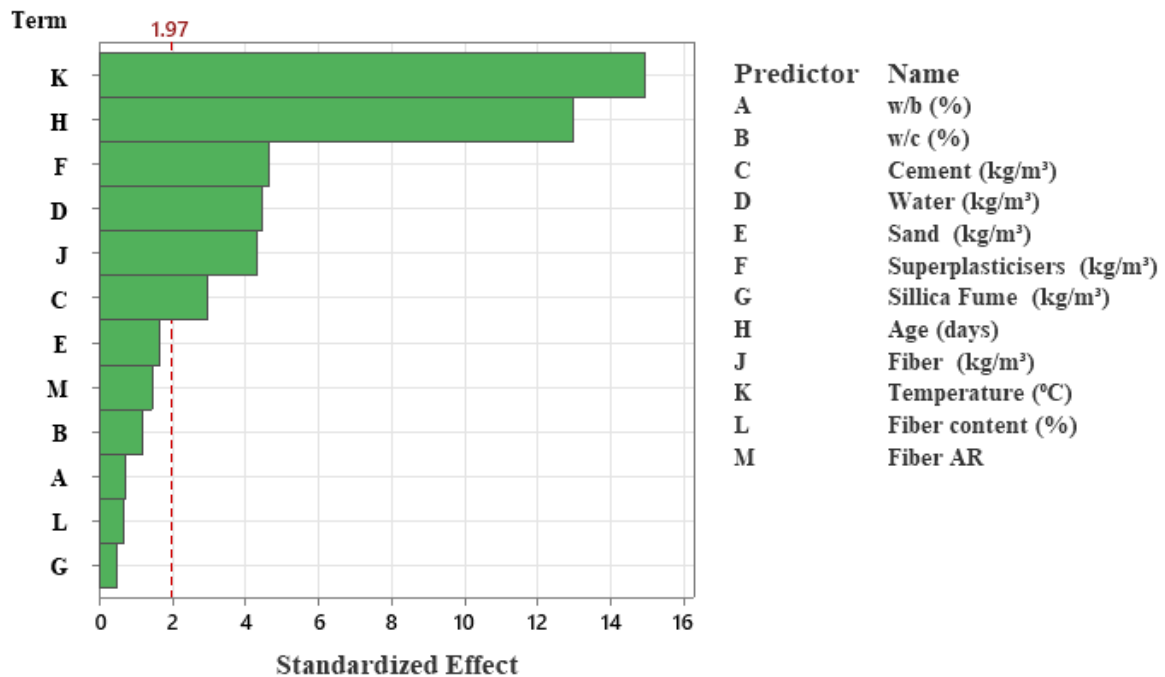


Fig. 13 - Pareto chart of the standardized effects of each independent variable on CS (sensitivity chart).

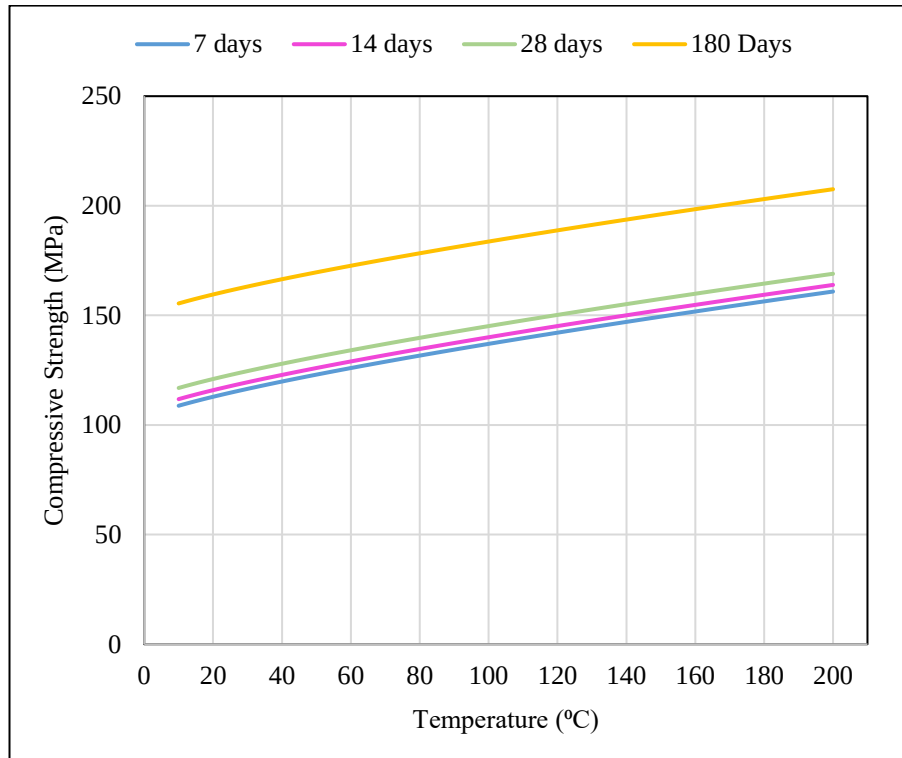


Fig. 14 - Compressive Strength of UHPFRC at 7, 14, 28, and 180 Days, Increasing Up to 200°C

5.2 Optimum Compressive Strength Investigation

Excessive fiber content can reduce compressive strength due to poor workability and uneven fiber distribution [62]. The compressive strength was optimized using a nonlinear regression model, which proved to be the most efficient soft-computing model in this study. Each variable in the experimental setting was increased to the highest possible value. Each variable in the experimental setting was increased to the highest possible value (W/B 0.33, W/C 0.36, Cement 1543 kg/m³, water 515 kg/m³, sand 1923 kg/m³, silica fume 350 kg/m³, fiber AR 1014.29) except for fiber content, temperature, and superplasticizers (SP) which were systematically varied to determine their unique effects on compressive strength. Additionally, the sensitivity analysis revealed that superplasticizers were the most influential constituent among the concrete constituents in affecting compressive strength. The superplasticizer content was adjusted to the lowest, average, and maximum levels to investigate its effect on compressive strength as the fiber content and temperature were gradually varied. This analysis was conducted at curing ages of 7, 14, 28, and 180 days to track the improvement in strength of UHPFRC. The investigation found that the optimal fiber content ranges from 2.05 to 2.09, which varies depending on the age of the concrete. The highest compressive strength achieved was 170.7638 MPa in 180 days at maximum SP. Fig 15. (a) Shows that at the age of 7, when SP is at its lowest, the maximum compressive strength is 100.4026 MPa with a fiber content of 2.09%; when SP is at its average, the maximum CS is 113.2927 MPa with fiber content of 2.05% and 2.09%; and when SP is at its highest, the maximum compressive strength is 124.0936 MPa with a fiber content of 2.05%. Fig 15. (b) illustrate that at the age of 14, when SP is at its lowest, the maximum compressive strength is 103.4157 MPa with a fiber content of 2.09%; when SP is average, the maximum CS is 116.3058 MPa with a fiber content of 2.05% and 2.09%; and when SP is at its highest, the maximum compressive strength is 127.1066 MPa with a fiber content of 2.05%. At 28 days, compressive strength results show that when the superplasticizer is at its lowest level, the maximum compressive strength is 108.5087 MPa with a fiber content of 2.09%. When the superplasticizer is at an average level, the maximum compressive strength rises to 121.3988 MPa with fiber content of 2.05% and 2.09%. At the most significant level of superplasticizer, the maximum compressive strength increases to 131.8447 MPa, corresponding to a fiber content of 2.05%, as shown in Fig.15 (c). At the age of 180, when SP is at its lowest, the maximum compressive strength is 147.0728 MPa with a fiber content of 2.09%; when SP is at its average, the maximum CS is 159.9629 MPa with fiber content of 2.05% and 2.09%; and when SP is at its highest, the maximum compressive strength is 170.7638 MPa with a fiber content of 2.05% as shown in Fig 15 (d). A noticeable pattern was observed at all the curing ages (7, 14, 28, and 180 days). Wherein the maximum compressive strength was achieved at a fiber

content of 2.05% when the superplasticizer content was at its highest value (89.7 kg/m^3), at 2.09% fiber content when the SP amount was at its lowest value (1.05 kg/m^3), and at both 2.05% and 2.09% fiber contents when the SP dosage was at the average level (40.11 kg/m^3).

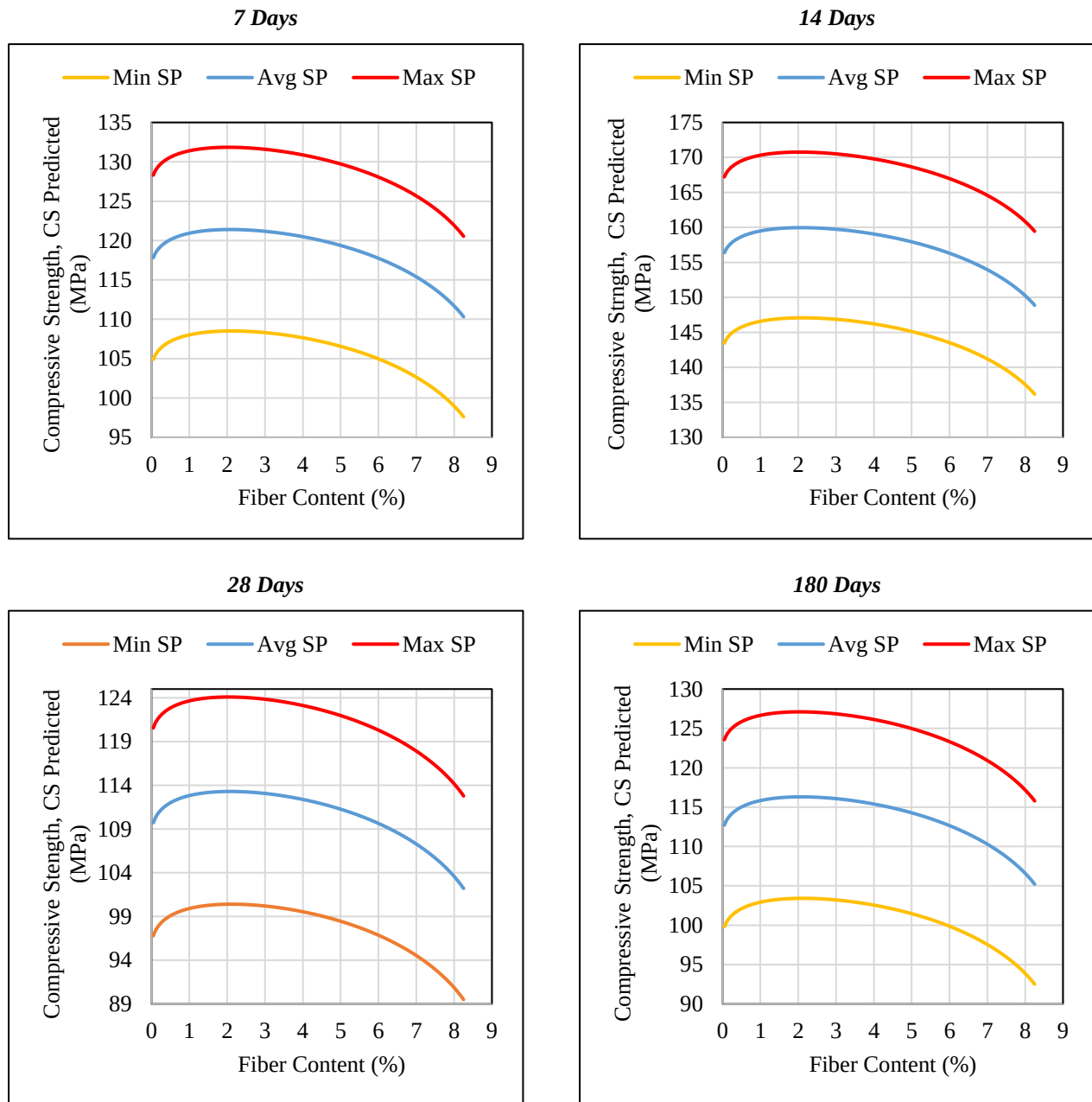


Fig. 15 - Effect of Superplasticizer Levels on Maximum Compressive Strength at Different Curing Ages (7, 14, 28, and 180 Days)

6 Conclusions

This study provided insight into the behavior of Ultra-High-Performance Fiber-Reinforced Concrete (UHPFRC), specifically the effect of fiber content and curing temperature on compressive strength. The study determined the optimal fiber content that produced the maximum CS, underlining the importance of fiber reinforcement in improving the material's structural performance. Furthermore, the study highlighted the beneficial effects of superplasticizers, which enhanced the uniformity of the mix and facilitated higher fiber dispersion, ultimately leading to increased compressive strength. Furthermore, it was discovered that the curing temperature is essential for optimizing fiber-matrix bonding, with a controlled temperature range resulting in increased compressive strength. These findings highlight the importance of carefully adjusting

both fiber content and curing conditions, as well as using superplasticizers, to maximize UHPFRC's CS for demanding high-performance construction applications. Nevertheless, this study effectively developed five different models to predict the compressive strength of UHPFRC. The sensitivity analysis reveals that temperature and age have the most significant impact on compressive strength, with impact values of 14.91 and 12.96, respectively.

Based on the collected data and results, the following conclusions were reached.

- With 70.08 MPa for the training dataset and 21.10 MPa for the testing dataset, the ANN model ranked first according to the OBJ value. The training dataset's SI values of 0.024 and the testing dataset's SI values of 0.026 also achieved the lowest SI values.
- R^2 , RMSE, and MAE were used to evaluate model performance. The ANN model achieved the highest R^2 (0.9739), RMSE (3.23 MPa), and MAE (134.13 MPa) on the training dataset, with the M5P tree model following closely behind.
- The sensitivity chart showed that the most important factors influencing the prediction of UHPFRC's compressive strength were temperature and age; superplasticizer content also played an important role.
- Compressive strength peaked at 158 °C and 2.05% fiber content, indicating a critical temperature-fiber content balance point. Also, Compressive Strength was significantly increased by the maximum superplasticizer content, which was recorded to be (89.7 kg/m³). These findings highlight the impact of temperature, age, and superplasticizer on compressive strength.

Declaration of AI and AI-Assisted Technologies in the Writing Process

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.

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