Machine Learning-Based Prediction of Compressive Performance in Circular Concrete Columns Confined with FRP

Nilam Dhakal
Department of Engineering and Construction, ACE, UEL,
London, United Kingdom
u2238137@uel.ac.uk

Ali Abbas
Department of Engineering and Construction, ACE, UEL,
London, United Kingdom
a.abbas@uel.ac.uk

Husham Ahmed
Principal Civil/Strcutural
Jacobs
London, United Kingdom
husham.ahmed@jacobs.com

Mhd Saeed Sharif
Department of Computer Science and Digital Technologies,ACE, UEL,
London UK.
s.sharif@uel.ac.uk

***Abstract*—This article presents a comprehensive investigation, focusing on the prediction and formulation of the design equation of compressive strength of circular concrete columns confined with Fiber Reinforced Polymer (FRP) using advanced machine learning models. Through an extensive analysis of 170 experimental data specimens, the study examines the effects of six key parameters, including concrete cylinder diameter, concrete cylinder-FRP thickness, compressive strength of concrete without FRP, initial compressive strain of concrete without FRP, elastic modulus and tensile strength of FRP, on the compressive strength of the circular concrete columns confined with FRP. The predictive model and design equation of compressive strength is developed using a machine learning technique, specifically the artificial neural networks (ANN) model. The results demonstrates strong correlations between the compressive strength of the circular concrete columns confined with FRP and certain factors, such as the compressive strength of the concrete and compressive strain of the concrete column without FRP, elastic modulus of FRP, and tensile strength of FRP. The ANN model specifically developed using Neural Designer, exhibits superior predictive accuracy compared to other constitutive models, showcasing its potential for practical implementation. The study's findings contribute valuable insights into accurately predicting the compressive performance of circular concrete columns confined with FRP, which can aid in optimizing and designing civil engineering structures for enhanced performance and efficiency.**

Keywords—circular concrete columns confined with FRP, artificial neural networks, compressive strain, compressive strength, elastic modulus, tensile strength, optimization

I. Introduction

Over the past four decades, Fiber Reinforced Polymer (FRP) has emerged as a prominent material widely employed in diverse industries, such as Construction, Aerospace, Marine, Automotive, and more. Its popularity stems from its remarkable attributes, including high tensile strength, lightweight nature, excellent strength-to-weight ratio, impressive corrosion resistance, minimal impact on the shape and size of existing structures [1]. Additionally, FRP boasts non-magnetic and non-conductive properties, presents an aesthetically pleasing appearance, and adapts well to various environmental conditions [4]. In construction industry, FRP is used to reinforce and strengthen the concrete structures such as bridges, buildings, and tunnels, existing and new buildings and it can also be used to create prefabricated structural elements such as beams and columns as the usage of FRP has shown the increased the durability of the structure over the period.

Researchers have explored the mechanical behavior of FRP-confined circular concrete columns through limited experimental studies. The confinement is achieved by wrapping FRP jackets around the columns or placing them inside FRP tubes with the help of bonding agents. These studies involved subjecting columns both with and without FRP to triaxial loading, revealing an increase in compressive strength due to the use of FRP. These FRP confined columns strength and durability is influenced by various factors, including the type and amount of FRP used the diameter, height, and confinement level of the column etc. Different researchers investigated parameters like the numbers of FRP ply and its thickness, as well as the tensile strength (ffrp), elastic modulus (Efrp), and ultimate tensile strain (efrp) of the FRP material. Properties of core concrete such as its diameter, compressive strength (fco), the strain (eco), had a control over the mechanical behaviors of circular concrete columns confined with FRP. Researchers subsequently put forward their compression models [1].

Experimental investigation is time consuming and is very expensive to carry out. However, Artificial Neural Networks (ANNs) have shown promising results in predicting the mechanical behavior of structural elements over the years. The main advantage of ANNs for structural behavior prediction is that they can be trained on a large amount of data, making them capable of capturing subtle patterns and nonlinear relationships that may be difficult to identify using traditional analytical or statistical methods. ANNs have demonstrated their effectiveness in predicting structural behaviors, ranging from structural response to damage detection and structural health monitoring. For instance, they have been successfully deployed to predict the deformation and stress distribution of concrete beams under diverse loading conditions, detect damage in bridges through sensor data, and forecast the remaining fatigue life of steel structures [22].

In the realm of predicting the compressive behavior of FRP confined concrete circular columns, both experimental and artificial neural network (ANN) models have been proposed by researchers. However, a prevailing limitation in many of these models is their focus on parameters like compressive strength without FRP and confining pressure, while overlooking the significant correlation of the compressive strain parameter with the final compressive strength. This research seeks to overcome this limitation by incorporating the compressive strain parameter, while omitting the consideration of the confining pressure parameter. Addressing the inadequacy and insufficiency of current methods for predicting the compressive performance of these columns is the central problem tackled by this research. The research aims to enhance the accuracy and credibility of these methods through the development of an ANN based prediction model.

Neural designer is one of the ANN software's applications that enable users to create and train neural networks for data analysis and prediction. It is a powerful tool for machine learning and data mining applications that provides an intuitive graphical user interface (GUI) for building and training neural networks without the need for extensive programming skills. The software offers a range of features for creating and optimizing neural networks, including data preprocessing, feature selection, neural network design, training, and validation. It supports various types of neural networks, including feed forward, recurrent, and convolutional neural networks, and allows users to customize the network architecture and activation functions.

One of the main advantages of Neural Designer is its ease of use, which makes it accessible to users with limited programming skills or experience in machine learning. The software provides a user-friendly interface for data import, data preprocessing, and neural network design, and allows users to visualize the data and the neural network architecture in real-time. Another advantage of Neural Designer is its flexibility and scalability. The software can handle large dataset and supports parallel processing to speed up the training and validation of neural networks. It also allows users to export the trained models in various formats, including Python, R, and MATLAB, for further analysis or deployment in other applications.

Neural Designer has been used in various fields, including finance, healthcare, engineering, and social sciences, for applications such as prediction, classification, clustering, and optimization. The software has been evaluated in several studies, which have shown its effectiveness and efficiency in building and training neural networks for various data analysis and prediction tasks. Its ease of use, flexibility, and scalability make it a valuable tool for researchers, engineers, and analysts working in various fields. The main objective of the proposed research is to create an ANN-driven model for predicting the compressive performance of concrete circular columns confined with FRP while also gaining deeper insights into precise test data specimens. This model will present an efficient and time-saving approach for designing and analyzing these columns, offering valuable benefits to structural and civil engineers and researchers in the relevant field.

II. Background

Experimental investigations were carried out by various researchers to investigate the behavior of circular concrete columns with FRP in different loading conditions. Pessiki et al. (2001) presented the results of experiments on small-scale and large-scale concrete specimens and columns confined with FRP composite jackets. FRP encased concrete members have improved deformation and axial load carrying capacity when compared to the unjacketed ones. The study reported improved deformation capacity for FRP-jacketed concrete members compared to unjacketed ones. Factors affecting the axial stress-strain behavior, such as transverse dilation, were also studied. Lam and Teng (2004) compared ultimate tensile strains obtained from various experiments and concluded that the curvature of the FRP jacket, deformation localization of cracked concrete. Vincent and Ozbakkaloglu (2013) investigated the effect of concrete compressive strength and confinement method on high and ultra-high-strength concrete through axial compression tests. Their study included 55 FRP-confined concrete specimens and indicated that the concrete strength increases with decrease in axial performance of FRP-confined concrete decreases, while exhibiting highly ductile behavior. Jiang and Wu (2020) performed axial compression tests on FRP-confined concrete circular columns with varying levels of eccentric loading. Their findings indicated that FRP confinement improved the energy absorption capacity and ductility of the columns under eccentric loading. They also proposed an empirical formula to calculate the compressive strength of circular concrete columns confined with FRP considering confinement ratio, eccentricity ratio, and concrete strength.

Along with Analytical and Numerical techniques Artificial intelligence (AI) techniques have also been applied to predict the compressive behavior of circular concrete columns confined with FRP using machine learning and deep learning algorithms. Abdulkadir Cevik et al. (2007) proposed the neural network model (NN) model for the design of strength enhancement of CFRP (carbon fiber reinforced plastic) confined concrete cylinders. S.M. Mousavi et al. (2010) modeled the compressive strength using a hybrid method coupling Genetic programming (GP) and Simulating annealing (SA) called GP/SA. The authors used numerical simulation data to train and validate the model and found that the model can provide accurate predictions of the compressive strength of FRP confined concrete circular columns under different loading conditions.

Existing compression formulations for circular concrete columns confined with FRP are shown below.

Existing Models for strength enhancement of FRP confined concrete cylinders

S.N	Model	Expression
1.	Fardis	$\frac{f'_{cc}}{f'_{co}} = 1 + 4.1\frac{P_u}{f'_{co}}$
2.	Khalili	$\frac{f'_{cc}}{f'_{co}} = 1 + 3.7\left(\frac{P_u}{f'_{co}}\right)^{0.36}$
3.	Lam & Teng	$\frac{f'_{cc}}{f'_{co}} = 1 + 2\frac{P_u}{f'_{co}}$
4.	Mander	$\frac{f'_{cc}}{f'_{co}} = 2.254\sqrt{\left(1 + \frac{7.94P_u}{f'_{co}}\right)} - 2\frac{P_u}{f'_{co}} - 1.254$

Note:

P_u = Lateral confining pressure (E_{frp} * E_{co} = 2*t*f_{frp}/D)
f'_{cc} = compressive strength of FRP-confined circular concrete columns (MPa)
f'_{co} = compressive strength of core concrete (MPa)
ε_{co} = strain corresponding to compressive strength of core concrete (με)
f_{frp}: tensile strength of FRP (MPa)
E_{frp}: elastic modulus of FRP (GPa)
D: Diameter of specimen (mm)

III. Neural Designer

Neural networks serve as powerful tools for unveiling connections, identifying patterns, forecasting trends, and discerning associations within data.

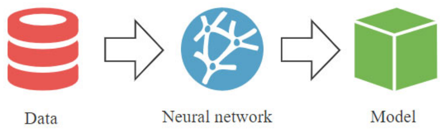

Fig. 1. Layout of Neural Designer

The most common model for neural networks using Neural designer are Approximation model, Classification model and forecasting model.

A. Approximation Model

The approximation model in Neural Designer refers to a specific type of neural network model employed to approximate complex functions or mappings between input and output variables. By leveraging the power of neural networks, the approximation model enables the estimation and prediction of values within a given range, even in the absence of a precise mathematical equation. These models are constructed by training the neural network on a dataset comprising input-output pairs, allowing it to learn and capture the underlying patterns and relationships present in the data.

During the training process, the neural network's internal parameters, also known as weights, are fine-tuned using iterative optimization algorithms like gradient descent. This optimization aims to reduce the difference between the predicted outputs and the actual values in the training dataset. As the training progresses, the approximation model gradually improves its ability to generalize and make accurate predictions on unseen data.

Once the approximation model is trained, it can be utilized for various purposes, including function approximation, regression analysis, and prediction tasks. For example, it can be employed to estimate the behaviour of complex systems, simulate physical processes, or predict outcomes based on historical data. The approximation model in Neural Designer empowers users to gain valuable insights, make informed decisions, and solve problems across a wide range of domains, including engineering, finance, healthcare, and more.

B. Classification Model:

The classification model in Neural Designer harnesses the capabilities of neural networks to categorize or classify input data into distinct classes or groups based on their inherent characteristics or features. These models are built by training the neural network on labeled dataset, where each input is associated with a corresponding class label. During the training process, the neural network studies the underlying arrangements and relationships present in the data, enabling it to make precise predictions on unseen data.

The training process entails modifying the neural network's internal parameters, or weights, by utilizing optimization algorithms like back propagation. The objective is to reduce the disparity between the predicted class labels and the actual class labels presented in the training dataset. Through iterative training, the classification model enhances its ability to generalize and correctly classify new instances.

Once the classification model is trained, it can be employed to classify unseen data into their respective classes. The model takes input data and applies a series of mathematical operations to compute a probability distribution over the possible classes. The highest probability among the classes is chosen as the predicted class for the input data.. Neural Designer's classification model offers a wide range of capabilities, including handling multi-class classification problems, dealing with imbalanced dataset, and providing options for model evaluation and performance metrics. Users can fine-tune the model parameters, select different network architectures, and explore various preprocessing techniques to optimize the classification performance.

With the classification model in Neural Designer, users can tackle complex classification tasks with ease, utilizing the power of neural networks to accurately categorize data and make informed decisions. Whether in image recognition, natural language processing, or fraud detection, the classification model empowers users to unlock valuable insights and drive impactful outcomes from their data.

C. Forecasting Models:

The forecasting models in Neural Designer uses the capabilities of neural networks to predict future values based on historical data. These models are specifically designed to analyze time series data and provide accurate forecasts for a wide range of applications. In Neural Designer, users have access to diverse neural network architectures, including Long Short-Term Memory (LSTM) networks and Recurrent Neural Networks (RNNs). These architectures are particularly adept at capturing patterns and temporal dependencies in time series data. These architectures allow the model to learn from past observations and make accurate predictions for future time steps.

The forecasting models in Neural Designer undergo a rigorous training process. Users provide historical time series data as input, and the model learns from this data to optimize its internal parameters, known as weights, through sophisticated optimization algorithms. This training process involves minimizing the discrepancy between the actual values and predicted values in the training dataset. Once the forecasting model is trained, it can be deployed to make predictions on unseen or future time steps. By considering the historical patterns and trends learned during training, the model can estimate future values with a high degree of accuracy. Neural Designer provides features to assess the performance of the forecasting model, such as error metrics and visualization tools, allowing users to evaluate the quality of the predictions and fine-tune the model if necessary.

Additionally, Neural Designer offers a range of preprocessing techniques to enhance the forecasting process. Users can apply data transformations, such as normalization, smoothing, or detrending, to preprocess the time series data and improve the accuracy of the forecasts. With the forecasting models in Neural Designer, users can effectively forecast future values in various domains, including finance, sales, demand planning, and resource allocation. These models enable users to make informed decisions, optimize strategies, and gain valuable insights from time series data, all while leveraging the power of neural networks to deliver accurate and reliable forecasts.

The aim of the research is to estimate the compressive strength of circular concrete columns confined with FRP (fcc) based on five different input variables (x). The task at hand involves fitting a function to the given data, which aligns with the core goal of an approximation problem. Specifically, the objective is to create a model that effectively captures and represents the connection between the target variable (compressive strength) and the input variables. Thus, an approximation model is chosen as the appropriate approach to tackle this challenge.

IV. DATASET

A total of 200 test data specimens were collected for this study [2, 4-7]. Any missing data points were omitted. The collected data for this research project consisted of values that fall within a continuous range. Therefore, the variables used in the analysis can be classified as continuous variables. Continuous variables are quantitative in nature and can take on any numerical value within a specific range. By working with continuous variables, the research aims to capture the fine-grained variations and subtle changes in the data. This allows for a more precise modeling of the relation between the input and the target variables, which is the compressive strength of Circular concrete columns confined with FRP (fcc). Utilizing continuous variables in the analysis provides a more comprehensive understanding of the underlying patterns and trends that contribute to the compressive strength. It allows for a more nuanced examination of how variations in the input variables impact the target variable, enabling more accurate estimations and predictions. The collected data were preprocessed from the models learning the input target correlations to prepare it for use in the machine learning models. The preprocessing involved the selection of parameters, including the initial confined compressive strength of concrete column without FRP (fco), initial compressive strain of column (eco), Diameter to thickness ratio (D/t), Elastic modulus (Efrp) and Tensile strength (ffrp) of FRP, and compressive strain of FRP(efrp), Type of FRP, compressive strain (ecc) and the final compressive strength (fcc) of circular concrete column with FRP. Based on the analysis of input target correlations, the decision was made to omit parameters that had the least impact on the target variable. As a result, six parameters were selected for further consideration: D/t, εco, fco, Efrp, ffrp, εfrp and fcc. These parameters were deemed to have the most significant impact on the target variable and are therefore considered to be the most important for the analysis. As a result, there were 170 test data specimens that remained for further analysis. The processed data are further trained using Neural Designer. The database statistics for the variables used in this research are given in Table 3.

The diameter to thickness ratio (D/t) ranges from 27.88 to 1299.15, with a mean value of 369.157 and a deviation of 417.131. Most of the values lied in the range of 900-1200. The compressive strength without FRP (fco) ranges from 24 MPa to 112 MPa, with a mean value of 48.899 MPa and a deviation of 21.609. The highest data % lied in the range of 30 MPa to 50 MPa. The compressive strain of concrete columns without FRP (eco) had a narrow range from 0.002 to 0.021, with a mean value of 0.003 and a deviation of 0.001. Maximum data points lied in the range of 0.0025-0.003 while least data points occurred at 0.0035-0.004. The tensile strength of FRP (ffrp) had a wide range from 325 to 4203, with a mean value of 2081.858 and a deviation of 1647.188. Maximum number of ffrp lied in the range from 2000-4000 MPa. The elastic modulus of FRP (Efrp) had a wide range from 19.1 to 245.687, with a mean value of 117.196 and a deviation of 100.104. No data points were observed in the range of 0.003-0.004. The strain of FRP (efrp) had a range from 0.014 to 0.047, with a mean value of 0.022 and a deviation of 0.012.

TABLE I. DATA BASE STATISTICS

Param eters	Statistics			
	Minimum	***Maximum***	***Mean***	***Deviation***
D/t	27.88	1299.15	369.157	417.131
fco	24	112	48.899	21.609
eco	0.002	0.021	0.003	0.001
Ffrp	325	4203	2081.858	1647.188
Efrp	19.1	245.687	117.196	100.104
efrp	0.014	0.047	0.022	0.012

These statistics provide important information about the distribution and variability of the input variables used in the study, which can help in understanding the behavior and performance of concrete circular columns confined with FRP.

For the training of the models, the data was randomly divided into three sets: 60% of test data specimens were used for training, 20% of the data were in selection sets, and the remaining 20% were used for prediction tests in Neural Designer. Correlation of the inputs was studied, error % was studied, and histograms were plotted to identify any patterns or trends in the data.

V. DATA ANALYSIS

The correlation analysis revealed that the compressive strength without FRP (fco) and the target output have a moderate positive correlation, indicating that an increase in compressive strength without FRP could result in a corresponding increase in the compressive strength of concrete circular columns confined with FRP. On the other hand, the tensile strength of FRP (ffrp) and elastic modulus of FRP (Efrp), the compressive strain of concrete columns without FRP (eco) and the strain of FRP (efrp) showed weak positive correlations with the target output, suggesting that these factors may have a minor influence on the compressive strength of concrete circular columns confined with FRP.

The diameter to thickness ratio (D/t) exhibited a weak negative correlation with the target output, indicating that a decrease in the ratio may lead to a slight positive effect on the compressive strength of concrete circular columns with FRP.

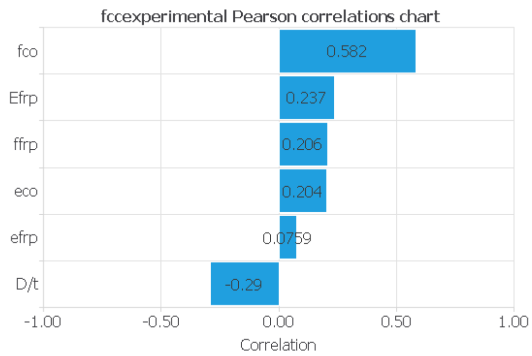

Fig. 2. fcc input-target correlations chart

Overall, the correlation coefficients obtained through the ANN model indicate that the compressive strength without FRP has the strongest correlation with the compressive strength of circular concrete columns confined with FRP, followed by the tensile strength and elastic modulus of FRP, the compressive strain of concrete columns without FRP, and the strain of FRP while diameter to thickness ratio showed a weak negative correlation.

Parametric Analysis of each parameter is shown in figures below.

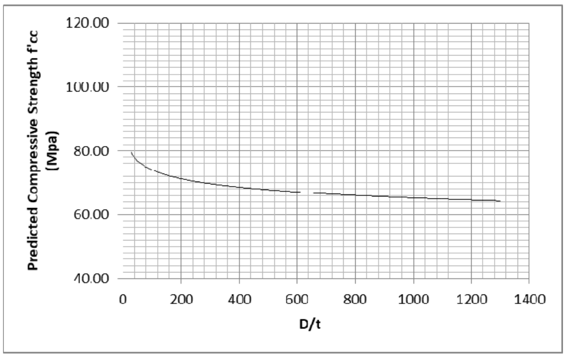

Fig. 3. Influence of D/t on Circular concrete columns confined with FRP compressive strength

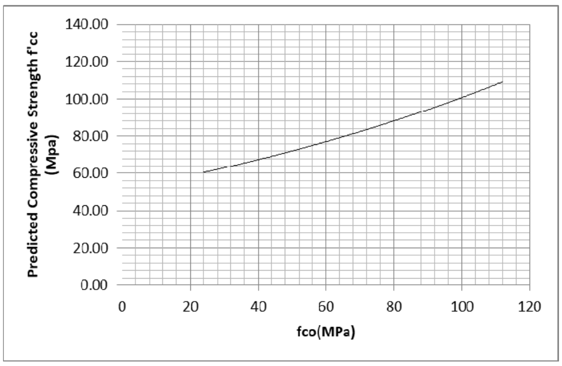

Fig. 4. Influence of fco on Circular concrete columns confined with FRP compressive strength

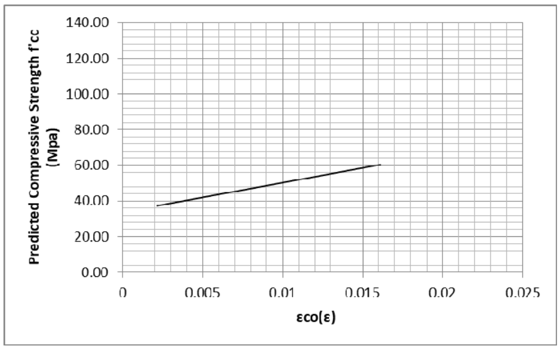

Fig. 5. Influence of eco on Circular concrete columns confined with FRP compressive strength

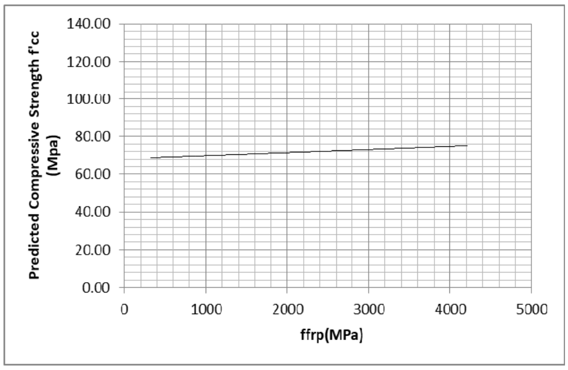

Fig. 6. Influence of ffrp on Circular concrete columns confined with FRP compressive strength

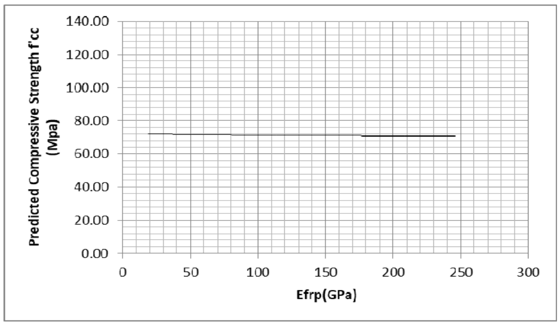

Fig. 7. : Influence of Efrp on Circular concrete columns confined with FRP compressive strength

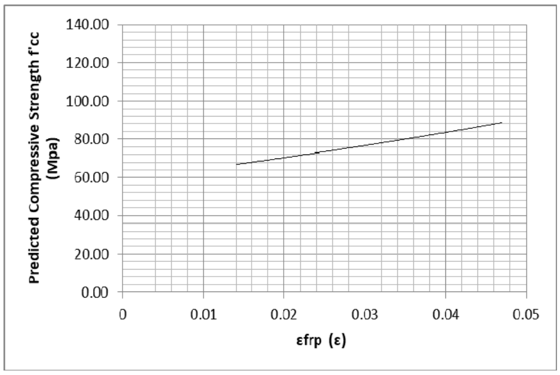

Fig. 8. Influence of efrp on Circular concrete columns confined with FRP compressive strength

The final compressive strengths increase with an increase in parameters such as fco, eco, ffrp, Efrp and εfrp. This suggests that higher values of these parameters contribute to enhanced compressive strength.

On the other hand, with an increase in the D/t ratio the final compressive strength decreased. This indicates that as the ratio between the diameter and thickness of the component increases, the compressive strength tends to decrease.

VI. Model Evaluation

The ANN models were validated by comparing their predicted values with the corresponding experimental data. The predicted values were compared with existing constitutive models given by Lam, Mander and Fardis which are widely used model. Lam model has the highest predictive accuracy among the existing models. The predicted values were obtained by inputting the parameters of the test set into the trained models.

The results obtained from the machine learning models were subjected to statistical analysis to evaluate the reliability and accuracy of the prediction models. The statistical analysis involved calculating several metrics, including the mean square error (MSE), root mean square error (RMSE), Mean Absolute Error (MAE), and correlation coefficient (R^2). R^2 measures the degree of correlation between the independent and dependent variables, where a higher value indicates a stronger relationship between the predicted and actual values. The Mean Squared Error (MSE) measures the average error between the predicted and actual values, with a lower MSE indicating a smaller deviation between the two. Similarly, the Mean Absolute Error (MAE) represents the average magnitude of errors, and a smaller MAE indicates a closer approximation of the predicted value to the actual value. These statistical analyses are widely used to assess the predictive accuracy of Neural Network models [1].

VII. Model Construction

Based on the outcomes of the neuron selection algorithm, eight optimal numbers of neurons and their corresponding network architectures were chosen. The network architecture consists of a scaling layer with 6 neurons, two perceptron layers with 8 and 1 neurons respectively, an unscaling layer with 1 neuron, and a bounding layer with 1 neuron. The network has 6 inputs and 1 output. The optimal number of neurons was found to be 8, and the minimum selection error of 0.7895 was achieved. The minimum percentage error recorded was 0.188614%, while the maximum percentage error was 22.8476%. The mean percentage error was 3.72352%. The results indicate that the neural network model has effectively fit the given data, enabling it to make accurate predictions and is shown in goodness fit chart.

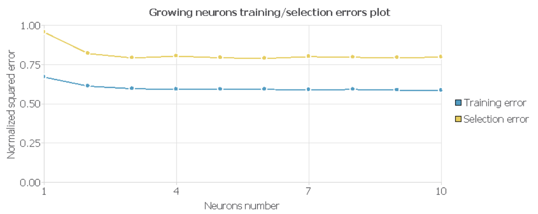

Fig. 9. Growing neurons errors plot

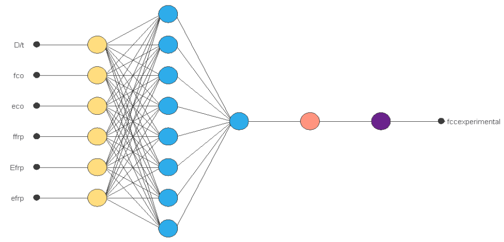

Fig. 10. Network architecture with 8 neurons

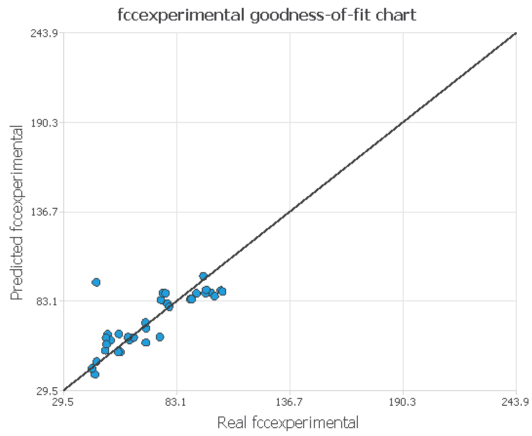

Fig. 11. Goodness of Fit chart

VIII. Mathematical Expression

The predictive model is in the form of a function that relates the outputs to the inputs, and it can be incorporated into other software for production purposes in production mode.

scaled_D_div_t = (D_div_t-369.1570129)/417.131012 (1)
scaled_fco = (fco-48.8987999)/21.60880089 (2)
scaled_eco = (eco-0.00280945003)/0.001461460022 (3)
scaled_ffrp = (ffrp-2081.860107)/1647.189941 (4)
scaled_Efrp = (Efrp-117.1959991)/100.1039963 (5)
scaled_efrp = (efrp-0.02169810049)/0.01154839993 (6)

perceptron_layer_1_output_0 = tanh(0.664428 + ((1)*-0.717272) + ((2)*0.428432) + ((3)*0.631791) + ((4)*-0.396432) + ((5)*-0.839921) + ((6)*0.814637)) (7)
perceptron_layer_1_output_1 = tanh(0.922491 + ((1)*0.110663) + ((2)*0.636034) + ((3)*-0.823965) + ((4)*-0.763382) + ((5)*-0.787037) + ((6)*0.484072)) (8)

perceptron_layer_1_output_2 = tanh(-0.600252 + ((1)*-0.0127548) + ((2)*0.0694091) + ((3)*0.516858) + ((4)*-0.664627) + ((5)*0.0665895) + ((6)*-0.992946)) (9)

perceptron_layer_1_output_3 = tanh(-0.467709 + ((1)*-1.47234) + ((2)*0.154972) + ((3)*0.376399) + ((4)*-1.69545) + ((5)*1.98686) + ((6)*1.05936)) (10)

perceptron_layer_1_output_4 = tanh(0.479843 + ((1)*0.996717) + ((2)*-0.182735) + ((3)*0.343448) + ((4)*-1.01944) + ((5)*-0.166606) + ((6)*1.74639)) (11) perceptron_layer_1_output_5 = tanh(0.556007 + ((1)*0.231112) + ((2)*0.0314288) + ((3)*-0.416626) + ((4)*-1.03645) + ((5)*-0.904588) + ((6)*0.0516162)) (12)

perceptron_layer_1_output_6 = tanh(1.17147 + ((1)*-0.6576) + ((2)*0.382531) + ((3)*-0.387669) + ((4)*-0.671911) + ((5)*-0.415207) + ((6)*-1.0343)) (13)

perceptron_layer_1_output_7 = tanh(0.626514 + ((1)*-0.562423) + ((2)*0.579186) + ((3)*-0.891775) + ((4)*-0.476279) + ((5)*0.939974) + ((6)*0.51672)) (14)

perceptron_layer_2_output_0 = (0.467827 + ((7)*-1.36211) + ((8)*1.88085) + ((9)*0.803916) + ((10)*1.51679) + ((11)*-1.06072) + ((12)*-0.145515) + ((13)*-1.12802) + ((14)*0.373271)) (15)

unscaling_layer_output_0=(15)*31.89170074+75.24449921

IX. Results

The study involved comparing the constructed ANN model with three other constitutive models (Fardis, Lam & Teng, and Mander) using statistical metrics such as MSE, RMSE, MAE, and R2. The results demonstrated that the ANN model outperformed the other three models in predicting the compressive behavior of FRP confined concrete circular columns.

Specifically, the ANN model achieved lower values of MSE, RMSE, and MAE (863.83, 29.39, and 17.37, respectively) compared to the other models. Additionally, the ANN model obtained a higher R2 value of 0.45, indicating its ability to explain 45% of the variance in the data. The Fardis model showed the poorest fit with the highest MSE, RMSE, and MAE values (7417.57, 86.12, and 59.18, respectively). The Lam & Teng and Mander models performed better than the Fardis model but were still outperformed by the ANN model. The Lam & Teng model obtained an R2 value of 0.301, and the Mander model obtained an R2 value of 0.357.

These results indicate that the developed ANN model is a powerful tool for predicting the compressive strength of concrete circular columns confined with FRP. It can be utilized in the design of concrete structures confined with FRP, enabling engineers to make accurate predictions of their compressive behavior. Furthermore, the study's findings may contribute to the advancement of latest constitutive models for FRP confined concrete structures.

X. Conclusion and Recommendations

The study aimed to utilize ANN for predicting the compressive strength of circular concrete columns confined with FRP. A total of 170 test data samples were used, and the ANN model showed the best predictive accuracy with a MSE of 863.83, RMSE of 29.39, MAE of 17.37, and R2 of 0.45. The ANN model revealed strong correlations between the compressive strength of circular concrete columns confined with FRP and various factors such as the compressive strength of columns without FRP, tensile strength and elastic modulus of FRP, and strains. The diameter to thickness ratio had a weak negative correlation with compressive strength.

The ANN model can be used for product development, and engineers are recommended to incorporate it into the design process. Future studies should focus on enhancing the ANN model's accuracy and exploring other machine learning models. Additionally, increasing the sample size is recommended to improve understanding and design guidelines for circular concrete columns confined with FRP. The findings of such studies could be used to improve design guidelines for circular concrete columns confined with FRP and enhance safety and performance of concrete structures.

References

[1] P. Chen, H. Wang, S. Cao and X. Lv, “Prediction of Mechanical Behaviours of FRP-Confined Circular Concrete Columns Using Artificial Neural Network and Support Vector Regression: Modelling and Performance Evaluation,” mdpi journals/material, 15, 4971, July 2022.

[2] S. Pessiki, K.A. Harries, J.T. Kestner, R. Sause and J.M. Ricles, ”Axial behavior of reinforced concrete columns confined with FRP jackets,” Journal of composites for construction, 5, pp. 237–245, 2001.

[3] P. Zohrevand, M. ASCE, A. Mirmiran and F. ASCE, "Behavior of Ultrahigh-Performance Concrete Confined by Fiber-Reinforced,” Journal of Materials in Civil Engineering, 23, pp. 1727-1734, 2011.

[4] M. Touhari and R.M. Kettab, “Behaviour of FRP Confined Concrete Cylinders: Experimental Investigation and Strength Model,” Periodica Polytechnica Civil Engineering, 60, vol. 4, pp. 647–660, 2016.

[5] T. Vincent and T. Ozbakkaloglu, “Influence of concrete strength and confinement method on Compressive behvaiour of FRP confined high and ultra high strength concrete,” Composites Part B-Engineering, 50, pp-413-428, 2013.

[6] L. Lam and J.G. Teng, “Ultimate Condition of Fiber Reinforced Polymer-Confined Concrete,” Journal of Composites for Construction, 8, vol. 6, pp. 539-548, 2004.

[7] A. Nanni and N.M. Bradford, “FRP jacketed concrete under uniaxial compression,” Construction and Building Materials, 9, vol. 2, pp. 115-124, 1995.

[8] A. Cevika and I.H. Guzelbeyb, “Neural network modeling of strength enhancement for CFRP confined concrete cylinder,” Building and Environment Science Direct, 43, pp. 751–763, 2008.

[9] S. Mousavi, A.H. Alavi, M.A. Esmaeili and M. Gandomi, “A data mining approach to compressive strength of CFRP-confined concrete cylinders,” Structural Engineering and Mechanics, 36, vol. 6, pp. 759-783, 2010.

[10] A. Cevik and A.F. Cabalar, “A Genetic–Programming–Based Formulation for the Strength Enhancement of Fiber–Reinforced–Polymer– Confined Concrete Cylinders,” Journal of Applied Polymer Science, 110, pp. 3087–3095, 2007.

[11] Neural networks tutorial: Application types. Available at: https://www.neuraldesigner.com/learning/tutorials/neural-networks-applications (Accessed: 01 February 2023).

[12] J.B. Mander and M.J.N. Priestley, “Theoretical stress-strain model for confined concrete,” Journal of Structural Engineering, 114, pp. 1804–1826, 1998.

[13] M.N. Fardis and H. Khalili, “Concrete encased in fiberglass-reinforced plastic,” ACI Structural Journal, 78, pp. 440–446, 1997.

[14] A.R. Rahai, P. Sadeghian and M.R. Ehsani, “Experimental Behavior of Concrete Cylinders Confined with CFRP Composites,” [The 14th World Conference on Earthquake Engineering, 2008].

[15] R.F. Tufail, X. Feng, D. Farooq, N. Abdelmelek,, E. Lublóy and A. Maqsoom, “Behavior and Strength Predictions for CFRP Confined Rubberized Concrete under Axial Compression,” Periodica Polytechnica Civil Engineering, 66, vol. 1, pp. 164–178, 2022.

[16] 440.2R-08 guide for the design and construction of externally bonded d FRP Systems for Strengthening Concrete Structures. Available at: https://edisciplinas.usp.br/pluginfile.php/3435659/mod_resource/content/1/4402r_08.pdf (Accessed: 10 March 2023).

[17] S. Wang, “Long-term behavior of fiber reinforced polymer (FRP) confined concrete cylinders subjected to severe weather and seawater

solution conditions," Doctoral Dissertations. 2900, 2018. Available at: https://scholarsmine.mst.edu/doctoral_dissertations/2900

[18] T.M. Pham and M.N.S. Hadi, "Confinement model for FRP confined normal- and high-strength 4 concrete circular columns," Journal of Construction and Building Materials, 5615, 2014.

[19] A. Khalifa, A. Nanni and G. Tadros, "Effect of FRP confinement on concrete columns," Journal of Composites for Construction, 10, vol. 2, pp. 96-106, 2006 .

[20] C. Jiang and Y.F. Wu, "Eccentrically loaded FRP-confined concrete short columns," MDPI, polymers, 12, vol. 6, 1261, 2020.

[21] M. Touhari and R. Mitiche-Kettab, "Behavior of FRP confined concrete cylinders: Experimental investigation and strength model," Period. Polytech. Civ. Eng., 60, pp. 647–660, 2016.

[22] D. Kim, J. Kim and J. Park., "Fatigue life prediction of steel structures using artificial neural network," International Journal of Fatigue, 123, pp. 203-210, 2019.

[23] B. Piscesa, M.M. Attard and A.K. Samani, "3D Finite element modeling of circular reinforced concrete columns confined with FRP using a plasticity based formulation," Journal of Composite Structures, 194, pp. 478-493, 2018.

[24] V.Q. Tran, V.Q. Dang and L.S. Ho, "Evaluating compressive strength of concrete made with recycled concrete aggregates using machine learning approach," Construction Building Material, 323, 126578, 2022.