DEVELOPMENT OF SHEAR STRENGTH PREDICTION MODEL FOR RC BEAMS STRENGTHENED WITH FRP STRIPS BASED ON A NOVEL ENSEMBLE LEARNING MODEL

Huynh P. Nam[1], Nguyen D. D. Nam[1], Nguyen H. Thinh[1], Phan H. Nam[1]*
Ho M. Hung[1], Do V. Hai[1], Phan D. Thao[2]

[1]*The University of Danang – University of Science and Technology, Vietnam*
[2]*The College of Technology, Economics and Irrigation of the Central Region, Vietnam*

*Corresponding author: phnam@dut.udn.vn

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Abstract – The use of fiber-reinforced polymer (FRP) strips as an external strengthening method has gained widespread acceptance for enhancing the capacity of aging reinforced concrete (RC) beams. Despite extensive research and practical applications, there exist unresolved issues necessitating further investigation, including interface bonding, failure mechanisms, and the development of accurate predictive models for shear strength, considering diverse parameters. This paper systematically reviews shear strength formulas applied in the strengthening of RC beams using FRP strips. An extensive experimental dataset is compiled from diverse sources to support the analysis. Utilizing this dataset, a novel ensemble learning model is developed for predicting the shear strength contributed by FRP strips. Following the training of this model, the important score of each input parameter is also assessed. The findings presented herein contribute to a deeper understanding of the strengthening effectiveness of FRP strips on RC beams.

Keywords – Shears strengthening; RC beam; shear strength; assemble learning; FRP strips

1. Introduction

The enhancement and augmentation of structural capacity, particularly in the case of existing reinforced concrete beams (RC), represent a pervasive challenge that captivates the focus of both engineers and scientists. Ongoing research has spurred the development and application of numerous contemporary methods. Among these, the external bonding technique for RC beams has gained significant traction owing to its simplicity in fabrication and construction. In employing this method, the reinforcement of RC beams involves encasing the weakened sections with wrapping materials.

As the construction materials industry undergoes swift advancements, cutting-edge materials are increasingly integrated into various methodologies. Among these, the utilization of fiber-reinforced polymer (FRP) strips in the wrapping technique has emerged as the foremost choice. The widespread adoption of FRP is attributed to its exceptional mechanical properties and durability, presenting a gateway to refined design optimization and enhanced capacity for RC beams. Moreover, the versatility of FRP extends beyond RC beams, finding application in diverse structures, encompassing both onshore and offshore constructions [1-4].

FRP, derived from diverse materials like carbon (CFRP) or glass (GFRP), exhibits a high flexibility, making it adaptable to numerous applications with distinct requirements. Its exceptional attributes, including lightweight, high tensile strength, and resistance to external erosive factors, render it an outstanding choice.

In comparison to alternative materials for exterior wrapping, FRP boasts superior tensile strength, outperforming conventional concrete mortar or fiber-reinforced concrete. Its lightweight and slender structure surpasses those of ultra-high-strength concrete (UHPC), while its corrosion resistance and resilience to external influences surpass steel panels. However, it is essential to acknowledge the limitations of FRP. Challenges such as bonding issues with RC beams and the imperative exploration of long-term durability must be researched.

To improve and solve the above-mentioned disadvantages, research around the world has focused on surface treatment methods [5-9] and developing reliable models for shear strength predictions of strengthened FRP strips [10-12]. Besides, the prediction of failure modes is almost important [13], and plays an important role in resulting in the effectiveness of strengthening methods.

Various studies have paid attention to developing shear strength formulas of RC beams strengthening with FRP strips which were implemented to the codes for practice use. Most of them were based on a limited of experimental tests; hence, the applicability is expected to some specific cases of strengthening. The most commonly used formula is in ACI 440.2R [14], where the shear contribution of FRP is calculated, considering two different configurations of external bonding, i.e., U-wrap and side bonded. CSA-S806 [15] improved ACI's formula with the proposal of effective strain of FRP for three configurations, i.e., full wrap, U-wrap, and side bonded.

Numerous investigations have underscored the inadequacies of both ACI and CSA formulas in accurately forecasting the shear contribution of FRP [16, 17]. This deficiency arises from the formulas being crafted for applications, focusing on a specific set of parameters to assess model effectiveness. Unfortunately, these formulations often overlook alternative applications or a broader array of parameters. Consequently, the development of a comprehensive model that encompasses the diverse parameters and responses of both FRP strips and RC beams presents a formidable challenge.

Over the past few years, there has been a pervasive adoption of machine learning techniques, marking a prevailing trend in addressing various engineering challenges. In line with this subject, several studies have applied machine learning techniques in predicting the shear strength of strengthened RC beams with FRP strips as well as the shear contribution of FRP [16-20]. In particular, various techniques have been used and compared, e.g., artificial neural networks, XGBoost, random forest, CatBoost, LightGBM, AdaBoost algorithms, etc.

This study aims to develop a different machine-learning model from the literature expected to accurately predict the shear strength contribution by FRP strips of strengthened RC beams. In which, a novel regression model named the ensemble learning (EL) model is adopted. The prediction mode is developed and optimized based on a comprehensive dataset collected from different sources. The dataset of 275 tests is composed of 11 key parameters related to wrapping schemes, geometry, and material parameters of both RC beams and FRP strips. Besides, an LE model-based sensitivity analysis is also conducted to investigate the effect of each parameter on the shear strength contributed by FRP strips.

2. Experimental data collection

The article presents a comprehensive database derived from 50 studies, encompassing a total of 275 experimental data of RC beams strengthened with FRP strips. The beam is a rectangular section and is expected to fail in shear. The dataset includes parameters of geometric dimensions, effective height, mechanical properties of materials, reinforcement methods, failure modes, total shear strength, and shear strength contributed by FRP, as outlined in Table 1, with dimension parameters illustrated in Figure 1.

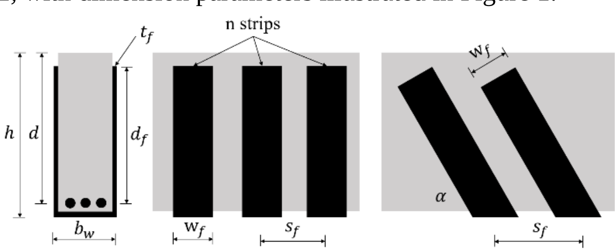


Figure 1. *The dimensional variables used in shear strengthening calculations for FRP strips*

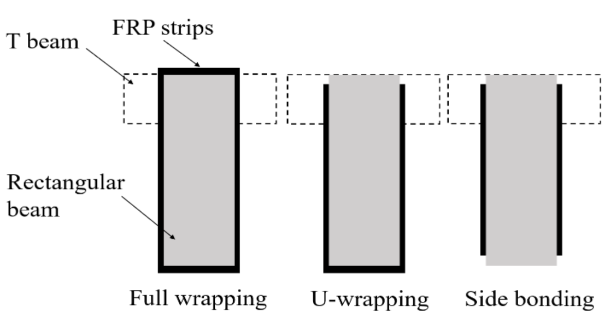


Figure 2. *Wrapping schemes for shear strengthening of RC beams using FRP strips*

It is observed that the dataset encompasses experiments conducted on the shear reinforcement of RC beams using only CFRP. These beams were strengthened with three wrapping schemes, as shown in Figure 2, i.e., full wrap (25.5%), U-wrap (41.5%), and two sides bonded (33%). The orientation of FRP strips was categorized into 45° (14.5%) and 90° (85.5%). The analysis yielded four primary forms of failure: debonding failure (62.9%), tensile rupture of FRP strips (22.2%), partial peeling off of FRP strips (8.4%), and other failure modes (6.5%). For other parameters, the range of values is presented in Table 1.

Table 1. *Parameters of RC beam and FRP strips of the collected dataset*

No	Parameter	Notation	Range
1	With of beam	b_w	70-600 mm
2	Height of beam	h	110-900 mm
3	Effective height of beam	d	100-800 mm
4	Shear span ratio	λ	0.71-4.88
5	Compressive strength of concrete	f_c	14-71 MPa
6	Volume ratio of transverse bar	ρ_{sv}	0-0.727 %
7	FRP wrapping scheme	W	1, 2, 3
8	Height of FRP strip	h_f	110-900 mm
9	Effective height of FRP strip	d_f	100-682 mm
10	Thickness of FRP strips	nt_f	0-3 mm
11	Width/centroid distance of FRP strips	w_f/s_f	0.083-1
12	Angle of FRP strip	α	45, 90
13	Elastic modulus of FRP strip	E_f	105-266 GPa
14	Tensile strength of FRP strip	σ_{fu}	960-5207 MPa
15	Ultimate strain of FRP strip	ε_{fu}	0.006-0.0228
16	Failure mode	F	1, 2, 3, 4
17	Total shear strength	V_u	16-1202 kN
18	Shear strength contributed by FRP strips	V_f	4-493 kN

Notes: W: 1-U-wrap, 2-side bonded, 3-full wrap; F: 1-bonding failure, 2-tensile rupture of FRP strips, 3-partial peeling off of FRP strips, 4-others.

3. Evaluation of existing formulas

3.1. Existing formulas

In this paper, three well-known formulas for the shear strength contributed by FRP strips from existing codes, i.e., ACI-440.2R [14], CSA-S806 [15], and FIB14 [21] are evaluated with the collected dataset. These formulas are widely used for the practice design of RC beams strengthened with FRP strips.

3.1.1. ACI – 440.2R

$$V_f = \frac{A_{fv} f_{fe} (\sin\alpha + \cos\alpha) d_{fv}}{s_f}, \tag{1}$$

where $A_{fv} = 2nt_f w_f$, $f_{fe} = \varepsilon_{fe} E_f$, for Full wraps: $\varepsilon_{fe} = 0.004 \le 0.75\varepsilon_{fu}$, for U-wraps and two sides bonded:

$$\varepsilon_{fe} = K_v \varepsilon_{fu} \le 0.004,\ K_v = \frac{k_1 k_2 L_e}{11900\varepsilon_{fu}} \le 0.75,$$

$$L_e = \frac{23300}{(nt_f E_f)^{0.58}},\ k_1 = \left(\frac{f_c}{27}\right)^{\frac{2}{3}},\ k_2 = \frac{d_f - L_e}{d_f} \text{ for U-wraps,}$$

and $k_2 = \frac{d_{fv} - L_e}{d_{fv}}$ for two sides bonded.

3.1.2. FIB14

$$V_f = 0.9\varepsilon_{fe}E_f\rho_f b_w d(\sin\theta + \cos\alpha)\sin\alpha, \tag{2}$$

where $\rho_f = \frac{2w_f t_f}{b_w s_f}$,

$$\varepsilon_{fe} = \min[0.65\left(\frac{f_c^{\frac{2}{3}}}{E_f\rho_f}\right)^{0.56} 10^{-3}, 0.17\left(\frac{f_c^{\frac{2}{3}}}{E_f\rho_f}\right)^{0.3} \varepsilon_{fu}.$$

3.1.3. CSA – S806

$$V_f = \frac{A_{fv}f_{fe}d_f(\sin\alpha + \cos\alpha)}{s_f}, \tag{3}$$

where $A_{fv} = 2nt_f w_f$, $f_{fe} = \varepsilon_{fe}E_f$,

$\varepsilon_{fe} = 0.006$ for full wrap,

$\varepsilon_{fe} = K_v\varepsilon_{fu} \leq 0.004$ for U-Wrap and two sides bonded.

3.2. Evaluation of existing code-based formulas with the collected dataset

The shear strength contributed by FRP strips is computed for each case. The regression plot, depicting the correlation between the experiment from the collected dataset and the calculation obtained by each formula, is illustrated in Figure 3.

Upon scrutiny of the regression plot, a certain deviation is evident, which exhibits significant dispersion. This observation underscores the diminished accuracy of the formulas in computing the increased shear strength attributable to FRP strips within the experimental dataset.

To quantify this discrepancy, the root mean square error (RMSE) and R coefficient of the regression model for the ACI 440.2R, CSA S-806, and FIB14 formulas are calculated, as shown in Table 2. These coefficients further substantiate the limited predictive accuracy of the formulas in capturing the nuanced variations in shear resistance resulting from the incorporation of FRP strips in the experimental dataset.

Table 2. *Performance of the shear strength formula in the existing codes*

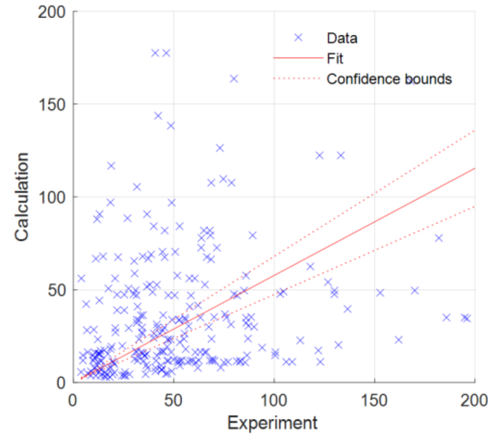
	ACI 440.2R	CSA S-806	FIB 14
RMSE	65.688	71.486	26.554
R	0.319	0.263	0.526

Several primary factors contribute to substantial errors when employing calculation formulas outlined in these codes:

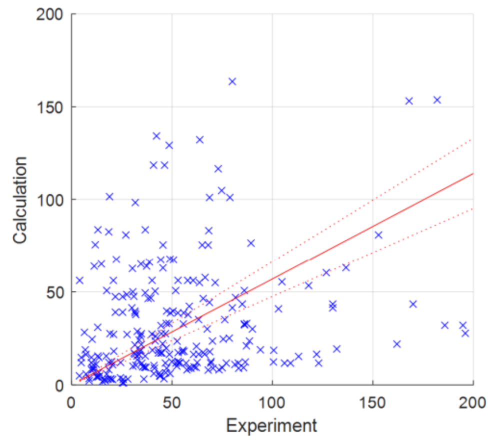
- Each formula relies on estimated coefficients and assumptions derived from previous experiments. Many of these formulas lack considerations for factors specific to the geometry and material of RC beam and FRP strips, and other crucial parameters associated with wrapping schemes. The absence of comprehensive coverage in the formulation hampers their applicability and accuracy.

- The formulas are constructed based on experimental data. However, this data is often limited and pertains only to specific cases. The narrow scope of the data used in formulating the formulas restricts their ability to accurately represent a broader range of scenarios, leading to inaccuracies in practical applications.

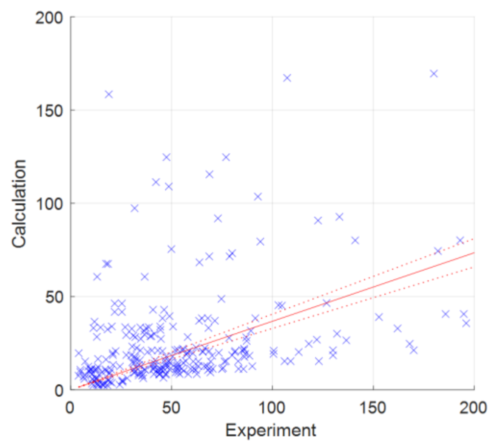
- The accuracy of the experimental model is significantly impacted by the limited scope of environmental conditions, testing equipment, and the number of samples examined during the formula's establishment. These constraints introduce variability and limit the generalizability of the formulas to a wider array of real-world situations.



(a) ACI-440.2R



(b) CSA-S806



(c) FIB14

Figure 3. *Regression models between experiment and calculation from formulas (the unit is in kN)*

Addressing these issues is crucial for improving the reliability and accuracy of the calculation formulas, necessitating a more comprehensive consideration of FRP-related parameters and an expanded, diverse dataset to better account for the complexities of real-world applications.

4. Development of shear strength prediction model

4.1. Ensemble learning model

EL is a method that combines predictions from multiple models to generate a final prediction that surpasses the accuracy of each model. The effectiveness of an ensemble lies in the diversity between models, achieved by training models on different data subsets or utilizing different algorithms.

Common ensemble methods include:

- Bagging: This approach employs multiple independent models, each trained on a subset of data sampled with replacement from the original training dataset.

- Boosting: This method builds models in a series, with each subsequent model aiming to correct the errors of the preceding one.

- Stacking: Stacking combines predictions from individual models and employs a final model to predict the ultimate result.

In this study, the ensemble boosting regression model is applied to construct a sequence of weak decision trees, as shown in Figure 4. Each tree is optimized to minimize the prediction error of the previous model. Specifically, least square boosting is utilized, following this sequence:

- Definition of training data:

+ Input: Training dataset (X, y), where X is the feature matrix, and y is the result vector.

+ Output: A regression model capable of predicting continuous values.

- Training process:

+ Step 1 (Initialization): Commence with a simple prediction, usually an average of the entire set of output values.

+ Step 2 (Iteration): For each iteration, (i) calculate pseudo-residuals by subtracting the current prediction from the actual value, (ii) train a regression model (typically a small decision tree) to predict pseudo-residuals, (iii) optimize the new model by incorporating it into the current model with a small learning rate to minimize the magnitude of the predicted pseudo-residuals.

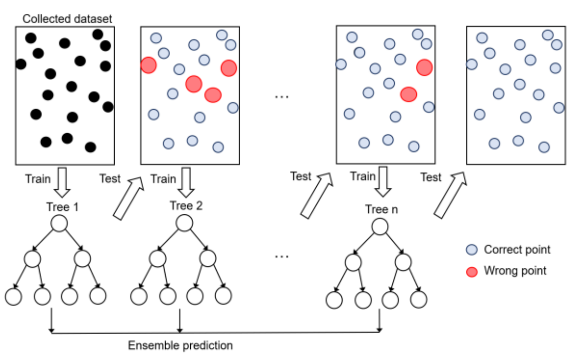


Figure 4. *An example of ensemble ensemble-boosting regression model*

- Prediction result: The final prediction is derived by aggregating predictions from all the individual trees.

To construct the model, two crucial parameters significantly impact the prediction are:

- Learning rate: The learning rate adjusts the size of the update step at each iteration, influencing the rate at which the model learns. It determines the extent to which the model adapts to the training data during each iteration. A lower learning rate makes the model learn more slowly but can enhance overall accuracy.

- Number of trees: This parameter signifies the total number of decision trees that need to be created in the ensemble. The number of trees is pivotal in shaping the complexity and robustness of the model. An optimal balance must be struck to avoid overfitting or underfitting, ensuring an effective representation of the underlying patterns in the data.

Fine-tuning these parameters is essential for achieving an optimal and accurate ensemble-boosting regression model, with the learning rate governing the pace of adaptation and the number of trees influencing the model's overall complexity and predictive capability.

4.2. Optimization of parameters for the ensemble learning model

As outlined in Section 4.1, the critical parameters influencing the estimation capabilities of the ensemble boosting learning model are the learning rate and the number of trees. Consequently, it is imperative to determine a final estimation model based on optimal parameters.

Utilizing the collected data, the model is constructed using MATLAB software. The initial step involves extracting the input variables from Table 1, along with the output variable, the shear strength contributed by FRP strips (V_f). By removing some duplicated and dependent features such as the beam and FRP strip heights, the elastic modulus of FRP. The final dataset used for training is comprised of 11 input features, b_w, λ, f_c, ρ_{sv}, W, h_{fe}, nt_f, w_f/s_f, α, σ_{fu}, ε_{fu}, and the output V_f. For the training and testing stages, the dataset is randomly divided into an 80% training set and a 20% testing set.

A deep decision tree (DDT) is first developed as the base for the comparison. To ensure satisfactory predictive performance, the complexity of the decision tree is adjusted using 5-fold cross-validation. Specifically, default values for tree depth controllers for regression trees are set, with a maximum of 10 splits, a minimum leaf size of 5, and a minimum parent size of 10.

To determine an optimal tree complexity, the following steps of 150 boosted regression trees using 5-fold cross-validation are conducted:

- Cross-validate a set of ensembles by exponentially increasing the tree complexity level for subsequent ensembles from a decision stump (one split) to at most $n-1$ splits $(2^0, 2^1, \ldots, 2^m)$, where n is the sample size. Also, vary the learning rate for each ensemble between 0.1 and 1.

- Estimate the cross-validated mean-squared error (MSE) for each ensemble.

- For each tree-complexity level, compare the cumulative cross-validated MSE of the ensembles by plotting them against the number of learning cycles.

- Choose the curve that achieves the minimal MSE and note the corresponding learning cycle and learning rate.

Based on the plots, as shown in Figure 5, the optimal parameters for the EL model of V_f are established as follows:

Num. Trees = 34

MaxNumSplits = 128

Learning Rate = 0.30

Having identified the optimal parameters, the subsequent step involves constructing the final decision tree model and optimizing the training process.

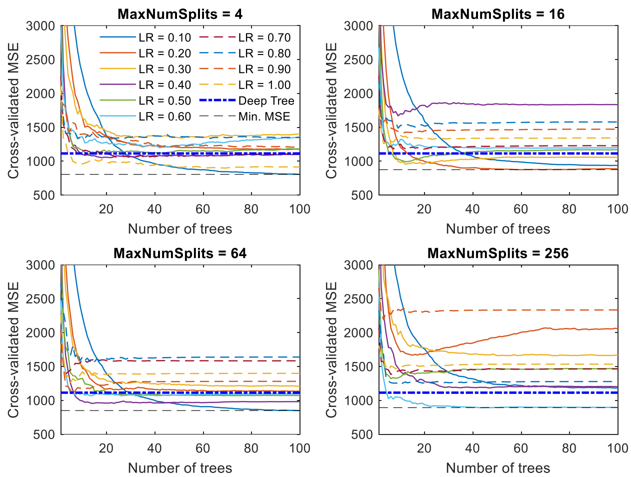


Figure 5. *A comparison of the prediction performance of different tree models and learning rates according to the number of trees*

4.3. Evaluation of the model

To assess the performance of the EL model, a test dataset is employed, and the regression plot for V_f is depicted in Figure 6. The graph compares the calculation results estimated from the EL model with the experimental results of the test dataset, constituting 20% of the overall dataset. Statistical analysis reveals that the EL model exhibits a high prediction performance, demonstrating an R-value of 0.834.

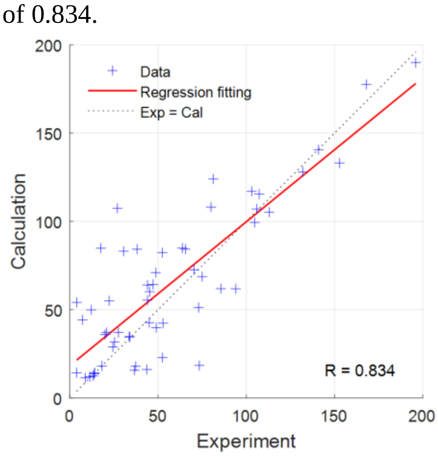


Figure 6. *Prediction performance of the EL model for the test set (the unit is in kN)*

Utilizing the trained EL model, the correlation and significance of each input variable on reinforcement effectiveness are determined through the unbiased predictor importance estimates algorithm. Figure 7 illustrates that the effective height of FRP strips exerts the most significant influence on the shear strength. Notably, geometric dimensions such as beam width also exhibit a high correlation with the output. Regarding beam materials, the compressive strength of concrete shows relative importance, and the wrapping method and strip thickness gain almost the same score.

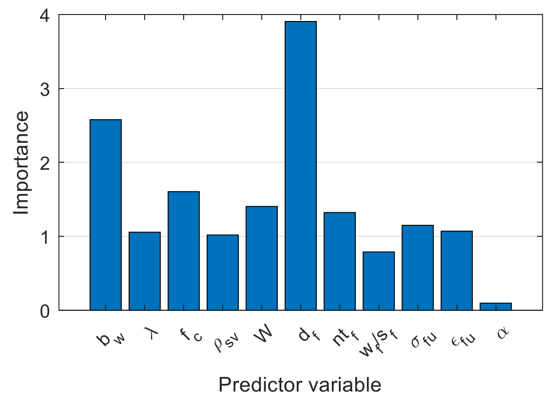


Figure 7. *Importance score of input variables to shear strengthening effectiveness*

On the flip side, although the ratio w_s/t_s and the FRP bonding angle are important factors affecting the shear strength contributed by FRP strips, as shown in the above formulas, however, from the analysis, the shear strength appears to be minimally influenced by the ratio w_s/t_s and the FRP bonding angle. This limited impact can be attributed to the poor data distribution observed for these two features in relationship with FRP's shear strength.

5. Conclusions

The paper aimed to evaluate the existing code-based formula and propose a novel EL method for the shear strength prediction of RC beams strengthened with FRP strips based on a comprehensive experimental dataset of 275 samples. Several noteworthy conclusions arise from these investigations:

The evaluation of shear strength calculations using ACI 440.2R, CSAS-806, and FIB 14 formulas revealed a notable deficiency in accuracy and compatibility with the gathered experimental dataset. This inadequacy stems from the formulas relying on outdated and constrained experimental datasets, failing to fully account for various influencing factors such as geometric properties, materials, and FRP wrapping schemes.

The study opted for EL, a machine learning method that amalgamates multiple prediction models to enhance overall accuracy, mitigating prediction errors. To construct optimal EL models and prevent overfitting, the study employed a deep decision tree, fine-tuning parameters like the number of trees, maximum splits, and learning rate, among others.

The optimized EL model exhibited a high predictive performance as compared with the existing formulas, with an R coefficient of 0.834. This surpasses the predictive accuracy of standard formulas and other machine-learning methods cited in reference materials.

Leveraging the trained EL model, the study discerned the impact of each input variable on reinforcement effectiveness. This insight holds significant value as a reference for practical applications in the calculation and design of reinforced concrete beams employing FRP material panels. It offers valuable guidance for engineers and practitioners seeking optimal outcomes in real-world scenarios.

While the proposed machine learning model exhibited considerable improvements in predictive performance, it faces challenges in deriving a concise mathematical representation. Unlike traditional formulaic models, its complexity can hinder straightforward interpretation. However, the ML model's superior predictive accuracy often outweighs the need for a readily interpretable mathematical model, particularly in complex real-world scenarios with intricate and nonlinear data relationships.

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