

# COMPRESSIVE STRENGTH MODEL OF CONCRETE WRAPPED WITH CARBON FIBER-REINFORCED POLYMER USING NEURAL NETWORK

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**ABSTRACT:** This study developed a predictive model for compressive strength utilizing a feedforward neural network (FNN) trained on the dataset from cylindrical specimens reinforced with carbon fiber-reinforced polymer (CFRP) wraps. Bridging a critical gap in the literature, the FNN model incorporates simultaneous effects of variables like concrete cylinder diameter, wrap thickness, CFRP laminate modulus of elasticity, and unconfined compressive strength. The optimized 4–10–1 FNN architecture, trained on 101 samples, exhibits exceptional precision and generalization, as evidenced by a high Correlation Coefficient of 0.99795, and low Mean Squared Error of 0.00024. This highlights its effectiveness in predicting compressive strength and identifying influential factors. A comparative analysis underscores the FNN model's superiority over existing approaches. The study's novelty lies in its focus on unconventional specimens, for which no established codes or standards currently exist. It introduces a new way for developing future guidelines for CFRP-wrapped structural elements in engineering applications, contributing valuable insights into enhancing predictive modeling for advanced composite materials.

*Keywords: Predictive model, Compressive strength, Concrete wrapped with CFRP, FNN*

## 1. INTRODUCTION

This study addresses challenges in predicting compressive strength in concrete structures, focusing on the application of Neural Networks and Carbon Fiber Reinforced Polymer (CFRP) reinforcement. Traditional methods face precision, time, and cost limitations, motivating a shift toward AI-based solutions. Inspired by the human brain, neural networks capture complex relationships within civil engineering, while integrating CFRP reinforcement enhances assessments by considering intricate material-curing interactions.

Compressive strength is a crucial parameter in concrete design due to its simplicity, affordability, and relevance to essential properties [1]; however, accurate prediction remains difficult because of the material's complexity and numerous influencing factors. Traditional methods, such as empirical equations and nondestructive testing, face limitations such as accuracy, time inefficiencies, and costs [2]. These methods often fail to consider interactions between variables, affecting prediction precision. Computer-aided engineering offers a costlier and time-consuming alternative. Traditional methods face challenges like concrete property variability, environmental effects, and adapting to new materials.

Researchers explore artificial intelligence methods to address these challenges as a promising solution. With advanced algorithms and machine learning, AI can analyze complex data patterns and relationships, offering faster, more accurate, and cost-

effective predictions than traditional methods [3]. The limitations and challenges of traditional approaches highlight the need for innovative solutions, positioning AI as a transformative tool in predicting compressive strength for concrete structures.

CFRP, a composite material with carbon fiber reinforcement, is a viable solution for concrete structures. Its advantages include lightweight, strength, corrosion resistance, and diverse applications in industries like aerospace and construction [4]. The study uses neural networks to predict compressive strength for cylindrical specimens wrapped with CFRP. Objectives involve analyzing a dataset, constructing a predictive model, and assessing its performance against conventional techniques. The research contributes pragmatic perspectives for CFRP reinforcing, streamlining approaches, guiding structural design, and enhancing structural soundness in civil engineering. Ultimately, it strives to provide a precise methodology for evaluating compressive strength, advancing the field's understanding and application.

Concrete, a frictional material, reacts positively to lateral stresses, exhibiting increased strength and axial deformation when uniaxially loaded—a phenomenon known as confinement. Steel reinforcement, spirals, hoops, ties, and Fiber Reinforced Polymers (FRP) are commonly used. FRP-confined concrete displays a distinctive response, with bi-linear axial and lateral behavior and a unique transition in volumetric response. The

characteristic response involves elastic deformations, crack formation, and plastic deformations [1,2,5]. Various constitutive models exist that address pressure sensitivity and path dependence. Experimental research on CFRP-confined concrete columns has led to proposed models for strength enhancement, considering factors like loading conditions. Fig. 1 states that the typical response of FRP-wrapped concrete cylinders showcases the enhanced structural performance due to the confinement provided by the FRP wrap. The FRP wrapping significantly increases the strength and ductility of the concrete cylinders compared to unwrapped specimens. This enhancement is attributed to the ability of the FRP to effectively confine the concrete, thus delaying the onset of cracking and ultimate failure. As a result, the FRP-wrapped cylinders exhibit a more gradual and ductile failure mode, which is crucial for applications requiring high strength and durability [4,6].

In the following sections, this paper provides a detailed exploration of the methodology, results associated with predicting compressive strength using a Feedforward Neural Network (FNN), and conclusion. The methodology section outlines the design of the FNN model, including the data preprocessing steps and the training process. Next, the Results and Discussion section presents and interprets the model’s performance metrics, including predictions, accuracy, and statistical analyses. The Conclusion section summarizes the key findings, discusses their implications, and demonstrates how the study fulfills its primary objective.

## 2. RESEARCH SIGNIFICANCE

The novelty of this research lies in its development of a neural network-based model to predict compressive strength in CFRP-wrapped concrete cylinders, a domain lacking established

prediction standards. Unlike traditional models, this study integrates multiple parameters, such as wrap thickness and cylinder diameter, into an optimized AI-driven framework. The approach offers enhanced prediction accuracy and robustness, demonstrating the potential of artificial intelligence in material strength modeling. The outcome aims to streamline design processes and improve reliability in structural engineering, especially where CFRP is applied as a retrofiting material.

## 3. MATERIALS AND METHODS

### 3.1 Experimental Setup Selection

From previous research, it can be deduced that the use of FRP wraps, particularly Glass Fiber Reinforced Polymer (GFRP) and CFRP, has proven effective for retrofitting and enhancing the performance of structural elements [7-8]. GFRP wraps, while cost-effective, primarily improve ductility, though their confinement effect may be limited with minimal layers. CFRP wraps exhibit superior strength, stiffness, and durability. Studies show that CFRP retrofitting can restore and enhance the load-bearing capacity of damaged columns, with full wrapping improving stiffness and delaying axial failure [9].

Advancements in computational modeling, such as artificial neural networks (ANNs), further enhance the application of CFRP wraps [10]. These innovations underscore the potential of predictive techniques to enable safer, more durable, and cost-efficient infrastructure. This study tackles the challenge of predicting compressive strength in CFRP-wrapped concrete by utilizing Feedforward Neural Networks (FNN). The findings demonstrate the superiority of AI-driven models, offering practical applications in improving construction safety, durability, and cost-efficiency.

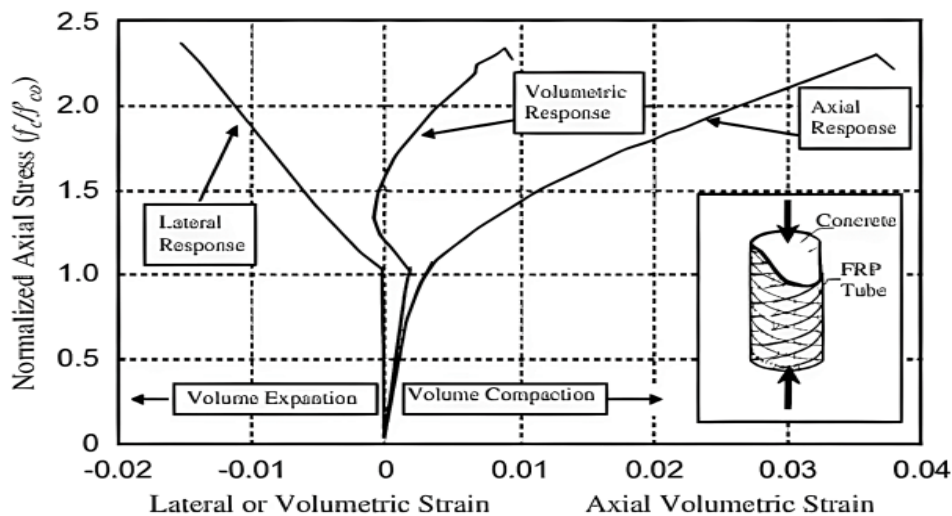


Fig.1 Typical response of FRP-wrapped concrete cylinders [4]

### 3.2 Data Gathering

A comprehensive literature review on experimental studies aimed at enhancing the strength of CFRP-wrapped concrete cylinders has been conducted, leading to the development of an extensive experimental database. All specimens in this database have a consistent length-to-diameter ratio of two, ensuring reliable comparisons. Table 2 presents data from 101 specimens across seven studies, each incorporating various influencing factors. This database provides researchers with critical insights into the effects of different parameters on CFRP-confined concrete performance. The uniform specimen dimensions strengthen comparative analysis and reinforce the study's reliability. Additionally, the dataset aids in validating predictive models and encourages further research into additional influencing factors. Emphasizing standardized testing methodologies, this work advances structural engineering research by improving accuracy in assessing CFRP confinement effects.

### 4. BRIEF OVERVIEW OF NEURAL NETWORKS

Neural networks, a subset of machine learning, emulate the human brain's structure and are pivotal in deep learning algorithms. Comprising layers of nodes, input, hidden, and output neural networks use

artificial neurons with weights and thresholds to process data [21]. The network relies on training data to improve accuracy, making it a powerful tool in speech and image recognition tasks. Each node functions as a linear regression model [22], with assigned weights determining the variable importance. Neural networks operate through activation functions, passing data to subsequent layers. The described network is an FNN, forwarding data from input to output layers. A practical example elucidates the concept: a node decides whether to go surfing based on factors like wave quality, crowd presence, and recent shark attacks.

Assigning weights and threshold: Bias 1 ( $W_1$ ), Bias 2 ( $W_2$ ), Bias 3 ( $W_3$ ), and, Variable 1 ( $x_1$ ), Variable 2 ( $x_2$ ), Variable 3 ( $x_3$ ) the model calculates an output  $\hat{y}$  using the Eq. (8).

$$\hat{y} = (x_1 * W_1) + (x_2 * W_2) + (x_3 * W_3) - bias \quad (8)$$

Influenced by its network architecture and parameter settings. Finding the optimal network architecture, including the ideal number of layers and

Table 1. Models for strength enhancement of FRP confined concrete cylinders

Model	Expression	Eq.
Fardis and Khalili [11]	$\frac{f'_{cc}}{f'_{co}} = 1 + 4.1 \frac{P_u}{f'_{co}}$	(1)
	$\frac{f'_{cc}}{f'_{co}} = 1 + 3.7 \left( \frac{P_u}{f'_{co}} \right)$	(2)
Saadatmanesh et al. [12]	$\frac{f'_{cc}}{f'_{co}} = 2.254 \sqrt{1 + 7.94 \frac{P_u}{f'_{co}}} - 2 \frac{P_u}{f'_{co}} - 1.254$	(3)
Miyauchi et al. [13]	$\frac{f'_{cc}}{f'_{co}} = 1 + 3.485 \frac{P_u}{f'_{co}}$	(4)
Kono et al. [14]	$\frac{f'_{cc}}{f'_{co}} = 1 + 0.057 p_u$	(5)
Samaan et al. [15]	$\frac{f'_{cc}}{f'_{co}} = 1 + 6.0 \frac{P_u^{0.7}}{f'_{co}}$	(6)
Toutanji [16]	$\frac{f'_{cc}}{f'_{co}} = 1 + 3.5 \left( \frac{P_u}{f'_{co}} \right)$	(7)

Table 2. Experimental database and ranges of variables

Reference	Number of Specimens	D (mm)	nt (mm )	E <sub>f</sub> (MPa)	f'co (MPa)
Miyauchi et al. [13]	10	100, 150	0.11-0.33	3481	31.2-51.9
Kono et al. [14]	17	100	0.16-0.50	3820	32.3-34.8
Samaan et al. [15]	9	153	0.36-1.25	2275	19.4-49
Matthys et al [17]	2	150	0.11-7.02	2600	34.9
Rochette and Labossiere [18]	7	100, 150	0.6-5.04	230, 1265	42-43
Miceilli [19]	8	100	0.16-0.35	1520	32-37, 3790
Rousakis [20]	48	150	0.16-0.84	2024	25.15-82.13

neurons in the hidden layers, is one of the most challenging tasks in NN studies. This determination often involves a trial-and-error approach, and there needs to be a well-defined rule or procedure for achieving the optimal configuration [23]. The assignment of initial weights and related parameters can also significantly impact NN performance. However, the lack of a systematic approach makes this process time-consuming.

In this study, the Matlab NN toolbox, designed explicitly for NN applications, is employed. Various feedforward training algorithms are utilized. The Matlab NN toolbox randomly assigns initial weights for each run, introducing variability in the NN's performance even when other parameters and architecture remain constant. To address this

challenge, a Matlab program is developed to automate the trial-and-error process. The program systematically explores various numbers of layers and neurons in the hidden layers for a fixed epoch, selecting the best NN architecture with the minimum mean absolute percentage error (MAPE) or root mean squared error (RMSE) on the testing set. The program iteratively refines the architecture, starting from a simple NN with one hidden node for the first and second hidden layers and progressing toward the optimal configuration. The entire process, depicted in the flowchart in Fig. 2, is repeated for different feedforward training algorithms, enhancing the efficiency of the network architecture selection process.

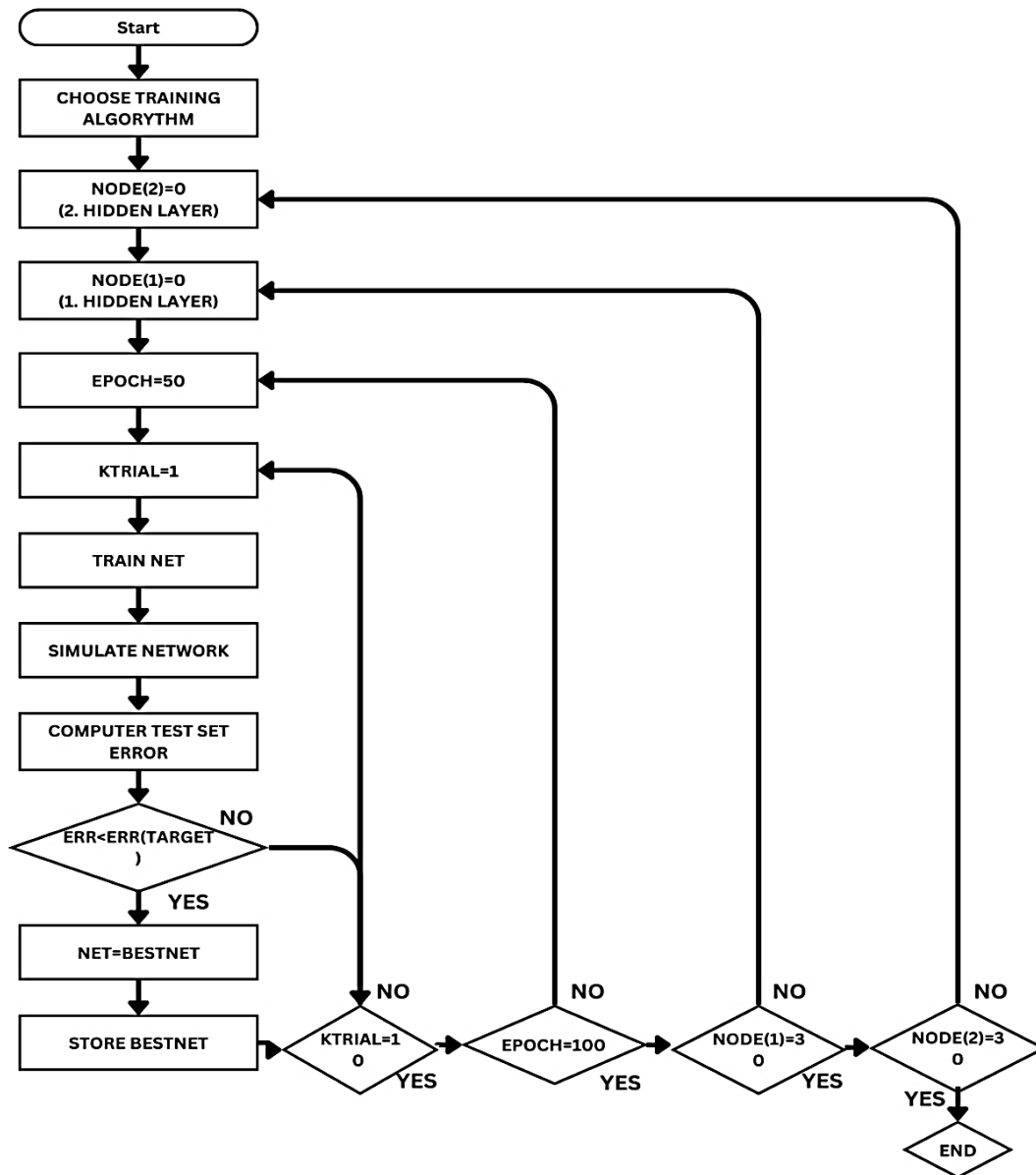


Fig. 2 Flowchart of optimal NN selection

## 5. RESULTS AND DISCUSSION

The primary focus of this study is the prediction of compressive strength in CFRP-wrapped concrete cylinders using an FNN model. This section discusses the predicted compressive strength values and provides a detailed statistical analysis based on the model's performance metrics. The NN model's performance is meticulously evaluated across diverse datasets, encompassing training, validation, and test sets. With a dataset of 101 observations, the training set comprises 71 data points, while 15 observations each are allocated to the validation and test sets. The NN architecture in Fig. 3, a 4–10–1 configuration employing a hyperbolic tangent sigmoid transfer function (tansig), undergoes training using the Levenberg–Marquardt algorithm.

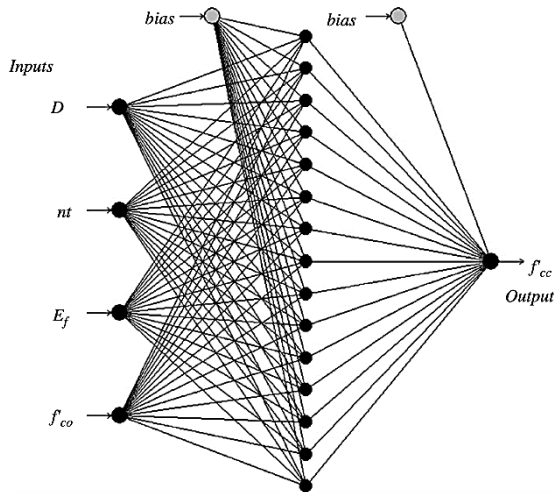


Fig. 3 NN architecture

The FNN model's predictions were closely compared with actual compressive strength values across the training, validation, and test datasets. The results demonstrate that the model effectively captures the underlying patterns and relationships between input variables and compressive strength.

### 5.1 Training Set:

The model's predictions closely match the observed values, reflecting its ability to learn and generalize from the training data.

### 5.2 Validation Set:

Predictions remain accurate, confirming that the model maintains its predictive capability when exposed to new data.

### 5.3 Test Set:

The model demonstrates robust performance with predictions that align well with actual measurements, underscoring its generalization ability.

### 5.4 Mean Squared Error (MSE):

The MSE for the training, validation, and test sets were 0.00830, 0.00160, and 0.01380, respectively. These values indicate that the model's predictions are very close to the actual compressive strength values, with low error across all datasets.

### 5.5 Correlation Coefficient (R):

The Correlation Coefficients for the training, validation, and test sets were 0.99889, 0.99764, and 0.99362, respectively. These high R values signify a strong positive correlation between the predicted and actual values, validating the accuracy of the FNN model.

### 5.6 Error Distribution:

Analysis of prediction errors reveals that they are randomly distributed without significant bias, suggesting that the model does not consistently overestimate or underestimate the compressive strength. This random error distribution supports the reliability of the model's predictions.

### 5.7 Confidence Intervals:

The predicted compressive strength values fell within narrow confidence intervals, which overlapped significantly with the actual observed values. This consistency further confirms the precision of the FNN model and its effectiveness in predicting compressive strength.

The results indicate that the FNN model is a powerful tool for predicting the compressive strength of CFRP-wrapped concrete cylinders. The model's high accuracy, as evidenced by low MSE and high R values, demonstrates its suitability for practical applications in construction engineering. Additionally, the model's ability to consistently outperform traditional predictive methods highlights its potential to become a standard in the industry. The robustness of the FNN model ensures reliable predictions across a wide range of conditions, making it a valuable asset for engineers seeking to enhance structural integrity. This study highlights the value of advanced computational techniques in engineering, leading to more resilient and cost-effective infrastructure.

Table 3. Statistical parameters of the proposed NN model

	Observation	MSE	R
Training	71	0.00830	0.99889
Validation	15	0.00160	0.99764
Test	15	0.01380	0.99362
All	101	0.00024	0.99795

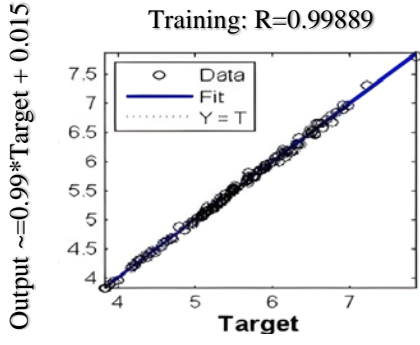


Fig. 4 Performance of Training Set

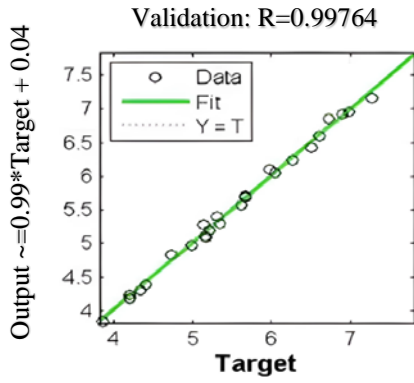


Fig. 5 Performance of Validation Set

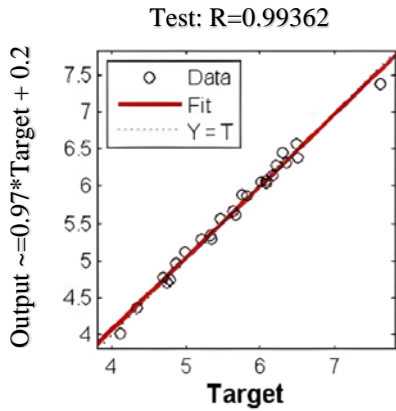


Fig. 6 Performance of Test Set

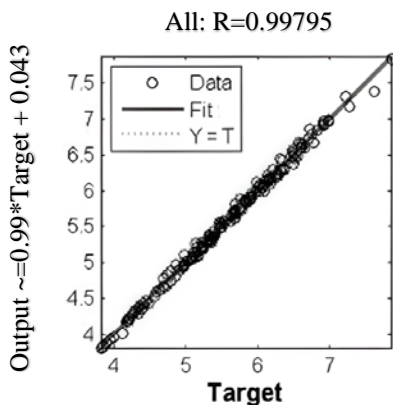


Fig. 7 Performance of All set

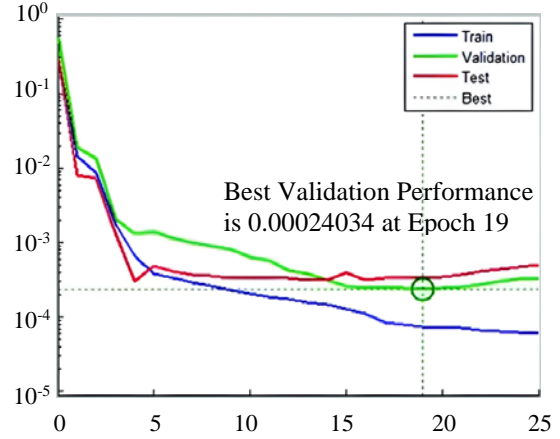


Fig. 8 Performance of MSE of proposed model

To derive a clear expression for the compressive strength of a concrete cylinder confined with CFRP, based on the variables presented in the following sequence:

$$F'_{cc} = f(D, nt, Ef, f_{co}) \quad (9)$$

By utilizing the well-trained NN parameters, which include biases and weights for both the input and hidden layer, as well as the normalization factors for both the inputs and outputs of the proposed NN model, the explicit formulation for the proposed NN model can be obtained. When it comes to the explicit formulation of NN models, the normalization process is an essential step that must be taken. For the calculations, the output has been normalized by 130, which has resulted in the output being less than 1. The output is multiplied by 130, as shown in Eq. (10), for this reason. A direct multiplication of the inputs' normalization values with the weights given in the equations below has been performed. In light of this, they are not provided explicitly because the process of deriving the explicit formulation is excessively complicated, particularly for individuals who do not have a background in NN. More straightforwardly, the same steps can be presented as shown:

$$f'_{cc} = 130 \left( \frac{2}{1+e^{-2w}} - 1 \right) \quad (10)$$

wherein:

$$\begin{aligned} W = & -2.2509 * \left( \frac{2}{1+e^{-2U_1}} - 1 \right) - 1.9608 * \\ & \left( \frac{2}{1+e^{-2U_2}} - 1 \right) + 1.5496 * \left( \frac{2}{1+e^{-2U_3}} - 1 \right) \\ & - 0.6984 * \left( \frac{2}{1+e^{-2U_4}} - 1 \right) - 0.3868 * \\ & \left( \frac{2}{1+e^{-2U_5}} - 1 \right) - 0.2610 * \left( \frac{2}{1+e^{-2U_6}} - 1 \right) - \\ & 1.0286 * \left( \frac{2}{1+e^{-2U_7}} - 1 \right) + 2.5760 * \end{aligned}$$

$$\left(\frac{2}{1+e^{-2U8}}-1\right)+2.3529*\left(\frac{2}{1+e^{-2U9}}-1\right)+2.8865*\left(\frac{2}{1+e^{-2U10}}-1\right)-2.98326$$

and wherein:

$$U1 = (0.036 * D) + (0.885 * nt) + (0.0006 * Ef) + (0.0555 * f co) + 21.03$$

$$U2 = (0.03255 * D) + (2.34 * nt) + (-0.00045 * Ef)$$

$$U3 = (-0.105 * D) + (-0.15 * nt) + (-0.00195 * Ef) + (0.1095 * f co) 24.18$$

$$U4 = (0.087 * D) + (-1.44 * nt) + (-0.0042 * Ef) + (-0.0615 * f co) + 2.13$$

$$U5 = (0.0915 * D) + (-0.207 * nt) + (-0.0009 * Ef) + (-0.09 * f co) - 6.03$$

$$U6 = (-0.09585 * D) + (-0.90255 * nt) + (-0.0021 * Ef) + (-0.04905 * f co) + 22.98$$

$$U7 = (-0.05475 * D) + (-0.6897 * nt) + (-0.0006 * Ef) + (0.10365 * f co) + 3.105$$

$$U8 = (-0.1026 * D) + (0.2601 * nt) + 0.0009 * Ef) + (-0.05715 * f co) + 13.995$$

$$U9 = (0.0066 * D) + (0.4449 * nt) + (0.0012 * Ef) + (0.1104 * f co) - 10.23$$

$$U10 = (0.08385 * D) + (2.09355 * nt) + (0.0006 * Ef) + (0.0240 * f co) - 15.87$$

The performance metrics, Coefficient of Determination ( $R^2$ ) shown in Fig. 9-16 and Mean Absolute Error (MAE) shown in Appendix B, provide a clear indication of the predictive accuracy of each method.

### 5.8 Coefficient of Determination ( $R^2$ ):

The FNN model achieves an exceptionally high  $R^2$  value of 0.996, demonstrating its ability to explain 99.6% of the variance in the compressive strength data. This high level of accuracy indicates that the FNN model closely aligns with the actual observed data, making it a highly reliable predictive tool. In contrast, the traditional equations (Eq.1 to Eq.7) exhibit significantly lower  $R^2$  values, ranging from 0.436 to 0.784, with Eq.7 having an  $R^2$  of 0.596. These lower  $R^2$  values suggest that these equations are less effective in capturing the underlying patterns within the data, making them less reliable for prediction purposes.

### 5.9 Mean Absolute Error (MAE):

The FNN model also outperforms the traditional methods in terms of MAE, with a value of 0.956. This low MAE indicates that the FNN's predictions are much closer to the actual values, resulting in minimal prediction error. The traditional equations show much higher MAE values, ranging from 9.898 to 23.782, with Eq.7 having an MAE of 21.403. These higher MAE values indicate greater discrepancies between predicted and actual compressive strengths, reinforcing the superiority of the FNN model.

The results clearly demonstrate that the FNN is a robust and highly accurate method for predicting compressive strength. Its superior performance, as evidenced by the highest  $R^2$  and lowest MAE values, highlights its effectiveness in capturing complex data relationships and producing precise predictions. In comparison, the traditional equations exhibit significant limitations in accuracy, making the FNN model a far more reliable choice for predicting compressive strength in engineering applications.

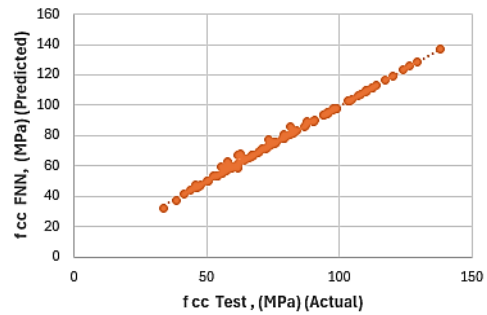


Fig. 9 Comparison of Actual test vs. Predicted FNN Strength

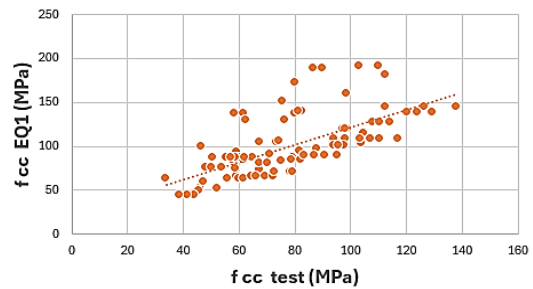


Fig. 10 Comparison of Actual test vs. Predicted Eq. (1) Strength

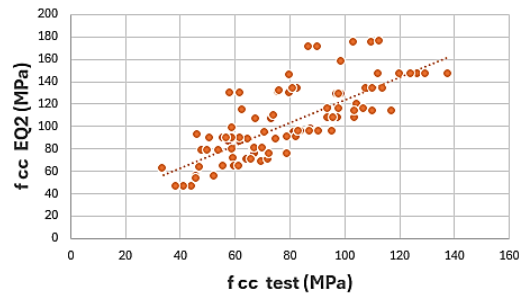


Fig. 11 Comparison of Actual test vs. Predicted Eq. (2) Strength

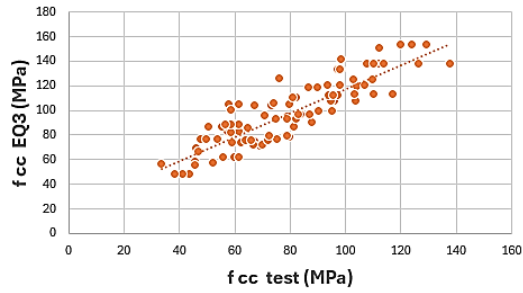


Fig. 12 Comparison of Actual test vs. Predicted Eq. (3) Strength

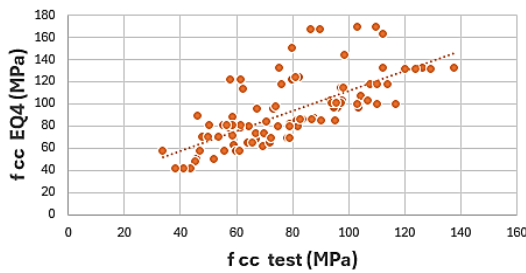


Fig. 13 Comparison of Actual test vs. Predicted Eq. (4) Strength

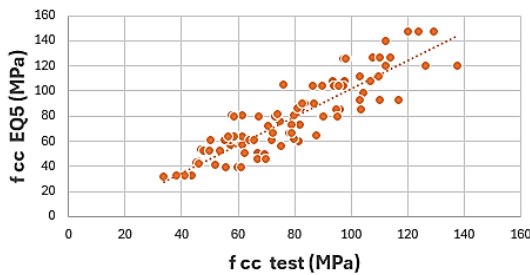


Fig. 14 Comparison of Actual test vs. Predicted Eq. (5) Strength

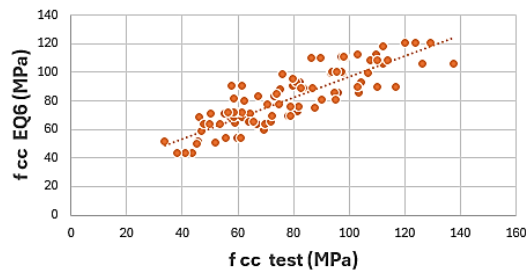


Fig. 15 Comparison of Actual test vs. Predicted Eq. (6) Strength

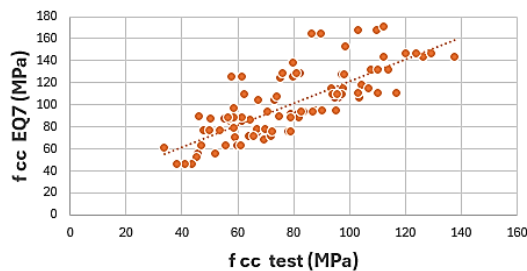


Fig. 16 Comparison of Actual test vs. Predicted Eq. (7) Strength

## 6. CONCLUSION

This study highlights the exceptional performance of the Feedforward Neural Network (FNN) model in predicting the compressive strength of CFRP-wrapped concrete cylinders. The FNN model has demonstrated remarkable accuracy, consistently providing precise predictions across training, validation, and test datasets. This accuracy is reflected in the model's strong correlation coefficient of 0.99795 and a low Mean Squared Error (MSE) of 0.00024034, both of which underscore its effective capture of underlying patterns and its robust generalization capabilities. The model's ability to predict compressive strength with high precision is crucial for practical engineering applications where accurate material strength assessment is essential.

A significant finding from this study is the identification of wrap thickness and cylinder diameter as pivotal factors influencing compressive strength. The FNN model effectively integrates these variables, showing a direct positive correlation with the predicted strength, which aligns with expected engineering principles that increased wrap thickness and cylinder diameter enhance structural integrity. This incorporation of critical factors not only demonstrates the model's alignment with engineering expectations but also enhances its practical utility.

Furthermore, the FNN model outperforms traditional predictive models and eight alternative FNN approaches, proving its superior accuracy and precision. This comparative performance establishes the FNN as a reliable tool for predicting compressive strength in CFRP-wrapped concrete cylinders, effectively handling complex data relationships.

In summary, the study confirms that the FNN model is a highly effective and reliable method for predicting compressive strength. Its high accuracy, demonstrated through excellent correlation and minimal error, combined with its capability to account for key influencing factors, makes it a valuable tool for engineering professionals. The FNN model's superior performance highlights its potential for advancing predictive modeling in concrete engineering and offers a strong foundation for future research and application in material strength assessment.

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