APPLICATION OF MACHINE LEARNING MODELS IN PREDICTING THE COMPRESSIVE STRENGTH OF GFRP-CONFINED CONCRETE

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Abstract - Accurately predicting the compressive strength of GFRP-confined concrete plays a key role in the use of GFRP in strengthening reinforced concrete structures. This study predicts the compressive strength of GFRP-confined concrete using five machine learning (ML) models. The performance of the ML models was compared with that of the design-oriented stress-strain model suggested by ACI 440.2R-17 for FRP-confined concrete. A dataset of 167 test results of GFRP-confined concrete was used for training and testing the ML models. It has been found that the predicted results obtained from the ML models were in good agreement with the test results. Furthermore, the ML models outperformed the design-oriented stress-strain model in predicting the compressive strength of GFRP-confined concrete. Among the machine learning models, the RandomTree and RandomForest models demonstrated the highest prediction accuracy.

Key words - GFRP-confined concrete; Compressive strength of GFRP-confined concrete; Machine learning models; Predicting the compressive strength of GFRP confined concrete; Strengthening RC structures.

1. Introduction

The use of high-strength composite fabrics for strengthening the load-bearing capacity of reinforced concrete (RC) structures has become increasingly common in developed countries [1, 2]. Commonly used composite fabrics for structural strengthening include carbon fiber reinforced polymer (CFRP), glass fiber reinforced polymer (GFRP), aramid fiber reinforced polymer (AFRP), and basalt fiber reinforced polymer (BFRP) [3, 4].

The application of composite fabrics in strengthening RC columns significantly improves both the strength and ductility of the columns [5, 6]. Accurate prediction of the compressive strength of high-strength composite-confined concrete columns plays a crucial role in evaluating the load-carrying capacity of such strengthened RC columns [7, 8].

Numerous studies have been conducted in recent years to predict the compressive strength of composite-confined concrete columns. The compressive strength of these columns can be predicted either through experimental stress-strain models [7, 9] or by applying machine learning models [10-12].

Experimental studies on the compressive strength of composite-confined concrete columns over the years have proposed more than 80 experimental stress-strain models [13]. These models include design-oriented stress-strain models and analysis-oriented stress-strain models for FRP-confined concrete [13, 14]. Several experimental stress-strain models have been adopted in technical guidelines for the design of concrete structures strengthened with composite materials, such as the American Concrete Institute guideline ACI 440.2R-17 (2017) [15] and the International Federation for Structural Concrete guideline FIB Bulletin 14 [16]. Studies have shown that experimental models are developed based on specific experimental datasets; therefore, the application of these models to new datasets for high-strength composite-confined concrete may result in significant discrepancies between the predicted and experimental results.

The application of artificial intelligence in general, and machine learning models in particular, in the construction industry has been implemented for over 20 years in various fields such as structural engineering [17-20], geotechnical engineering [21-23], and material science [24-26]. Among these, the use of machine learning models for prediction tasks is recognized as one of the most powerful and reliable computational techniques. The application of machine learning models to predict the compressive strength of high-strength composite-confined concrete columns has been explored in recent years [10, 11, 27]. Cevik and Guzelbey [11] applied an Artificial Neural Network (ANN) model to predict the compressive strength of high-strength CFRP-confined concrete columns, where the input parameters included column diameter (D), total thickness of CFRP (nt_{frp}), elastic modulus of CFRP (E_{frp}) and compressive strength of unconfined concrete (f'_{co}). Their results indicated that the ANN model could accurately predict the compressive strength of high-strength CFRP-confined concrete columns. Cevik et al. [27] employed genetic programming and stepwise regression to predict the compressive strength of high-strength CFRP-confined concrete columns, using input parameters such as column diameter (D), total thickness of CFRP (nt_{frp}), lateral pressure induced by CFRP (f_{lu}) and compressive strength of unconfined concrete (f'_{co}). and compressive strength of unconfined concrete (D), column height (H); compressive strength of concrete (f'_{co}), elastic modulus of FRP (E_{frp}), tensile strength of FRP (f_{frp}) and total thickness of FRP (nt_{frp}). Their findings showed that the ANN model could predict the compressive strength of FRP-confined concrete columns with reasonable accuracy; however, the accuracy of the ANN model was comparable to that of one of the selected experimental models used for comparison.

A review of the literature reveals that most studies have focused on applying a limited number of machine learning models to predict the compressive strength of CFRP-confined concrete columns. There are very few studies that utilize machine learning models to predict the compressive strength of GFRP-confined concrete columns. Meanwhile, GFRP fabrics are increasingly being used for strengthening RC columns and as jackets in new construction of both plain and RC columns due to their low cost and high durability [28]. Therefore, this study applies machine learning models to predict the compressive strength of GFRP-confined concrete columns. Five machine learning models are used for this purpose, including ANN, M5P, M5Rules, Random Forest, and Random Tree models.

2. Model development

2.1. ANN model

The ANN model (hereafter referred to as the ANN model) is a mathematical model inspired by the structure and function of biological neural networks in the human brain. The ANN model consists of a system of interconnected nodes, similar to neurons in the brain. These neurons are organized into layers, with the first layer referred to as the input layer and the last layer as the output layer. The layers between the input and output layers are called hidden layers. Each neuron in the ANN receives one or more input signals from neurons in the preceding layer, with each input signal assigned a weight. Each neuron acts as a data processing unit that performs two main functions: (1) aggregating input data through a linear function and (2) determining the output value through an activation function.

The process of input signal aggregation and output determination is performed at each neuron in the ANN, and this process is iterated until the training error reaches a predefined value set by the algorithm.

2.2. M5P model

The M5P model is developed based on the M5 algorithm and is commonly used for regression problems. M5P combines decision trees and linear regression. The M5P model generates a tree structure similar to a decision tree, but at the leaves of the tree, linear regression models are fitted, whereas traditional decision trees have single predicted values at the leaves.

The tree-building process in the M5P model involves splitting the data into groups with similar characteristics at each node, based on the standard deviation. The splitting stops when the standard deviation at a node falls below a predefined threshold. After the tree is built, a linear regression equation is trained at each leaf to represent the characteristics of the data group at that leaf. Once the tree is fully developed, M5P applies a pruning technique to remove ineffective branches and to avoid overfitting.

2.3. M5Rules model

The M5Rules model is developed based on the M5 and M5P models. The tree-building process in M5Rules is similar to that of M5P, where branches are split based on the standard deviation. Unlike M5P, the path from the root to a leaf in the M5Rules model is constructed as a set of if-then rules, with each node representing a condition in the rule set. Similar to M5P, the characteristics of the data group at each leaf are represented by a linear regression model. M5Rules extracts the best leaf node rules to use as the model's rules.

2.4. Random Forest model

The random forest model is an ensemble learning method widely used for prediction tasks. This model consists of multiple decision trees operating in parallel, and predictions are made by averaging the outputs of individual trees.

To construct a random forest, random subsets of the original dataset are created using bootstrap sampling. Each random subset is then used to train a decision tree, where at each node, only a random subset of features is considered. The best feature among the subset is chosen to split the node. The average predicted value from all trees is used as the final prediction of the random forest.

2.5. Random Tree model

The random tree model is a variant of the decision tree, where the feature for splitting at each node is selected randomly rather than always choosing the best feature as in traditional decision trees. At each node of the random tree, only a random subset of attributes is considered, and the best attribute from this subset is chosen for splitting the node.

2.6. Experimental model ACI-440.2R-17

The design-oriented stress-strain model proposed in the ACI-440.2R-17 standard [15] is used to compare prediction accuracy with machine learning models. The design-oriented experimental model according to ACI-440.2R-17 (hereafter referred to as the ACI-440.2R-17 experimental model) uses the design-oriented stress-strain model developed by Lam and Teng [7]. The stress-strain model proposed by Lam and Teng [7] is one of the simplest and most accurate experimental models [13]. In the ACI-440.2R-17 model, the compressive strength of FRP-confined concrete columns, f'_{cc} is determined by the following equations:

$$f'_{cc} = f'_{co} + 3.3 f_l \tag{1}$$

$$f_l = \frac{2 E_f n t_f \varepsilon_{fe}}{D} \tag{2}$$

$$\varepsilon_{fe} = 0.58 \varepsilon_{fu} \tag{3}$$

Where: f'_{co} is the compressive strength of unconfined concrete; f_l is the lateral pressure applied to the concrete by the FRP jacket; ε_{fu} is the ultimate strain of the FRP material determined from standard tensile tests; ε_{fe} is the hoop strain of the FRP-confined concrete column; n is the number of FRP layers; t_f is the thickness of each FRP layer; E_f is the elastic modulus of the FRP fabric; and D is the diameter of the concrete column.

3. Experimental data

The dataset consists of 167 experimental results on the compressive strength of GFRP-confined concrete columns, which are used for training and evaluating the accuracy of the machine learning models and the design-oriented model. The experimental data were collected from 30 studies compiled and summarized by Ozbakkaloglu and Lim [29].

The machine learning models are used to predict the compressive strength of GFRP-confined concrete columns (f'_{cc}) with seven input parameters utilized for prediction: (1) diameter of the concrete column (D); (2) height of the concrete column (H); (3) compressive strength of the concrete (f'_{co}); (4) ultimate strain of the concrete (ε_{co}); (5) elastic modulus of GFRP (E_{frp}); (6) tensile strength of GFRP (f_{frp}); (7) thickness of GFRP (t_{frp}). The input parameters used in the machine learning models are denoted as x_1 to x_7 while the corresponding output is the compressive strength of the GFRP-confined concrete column, denoted as y. Table 1 provides a summary of the experimental data used for training and evaluating the accuracy of the machine learning models. Figure 1 illustrates the detailed distribution of the experimental data.

Table 1. *Descriptive statistics of the input and output parameters used for predicting compressive strength of GFRP-confined concrete*

Parameter	Sy.	Unit	Statistics			
			Min	Max	Average	Std.
Diameter (D)	x_1	mm	51	406.4	166.76	68.93
Height (H)	x_2	mm	102	812.8	338.07	141.97
Compressive strength of unconfined concrete (f'_{co})	x_3	MPa	14.8	54.5	36.32	7.59
Ultimate tensile strength of unconfined concrete (ε_{co})	x_4	(%)	0.14	0.49	0.24	0.03
Elastic modulus of GFRP (E_{frp})	x_5	GPa	4.9	80.5	46.63	25.89
Tensile strength of GFRP (f_{frp})	x_6	MPa	75	3240	1396.57	991.7
Thickness of FRP (t_{frp})	x_7	mm	0.15	15	1.70	2.075
Compressive strength of GFRP-confined concrete (f'_{cc})	y	MPa	30	135.8	65.76	22.37

Where Sy. is the abbreviation of the symbols.

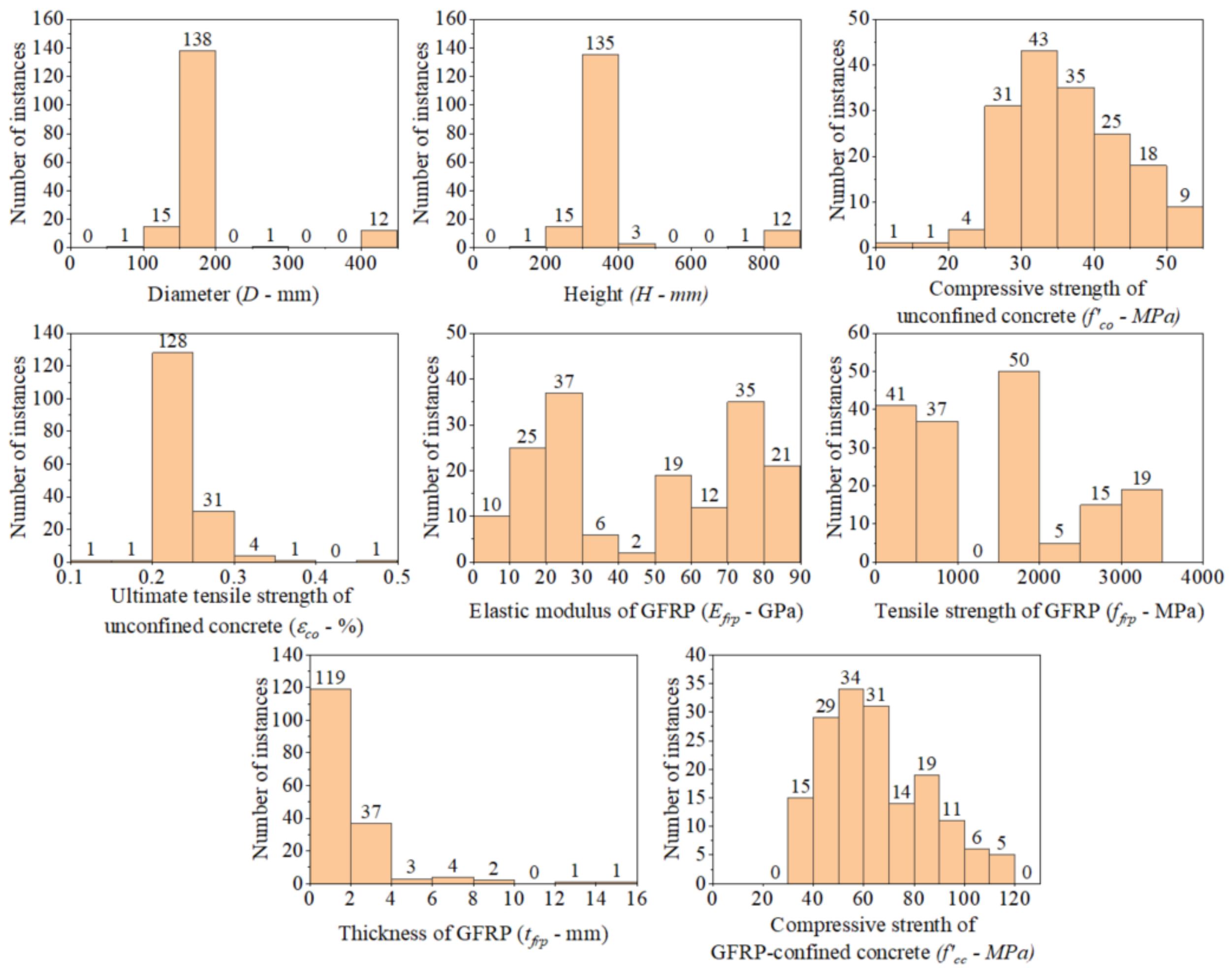

Figure 1. *Graphical representation of input and output parameters used for predicting the compressive strength of GFRP-confined concrete*

4. Evaluation of the predictive capability of machine learning models

4.1. Statistical indices

Four statistical indices, including the correlation coefficient (R), mean absolute percentage error ($MAPE$), root mean square error ($RMSE$), and mean absolute error (MAE), are used to evaluate the accuracy of the machine learning models. The indices R, $MAPE$, $RMSE$, and MAE are determined according to equations (4) to (7):

$$R = \frac{n\sum yy' - (\sum y)(\sum y')}{\left(\sqrt{n(\sum y^2) - (\sum y)^2}\right)\sqrt{n((\sum y'^2) - (\sum y')^2}} \quad (4)$$

$$MAPE = \frac{1}{n}\sum_{1}^{n}\left|\frac{y-y'}{y}\right| \quad (5)$$

$$RMSE = \sqrt{\frac{1}{n}\sum_{1}^{n}(y-y')^2} \quad (6)$$

$$MAE = \frac{1}{n}\sum_{1}^{n}|y-y'| \quad (7)$$

Where: y and y' are the actual and predicted values, respectively; n is the number of collected samples.

The R index reflects the correlation between the actual and predicted values and ranges from -1 to 1. The closer the absolute value of R is to 1, the higher the model's accuracy. The $MAPE$, $RMSE$, and MAE indices represent the difference between the actual and predicted values; therefore, the lower the values of $MAPE$, $RMSE$, and MAE, the higher the accuracy of the models.

4.2. Accuracy of the predictive models

The accuracy of the predictive models (five machine learning models and one design-oriented empirical model adopted from ACI 440.2R-17) is evaluated by comparing the predicted results with the experimental results. The predictive performance of the machine learning models is assessed using the 10-fold cross-validation technique. In this technique, the dataset is divided into 10 equal parts; one part is used as the test set and the remaining nine parts are used as the training set for each prediction iteration. This process is repeated 10 times, and the average result from the 10 prediction runs for each machine learning model is used to evaluate the accuracy of each model. The correlation between the predicted results from the predictive models (machine learning models and the ACI 440.2R-17 empirical model) and the experimental results is shown in Figure 2.

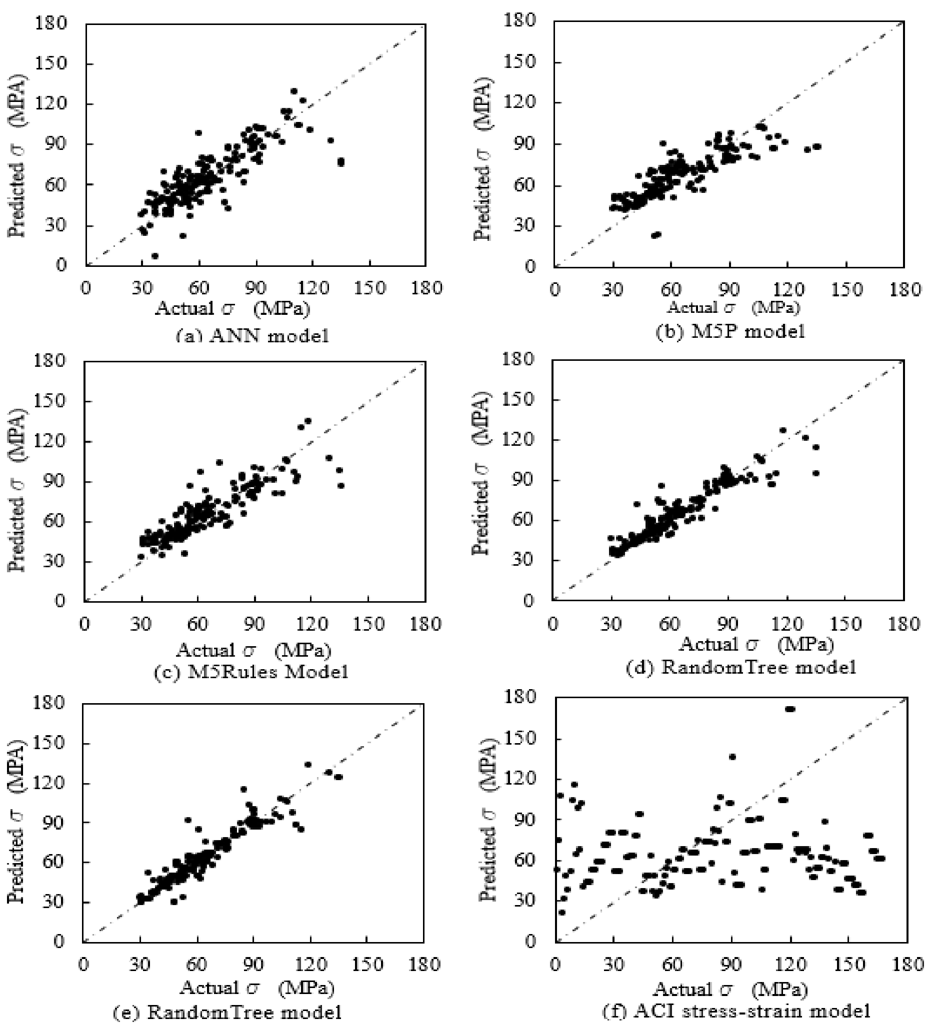

Figure 2. *The estimated compressive strength versus the actual compressive strength of GFRP-confined concrete*

In Figure 2, the data points representing the correlation between the predicted results of the five machine learning models and the experimental results are distributed along the diagonal of the correlation plot. In contrast, the points representing the correlation between the predicted results of the ACI 440.2R-17 empirical model and the experimental results are distributed farther from the diagonal. This distribution indicates that the machine learning models can predict the compressive strength of GFRP-confined concrete columns with relatively high accuracy, whereas the predictions from the ACI 440.2R-17 empirical model show a considerable deviation from the experimental results. The discrepancy between the predictions of the ACI 440.2R-17 empirical model and the experimental results is due to the empirical model proposed by Lam and Teng [7], which is used in ACI 440.2R-17 and was developed based on a specific dataset. Therefore, applying the empirical model from ACI 440.2R-17 to a new dataset will inevitably result in certain discrepancies. The distribution of predicted versus experimental values shows that the predictive accuracy of the artificial intelligence models is higher than that of the ACI 440.2R-17 empirical model.

Figure 2 also shows that, among the artificial intelligence models, the correlation points between the predicted and actual values for the Random Forest and Random Tree models are closer to the diagonal of the correlation plot than those for the ANN, M5P, and M5Rules models. This distribution indicates that, overall, the Random Forest and Random Tree models can predict the compressive strength of GFRP-confined concrete columns more accurately than the other three machine learning models (ANN, M5P, and M5Rules).

The statistical indices used to evaluate the accuracy of the predictive models are presented in Table 2. Meanwhile, Figures 3–5 compare the accuracy of the models based on the four statistical indices. Table 2 and Figures 3–5 show that the Random Tree model has the highest correlation coefficient (R) and the lowest values for $MAPE$, $RMSE$, and MAE. These results indicate that the Random Tree model achieves the highest accuracy in predicting the compressive strength of GFRP-confined concrete columns. The evaluation results based on the statistical indices are consistent with those based on the correlation plot between the predicted and experimental results. The statistical indices also show that the Random Forest model has R, $MAPE$, $RMSE$, and MAE values very close to those of the Random Tree model. This result indicates that the Random Forest model ranks just below the Random Tree model in predicting the compressive strength of GFRP-confined concrete columns. The remaining models can also predict the compressive strength of GFRP-confined concrete columns with reasonable accuracy; however, the use of different evaluation indices leads to different rankings of model accuracy. An interesting finding in this study is that, based on the correlation plot between predicted and experimental results, the ACI 440.2R-17 empirical model has the lowest accuracy, but when using the $MAPE$ index, the ACI 440.2R-17 empirical model is not the least accurate. This demonstrates the necessity of using multiple methods to evaluate the accuracy of predictive models.

Table 2. *Performance evaluation of the AI models*

No.	Model	Indicator			
		R	$MAPE$ (%)	$RMSE$ (MPa)	MAE (MPa)
1	ANN	0.82	15.07	12.90	9.19
2	M5P	0.83	15.90	12.84	9.73
3	M5Rules	0.87	12.49	10.99	7.79
4	RandomForest	0.93	8.35	8.24	5.30
5	RandomTree	0.94	7.56	7.83	4.85
6	ACI	0.77	15.45	15.84	10.85

Table 2 shows that, when using the correlation coefficient (R) to evaluate predictive accuracy, the Random Tree model provides the most accurate predictions (R = 0.94), while the ACI 440.2R-17 empirical model yields the least accurate results (R = 0.77). The prediction accuracy of the Random Tree model is 22.1% higher than that of the ACI 440.2R-17 empirical model.

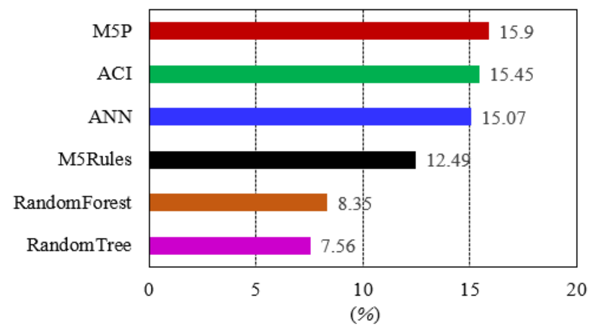

Figure 3. *Comparison of the predictive models using MAPE indicator*

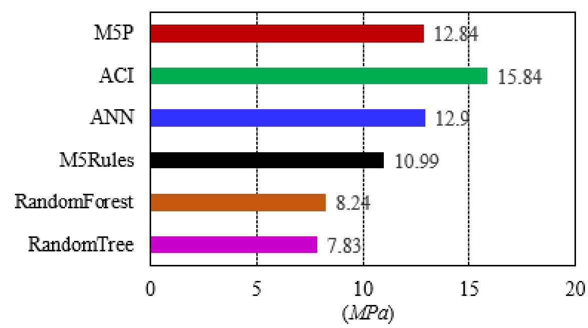

Figure 4. *Comparison of the predictive models using RMSE indicator*

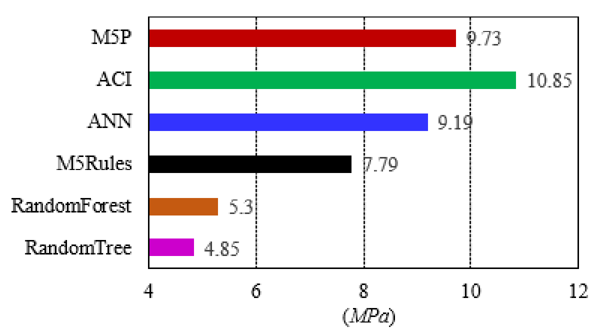

Figure 5. *Comparison of the predictive models using MAE indicator*

Data from Figures 3–5 also indicate that, when using the $MAPE$, $RMSE$, and MAE indices to assess predictive accuracy, the Random Tree model exhibits the highest accuracy, followed by the Random Forest model. Meanwhile, the ACI 440.2R-17 empirical model and the M5P machine learning model show the lowest accuracy. When using the $RMSE$ and MAE indices, the ACI 440.2R-17 empirical model yields the lowest accuracy in predicting the compressive strength of GFRP-confined concrete columns, followed by the M5P model. According to the RMSE index, the ACI 440.2R-17 empirical model is 23.4% less accurate than the M5P model and 92.2% and 102.3% less accurate than the Random Forest and Random Tree models, respectively. When using the MAE index, the ACI 440.2R-17 empirical model is 11.5% less accurate than the M5P model and 104.7% and 123.7% less accurate than the Random Forest and Random Tree models, respectively. However, when using the $MAPE$ index, the ACI model outperforms the M5P model, being 2.8% more accurate, but is 85.3% and 104.4% less accurate than the Random Forest and Random Tree models, respectively.

The performance evaluation results indicate that the machine learning models can predict the compressive strength of GFRP-confined concrete columns with high accuracy. The correlation plot between predicted and experimental results shows a distribution along the diagonal, with correlation coefficients ranging from 0.77 to 0.94, and $MAPE$, $RMSE$, and MAE indices ranging from 7.5 to 15.9, 7.8 to 15.9, and 4.8 to 10.9, respectively.

5. Conclusion

This study applies machine learning models to predict the compressive strength of GFRP-confined concrete columns. The predictive results of the machine learning models are compared with those of the design-oriented empirical model used in the ACI 440.2R-17 standard. Five machine learning models, including ANN, M5Rules, M5P, Random Forest, and Random Tree, were employed to predict the compressive strength of GFRP-confined concrete columns. The accuracy of the machine learning models was evaluated through the correlation plot between predicted and experimental results, as well as four statistical indices: correlation coefficient (R), mean absolute percentage error ($MAPE$), root mean square error ($RMSE$), and mean absolute error (MAE). The findings from this study indicate that:

(1) Machine learning models can predict the compressive strength of GFRP-confined concrete columns with high accuracy. These models provide more accurate predictions than the design-oriented empirical model used in the ACI 440.2R-17 standard. The correlation points between the predicted results of the machine learning models and the experimental results are distributed along and close to the diagonal of the correlation plot, whereas those of the design-oriented empirical model in ACI 440.2R-17 are distributed farther from the diagonal.

(2) The Random Tree model demonstrates the highest accuracy in predicting the compressive strength of GFRP-confined concrete columns. The Random Tree model achieves a correlation coefficient R = 0.94, with $MAPE$, $RMSE$, and MAE values of 7.56%, 7.83 MPa, and 5.85 MPa, respectively. When evaluated using the $MAPE$, $RMSE$, and MAE indices, the accuracy of the Random Tree model is higher than that of the design-oriented empirical model in ACI 440.2R-17 by 51.1%, 50.6%, and 55.3%, respectively.

(3) In addition to the Random Tree model, the Random Forest model also provides highly accurate predictions of the compressive strength of GFRP-confined concrete columns. The accuracy of the Random Forest model exceeds that of the design-oriented empirical model in ACI 440.2R-17 by 50.0%, 48.0%, and 51.2% according to $MAPE$, $RMSE$, and MAE, respectively.

(4) The design-oriented empirical model in ACI 440.2R-17 shows the lowest accuracy when using the correlation plot, $RMSE$, and MAE indices. However, when using the $MAPE$ index, the empirical model outperforms the M5P model. Therefore, it is necessary to use multiple methods to evaluate the accuracy of predictive models.

(5) The compressive strength of GFRP-confined concrete columns can be predicted with high accuracy using machine learning models, especially the Random Tree and Random Forest models. Accurate prediction of the compressive strength of GFRP-confined concrete columns helps to precisely determine the load-bearing capacity of GFRP-strengthened RC columns, thereby ensuring structural safety.

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