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# A Decision-Oriented Modelling Framework for Sustainable Strengthening of Reinforced Concrete Structures Using Data-Driven Capacity Prediction

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**Abstract:** The application of fiber-reinforced polymer (FRP) for shear strengthening of concrete structures has become increasingly popular. However, the inherent scatter in shear test makes accurate prediction of the shear capacity a significant challenge, as traditional design code often struggle to capture the complex nonlinear interactions among multiple factors. To address this limitation, this study introduces a machine learning (ML) approach to develop a high-accuracy predictive model. A database comprising 552 experimental tests on FRP-strengthened concrete beams in shear was assembled. Three ensemble learning algorithms—Random Forest (RF), Adaptive Boosting (AdaBoost), and eXtreme Gradient Boosting (XGBoost)—were systematically compared and evaluated against predictions from three existing design codes: ACI 440.2-23, FIB Bulletin 14, and GB 50608-2020. Results indicate that all ML models significantly outperform the existing code-based calculations. Among them, the XGBoost model demonstrated the best performance, achieving a coefficient of determination ($\mathrm{R}^2$) of 0.94 and a mean absolute percentage error (MAPE) as low as 12.81% on the test set. Interpretability analysis based on shapely additive explanations (SHAP) values further identified and elucidated the physical significance of key influencing features, such as FRP bonded height ($h_f$), beam width ($b$), and stirrup reinforcement ratio ($\rho_{sv}$), and elucidated their physical significance on the shear capacity. This study confirms the superiority and engineering application potential of data-driven approaches for predicting the shear performance of FRP-strengthened members. Moreover, high-accuracy capacity prediction enables more economical and environmentally friendly strengthening designs. This contributes to reducing material overuse, lowering construction energy consumption and carbon emissions, thereby supporting the sustainability goals of structural engineering.

**Keywords:** Machine learning; Fiber-reinforced polymer strengthening; Shear strength; eXtreme gradient boosting

## 1 Introduction

Fiber-reinforced polymer (FRP) composites have become one of the primary materials for shear strengthening of concrete structures due to their advantages of high strength, light weight, and corrosion resistance [1, 2]. From a sustainable engineering perspective, FRP strengthening serves as a low-intervention and high-efficiency life-extension technique. It is significant for enhancing the service performance of existing infrastructure, avoiding large-scale demolition and reconstruction, and thereby conserving resources and reducing carbon emissions [3]. However, the shear mechanism of FRP-strengthened beams is complex, being interactively influenced by multiple coupled factors, including concrete strength, geometric dimensions, FRP type, and strengthening configuration [4–6]. Currently, design practice relies chiefly on formulas from codes such as ACI 440.2-23 and fib Bulletin 14. These formulas are often based on simplified assumptions and empirical regression, which limits their accuracy in handling the nonlinear interactions among multiple factors and their generalizability. Consequently, the inherent conservatism of these approaches often leads to overdesign, creating a gap with the resource-efficiency goals pursued by sustainable engineering [7, 8].

In recent years, machine learning (ML) has emerged as a new paradigm for addressing such complex nonlinear problems [9]. While existing studies have applied algorithms such as Support Vector Machines and Random Forests (RF) to predict the flexural capacity of FRP-strengthened beams, their application to shear strength prediction remains limited. Furthermore, these efforts are often constrained by issues such as small dataset sizes, insufficient model comparison, and weak mechanistic interpretability [10–12]. Moreover, the current research paradigm lacks a framework for situating high-accuracy predictive tools within broader sustainable engineering decision-making contexts, such as life-cycle management, system-level risk assessment, or quantification of resource and environmental benefits [13, 14]. The convergence of digital, intelligent, and sustainable transformations in infrastructure systems has brought to the fore the critical need to evolve data-driven performance prediction models into decision-analysis tools capable of supporting multidimensional trade-offs among safety, economic, and environmental goals.

Therefore, this study aims to develop an intelligent modeling framework for FRP shear strengthening, designed to support sustainable engineering decision-making. This framework systematically compares the performance of various algorithms and identifies key influencing factors, thereby enhancing both the accuracy and interpretability of shear strength prediction. This pursuit transcends a purely mechanical or algorithmic challenge, as it is intrinsically linked to engineering sustainability. Due to their inherent conservatism, traditional design codes often lead to overdesign. This results in the wasteful use of materials such as FRP, increased construction energy consumption, and higher carbon emissions over the lifecycle of the structure. In contrast, high-accuracy predictive models enable optimized strengthening designs. By ensuring safety, such designs can reduce material consumption, avoid unnecessary demolition and reconstruction, and extend the service life of existing structures. Consequently, they contribute positively to resource conservation, carbon emission reduction, and the promotion of long-lasting infrastructure. Therefore, this research also seeks to explore the potential value of data-driven methods in supporting sustainable strengthening decisions. The study ultimately aims to provide a methodological reference for the paradigm shift from precise prediction to intelligent decision-making.

## 2 Dataset Compilation and Feature Engineering

A dataset of experimental results for the shear capacity of FRP-strengthened concrete beams was compiled from both domestic and international literature. The compiled data underwent a rigorous screening process to ensure completeness and to eliminate apparent outliers. Following this screening, a total of 552 valid data samples were retained. Fourteen parameters were identified as input features, as detailed in Table 1. The experimentally measured shear capacity, denoted as $V_{\text{test}}$ , was defined as the output variable.

**Table 1.** Summary of input and output variables

| Parameter | Symbol | Unit |
|---|---|---|
| Beam width | $b$ | mm |
| Shear-span-to-depth ratio | $\lambda$ | – |
| Concrete compressive strength | $f_c$ | MPa |
| Yield strength of stirrups | $f_{sy}$ | MPa |
| Stirrup reinforcement ratio | $\rho_{sv}$ | % |
| FRP elastic modulus | $E_f$ | GPa |
| FRP tensile strength | $\sigma_{fu}$ | MPa |
| FRP thickness | $t_f$ | mm |
| FRP strip width to spacing ratio | $w_f/s_f$ | – |
| Bonding configuration | $RM$ | – |
| FRP bonding height | $h_f$ | mm |
| FRP strengthening orientation | $\alpha$ | ° |
| Presence of anchorage | $A$ | – |
| Failure mode | $FM$ | – |
| Experimental shear capacity | $V_{\text{test}}$ | kN |

## 3 Model Development: Empirical and Machine Learning Approaches

To evaluate the applicability and accuracy of ML models in predicting the performance of FRP-strengthened concrete structures, the Adaptive Boosting (AdaBoost), eXtreme Gradient Boosting (XGBoost), and RF models developed in this study were applied to the practical engineering dataset for training and validation.

AdaBoost employs a sequential modeling strategy [15]. It operates by iteratively training multiple weak decision tree models. In each iteration, the weights of the training samples are dynamically adjusted, directing subsequent models to focus on correcting the prediction residuals of their predecessors. This process mirrors an iterative optimization philosophy in engineering, whereby progressively focusing on the weak points in the system's predictions enables a gradual approximation of the underlying functional relationship.

XGBoost enhances the gradient boosting framework by incorporating second-order derivative information and regularization terms [16]. Its optimization objective encompasses both fitting data and explicitly controlling model complexity. These attributes enable XGBoost to achieve high accuracy while maintaining strong resistance to overfitting in engineering modeling. Consequently, it learns a more robust and generalizable feature-to-capacity mapping, rather than merely memorizing the training data.

RF operates by constructing a multitude of decision trees, each trained on a random subset of samples (via bootstrapping) and a random subset of features [17]. The final prediction is obtained by averaging (for regression) or majority voting (for classification) across all individual trees. The core modeling philosophy of this strategy is to reduce the uncertainty inherent in any single model by cultivating diversity within the ensemble. This approach yields more stable and reliable predictions, which is particularly advantageous when dealing with the inherent noise and scatter common in experimental engineering data.

This study employs decision trees as the fundamental modeling unit. Their decision-making process, which involves recursive logical splitting based on "feature-threshold" criteria, inherently learns and represents the complex interaction rules and nonlinear relationships among the various design parameters that influence shear capacity. RF, AdaBoost, and XGBoost exemplify two core ensemble modeling philosophies. The Bagging approach reduces prediction variance by constructing multiple parallel and diverse decision trees, operating on the hypothesis that the stability of a model collective surpasses that of any individual. In contrast, the Boosting approach constructs models sequentially, with each new model focusing on correcting the residuals of its predecessors. Its underlying hypothesis is that iterative refinement of systematic errors can progressively approximate the true function. These ensemble strategies thus embody distinct modeling philosophies for addressing uncertainty in engineering.

During the model training phase, 80% of the data was allocated as the training set for model learning. A grid search combined with cross-validation was then employed to optimize the key hyperparameters, thereby obtaining the optimal configuration for each model. Model performance was comprehensively evaluated and compared using four metrics: the coefficient of determination ($R^2$), root mean square error (RMSE), mean absolute error (MAE), and mean absolute percentage error (MAPE).

To further validate the engineering significance and reliability of the model predictions, this study conducts a systematic comparison between the predictions of the ML models and the theoretical calculations from major existing design codes. The selected codes comprise: ACI 440.2-23 [18] (*Guide for the Design and Construction of Externally Bonded FRP Systems for Strengthening Concrete Structures*) by the American Concrete Institute, fib Bulletin 14 [19] (*Externally bonded FRP reinforcement for RC structures*) by the *fib* (International Federation for Structural Concrete), and the Chinese National Standard GB 50608-2020 [20] (*Technical code for infrastructure application of fiber reinforced polymers*). This comparative analysis aims to elucidate the differences and commonalities between the ML approach and traditional code-based methods in terms of prediction accuracy, scope of application, and engineering conservatism. Ultimately, it seeks to provide a novel, data-driven perspective for the design and assessment of FRP strengthening techniques.

## 4 Results and Analysis

The performance of all models on the independent test set is summarized in Table 2. Furthermore, the predictions of the ML models were compared against those from three design codes—ACI 440.2-23, *fib* Bulletin 14, and GB 50608-2020—which served as baseline models. This comparative visualization is presented in Figure 1.

**Table 2.** Summary of model performance

| Model | Dataset | Results | | | |
|---|---|---|---|---|---|
| | | $R^2$ | RMSE | MAE | MAPE (%) |
| RF | Training Set | 0.99 | 6.87 | 4.55 | 2.94 |
| | Test Set | 0.92 | 39.67 | 24.85 | 15.30 |
| AdaBoost | Training Set | 0.99 | 12.23 | 9.79 | 7.30 |
| | Test Set | 0.93 | 37.78 | 24.44 | 15.92 |
| XGBoost | Training Set | 0.99 | 3.82 | 1.70 | 1.15 |
| | Test Set | 0.94 | 33.75 | 20.23 | 12.81 |
| ACI 440.2-23 | – | 0.57 | 120.93 | 84.85 | 43.06 |
| fib Bulletin 14 | – | 0.63 | 149.72 | 113.49 | 57.02 |
| GB 50608-2020 | – | 0.60 | 114.76 | 76.18 | 37.61 |

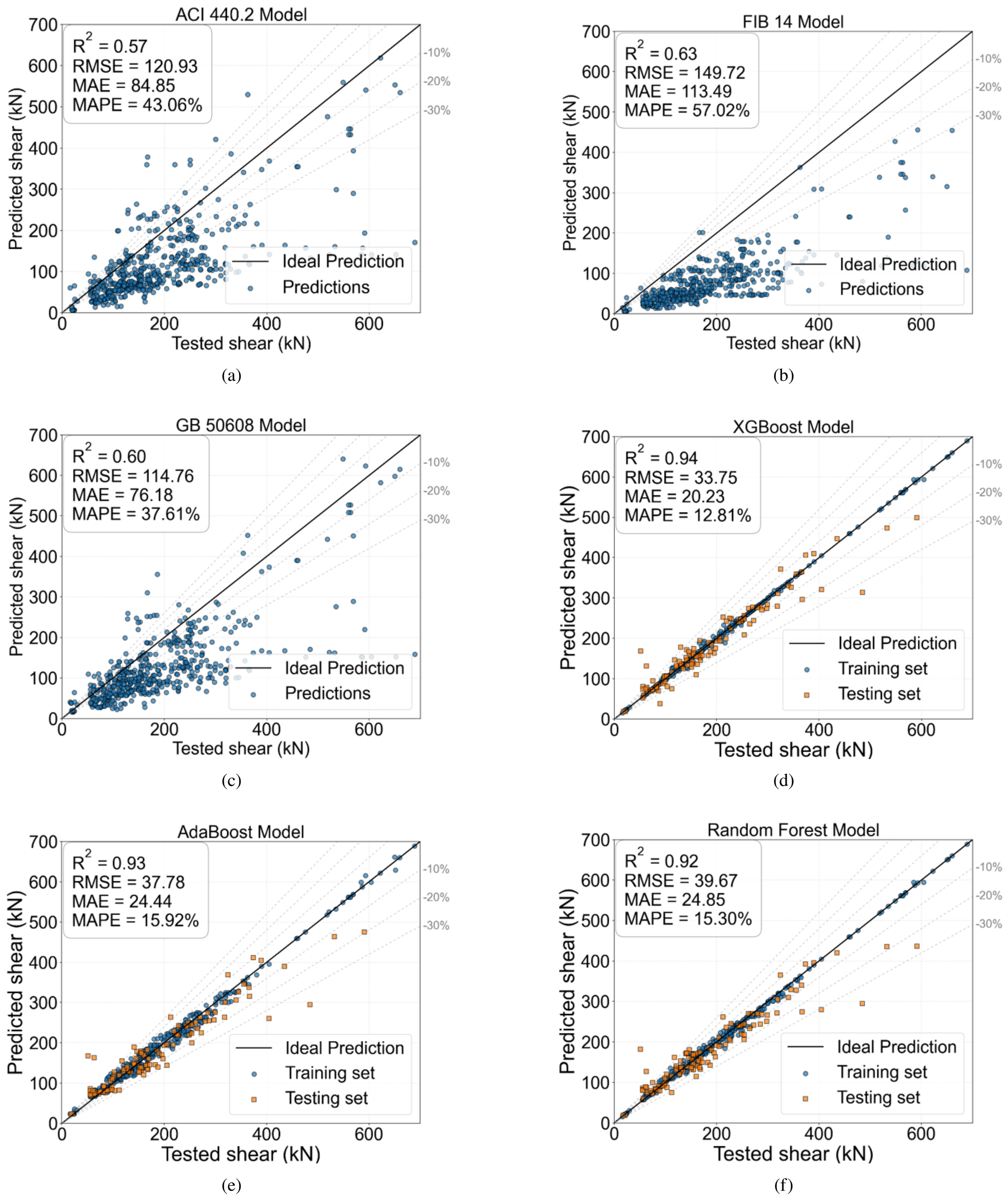


**Figure 1.** Comparative performance of the evaluated models: (a) ACI 440.2-23; (b) fib Bulletin 14; (c) GB 50608-2020; (d) XGBoost; (e) AdaBoost; (f) RF

This study systematically compared the predictive performance of three ensemble learning models (RF, AdaBoost, XGBoost) against three mainstream design codes (ACI 440.2-23, fib Bulletin 14, GB 50608-2020). The results demonstrate a significant advantage of the data-driven ML models in predicting the behavior of FRP-strengthened concrete structures. On the test set, all three ML models achieved a $R^2$ above 0.92 and a MAPE ranging from 12.81% to 15.92%. This level of predictive accuracy comprehensively surpasses that of the traditional code-based methods, for which the highest $R^2$ was 0.63 and the lowest MAPE was 37.61%. Among them, the XGBoost model delivered the optimal performance. It attained the highest $R^2$ value, along with the lowest RMSE, MAE, and MAPE on the test set, demonstrating exceptional generalization capability and predictive stability.

However, a noticeable performance gap was observed between the training and test sets for all ML models, indicating the presence of overfitting. This finding highlights potential for future improvement in model robustness through techniques such as feature refinement or enhanced regularization. In summary, this study confirms that the XGBoost algorithm is a highly effective and superior predictive tool for this category of engineering problems.

The trained models yield data-driven feature importance rankings. This metric quantifies the global contribution of each input variable to the prediction target, effectively transforming the model's predictive capability into a tool for analyzing the significance of influencing factors, thereby enhancing the engineering interpretability of the models. Although the current models are purely data-driven, the feature relationships they reveal show strong concordance with physical mechanisms. This agreement not only lays the groundwork for developing physics-informed models in the future but also points the way toward enhancing model generalizability and engineering credibility. To further uncover the specific relationship patterns between features and shear capacity, this study employs the SHapley Additive exPlanations (SHAP) [21–23] method to interpret the optimal XGBoost model. The results are presented in Figure 2 and Figure 3.

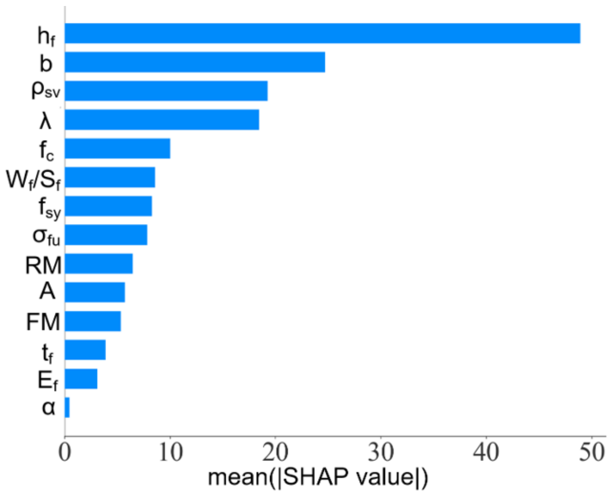


**Figure 2.** Ranking of feature importance

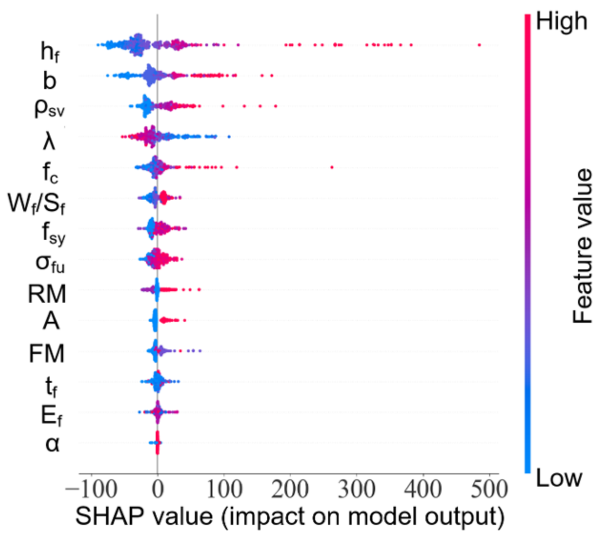


**Figure 3.** SHAP summary plot

Based on the feature importance analysis, five key features influencing the shear performance of FRP-strengthened concrete beams were identified, ranked by their contribution as follows: FRP bonding height ($h_f$), beam width ($b$), stirrup reinforcement ratio ($\rho_{sv}$), shear-span-to-depth ratio ($\lambda$), and concrete compressive strength ($f_c$). Among these, the FRP bonding height ($h_f$) was identified as the most influential positive feature. Its dominant role is primarily attributed to the direct increase in the effective bond area between the FRP and concrete, which significantly enhances the interfacial stress transfer efficiency and overall strengthening effectiveness.

The remaining features also demonstrate clear mechanical significance: beam width ($b$) contributes positively to the shear capacity by enlarging the effective concrete compression zone; the stirrup reinforcement ratio ($\rho_{sv}$) suppresses the development of diagonal cracks through enhanced confinement; the shear-span-to-depth ratio ($\lambda$), a key negative feature, leads to reduced capacity as its increase lengthens the shear span; and concrete compressive strength ($f_c$) enhances the load-bearing capacity by improving the strength of the concrete matrix.

In summary, the reliability of the model predictions is highly dependent on the parameter space encompassed by the training data. Within the conventional design range represented by the dataset constructed in this study, the model predictions demonstrate high credibility. This is evidenced by their concentrated error distribution and alignment with established physical principles, rendering them a reliable reference for scheme comparison and preliminary design. However, in extreme parameter regions where training data are sparse or absent, the model relies primarily on extrapolation. This leads to a significant increase in predictive uncertainty and carries substantial risk. Therefore, it is recommended that this model be considered a high-performance auxiliary tool within the known design space. When applied to engineering scenarios approaching or exceeding the boundaries of this space, its predictions must undergo prudent evaluation and validation, incorporating insights from traditional design codes, engineering judgment, and specific analytical methods.

Leveraging its high accuracy and interpretability, the ML model developed in this study offers a decision-support pathway for FRP shear strengthening projects. Its typical application scenarios include: (1) Scheme Design and Rapid Comparison: In the preliminary design phase, engineers can utilize the model to quickly evaluate the shear capacity enhancement under various parameter combinations, such as different FRP configurations, concrete strengths, or stirrup adjustments. This enables the efficient screening of optimal solutions that balance safety, economy, and material efficiency. (2) Assessment of Existing Structures and Prediction of Strengthening Effects: For existing beams requiring strengthening, once material and geometric parameters are known, the model can provide more accurate capacity predictions than traditional design codes. This assists in determining the necessity and urgency of strengthening, estimating the magnitude of performance improvement post-strengthening, and thereby supplying quantitative evidence for maintenance and retrofit decisions. Nevertheless, the core value of the model lies in providing data-driven, high-precision predictive and factor analysis capabilities. Its application should therefore be positioned as an aid to engineers for scheme optimization and risk assessment, not as a replacement for the safety checks mandated by design codes or for the comprehensive judgment of experienced engineers. Particularly within the context of pursuing sustainable engineering objectives, this tool facilitates the reduction of material overuse through precision design while ensuring safety margins. As such, it directly supports low-carbon and energy-efficient strengthening practices.

## 5 Conclusions

This study systematically evaluated the predictive performance of three ML models and three traditional design codes for the shear capacity of FRP-strengthened concrete beams. An in-depth analysis of the key influencing factors was also conducted. The main findings are summarized as follows:

1. The ML models demonstrated significantly higher predictive accuracy than the traditional design codes. Evaluated on the same dataset, the developed RF, AdaBoost, and XGBoost models achieved superior performance on the test set ($R^2$ > 0.92, MAPE < 16%), comprehensively outperforming the three selected design codes ($R^2$ < 0.63, MAPE > 37%). This result underscores the robust capability of the data-driven approach in addressing complex nonlinear engineering problems.

2. The XGBoost algorithm emerged as the optimal predictive model. Among the models compared, it demonstrated the best overall performance and generalization capability, achieving the highest $R^2$ (0.94) and the lowest values across all error metrics (RMSE, MAE, and MAPE) on the test set. Consequently, XGBoost is identified as the most robust and reliable predictive framework in this study.

3. The key influencing factors were quantitatively identified and mechanistically interpreted. Leveraging SHAP analysis, the top five critical features affecting shear capacity were determined, ranked in order of importance: FRP bonding height ($h_f$), beam width ($b$), stirrup reinforcement ratio ($\rho_{sv}$), shear-span-to-depth ratio ($\rho_{sv}$), and concrete compressive strength ($f_c$). This ranking not only quantifies the contribution of each factor but also reveals their positive or negative influence, findings that align with fundamental structural mechanics principles and significantly enhance the model's engineering interpretability.

4. Outlook and Future Work. Although the ML models achieved high accuracy, they still exhibit a degree of overfitting. Future work could focus on several avenues to enhance model robustness and generalizability further. These include expanding the dataset, incorporating more refined feature engineering, experimenting with other advanced algorithms, or integrating physics-informed constraints. Furthermore, actively exploring the extension of this modeling framework to a more macro scale is warranted. First, it could be integrated as a core module into the analysis of bridges or even infrastructure networks. This would bridge the gap from component-level performance prediction to system-level reliability assessment and asset management decision support. Second, the accurate capacity predictions could be embedded within a life cycle assessment framework. This integration would quantify the

long-term resource consumption and environmental impacts of different strengthening schemes, thereby promoting the deeper integration and practical application of data-driven methods in sustainable engineering decision-making.

5. Potential Value for Sustainable Engineering Practice. The high-precision predictive model developed in this study, particularly the XGBoost model, offers a more reliable tool for engineering practice. Its application has the potential to shift the paradigm of FRP shear strengthening from empirically based, conservative design toward performance-optimized design grounded in accurate prediction. This enables engineers to make more rational and resource-efficient decisions among various strengthening schemes. It helps avoid material waste and reduces the need for repeated construction and associated carbon emissions caused by either over-strengthening or under-strengthening. Looking ahead, by integrating with life cycle assessment methodology, the model could be further employed to quantify and optimize the environmental benefits of strengthening schemes. This directly contributes to the low-carbon and sustainable development goals within the civil engineering field.

## Author Contributions

Conceptualization, M.W. and Y.F.Z.; methodology, M.W.; software, M.W.; validation, M.W. and Y.F.Z.; formal analysis, M.W.; investigation, M.W.; resources, M.W.; data curation, M.W.; writing—original draft preparation, M.W.; writing—review and editing, M.W. and Y.F.Z.; visualization, M.W.; supervision, Y.F.Z.; project administration, Y.F.Z.; funding acquisition, Y.F.Z. All authors have read and agreed to the published version of the manuscript.

## Data Availability

The data used to support the findings of this study are available from the corresponding author upon request.

## Conflicts of Interest

The authors declare no conflict of interest.

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