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Prediction of Shear Capacity of Fiber-Reinforced Polymer-Reinforced Concrete Beams Based on Machine Learning

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Abstract: To address the existing challenges of lacking a unified and reliable shear capacity prediction model for fiber-reinforced polymer (FRP)-strengthened reinforced concrete beams (FRP-SRCB) and the excessive experimental workload, this study establishes a shear capacity prediction model for FRP-SRCB based on machine learning (ML). First, the correlation between input and output parameters was analyzed by the Pearson correlation coefficient method. Then, representative single model (ANN) and integrated model (XGBoost) algorithms were selected to predict the dataset, and their performance was evaluated based on three commonly used regression evaluation metrics. Finally, the prediction accuracy of the ML model was further verified by comparing it with the domestic and foreign design codes. The results manifest that the shear capacity exhibits a strong positive correlation with the beam width and effective height. Compared to the ANN model, the XGBoost-based prediction model achieves determination coefficients (R^2) of 0.999 and 0.879 for the training and test sets, respectively, indicating superior predictive accuracy. Furthermore, the shear capacity calculations from design codes show significant variability, demonstrating the superior predictive capability of ML algorithms. These findings offer a guideline for the design and implementation of FRP reinforcement in actual bridge engineering.



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Keywords: FRP reinforcement; reinforced concrete beams; capacity prediction; machine learning; ANN; XGBoost

1. Introduction

Reinforced concrete (RC) structures are prone to performance degradation or damage due to various environmental factors during long-term service, necessitating strengthening and repair. Common reinforcement techniques primarily include the section enlargement method, steel jacketing method, and external prestressing method [1–3]. Although these reinforcement methods have their own technical and economic advantages, they present several limitations such as poor durability of reinforcement materials and high maintenance costs in the later period. Hence, it is of vital significance to explore corresponding efficient reinforcement approaches to ensure the safety of in-service structural components. Fiber-reinforced polymer (FRP) is extensively utilized for RC structural reinforcement owing to its superior properties, including light weight, high strength, easy construction, excellent corrosion resistance, and good durability [4–6]. The existing FRP-strengthened RC beam

(FRP-SRCB) techniques mainly include externally bonded [7–9], end-anchored [10,11], and embedded [12,13]. Among these, externally bonded FRP is the most frequently applied shear reinforcement approach for RC structural components in engineering practice. For example, CFRP sheets were utilized to reinforce the RC box girder in Japan's Tomei Expressway viaduct project. The T-shaped beam was shear strengthened by CFRP sheets in the overpass of the Shanghai–Nanjing section of National Highway 312 in China [14].

Although the existing FRP reinforcement technology has been widely applied in engineering practice, how to accurately predict the shear capacity of FRP-SRCB is still a key scientific problem that needs to be urgently solved. The shear capacity of strengthened RC beams is impacted by various factors, including beam cross-sectional dimensions, concrete, steel bars, FRP material properties, and reinforcement forms. Figure 1 presents three typical FRP reinforcement methods: (a) full wrapping, (b) U jacketing, and (c) side bonding. The strengthened beams also have multiple potential failure modes, which results in complex conditions and numerous parameters to be considered for the prediction of the shear capacity [15,16]. Therefore, it is a hot and difficult point to predict the shear capacity of FRP-SRCB components reasonably and accurately.

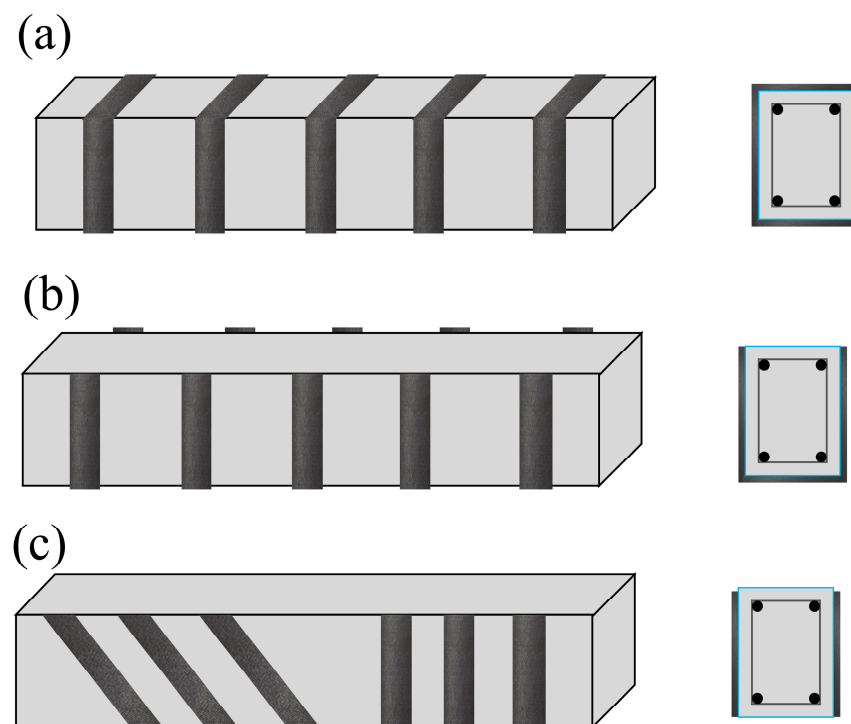


Figure 1. Different forms of externally bonded FRP shear strengthened RC beams: (a) full wrapping (FW-method); (b) U jacketing (U-method); (c) side bonding (S-method).

Thanks to the development of machine learning (ML), the data-driven FRP-SRCB shear capacity prediction method provides a new idea for solving the above problems [17–21]. The ML method can make full use of the historical test data and mine the mapping relationship between the input and output in the test data, so as to build an accurate and reliable prediction model. Perera et al. [22] and Tanarslan et al. [23] proposed an Artificial Neural Network (ANN) model to predict the shear performance of FRP-SRCB. The findings reveal that the model has strong prediction performance and generalization ability. Tanarslan et al. [24] developed two ANN models using backpropagation to predict the shear strength of RC beams externally bonded with CFRP plates. The models were compared with the shear strength calculated according to the American and Australian codes. The results show that the shear strength predicted by the proposed model significantly outperforms the

international standard. Based on the existing database of FRP shear reinforced RC beams, Yavuz et al. [25] discussed the prediction precision of ANN for the shear strength of RC beams and verified that the ANN model predicted the shear strength of FRP-SRCB better than the existing building code methods. Naderpour et al. [26] attempted to propose a fuzzy-based model (adaptive neuro-fuzzy inference system, ANFIS) to evaluate and predict the shear strength contribution in FRP-SRCB. Compared with existing code models, it was verified that the proposed ANFIS model has good prediction performance. Abuodeh et al. [27] established a resilient backpropagating neural network (RBPNN) to investigate the strengthening performance of side bonded and U-shaped FRP laminates on shear-defective RC beams, and this model was verified to have good applicability. Wang et al. [28] and Rahman et al. [29] adopted various ML algorithms to establish the shear capacity model for externally bonded FRP-SRCB and evaluated the impact of varying factors on the shear strength. The outcomes suggest that the XGBoost algorithm exhibits higher efficiency and accuracy in the considered models. Ke et al. [19] developed a shear bearing capacity prediction model for near-surface mounted (NSM) FRP-SCRB based on ML and innovatively proposed a strength calculation model for engineering design using genetic algorithm optimization. Meanwhile, Sung et al. [30] systematically investigated the bearing performance of prestressed concrete bridges in the initial stage of diagonal cracking and shear failure through nonlinear regression (NR) and genetic programming (GP). The findings indicate that the prediction accuracy of the NR model is slightly better than that of the GP model.

The above research demonstrates the advantages of the ML method in structural performance prediction, which can provide accurate prediction results based on input parameters. However, most studies only evaluate the prediction effect of a single model (ANN) in shear strength and lack systematic comparison of the applicability of different algorithms, which limits its application in engineering practice. Therefore, it is necessary to explore the practicability of different ML methods for enhancing the FRP-SRCB shear capacity model. This paper analyzes the relationship between different influencing factors and shear capacity by Pearson correlation coefficient and investigates the prediction performance of ANN and XGBoost algorithms on shear capacity. In addition, the formulas of various national codes are compared with ANN and XGBoost models to further validate the effectiveness and generalizability in predicting the shear capacity of FRP-SRCB, aiming to establish a shear bearing capacity prediction model with high precision and strong generalization ability. Its theoretical value lies in revealing the law of ML algorithms in the modeling of complex mechanical behavior, and its practical significance is reflected in providing a data-driven approach for engineering reinforcement design, thereby promoting the optimal application of FRP reinforcement technology.

2. Methodology

Due to the complex correlation among different factors affecting the shear capacity of FRP-SRCB, two representative ML algorithms were selected to predict the shear capacity from the perspective of single and integrated ML algorithms. It mainly includes Artificial Neural Network (ANN) and Extreme Gradient Boosting (XGBoost).

(1) ANN

ANN is an intelligent data processing technology that simulates the learning of biological neurons. It is composed of a set of connected nodes or units, which mainly consists of three parts: input layer, hidden layer, and output layer. In this study, ANN adopts a three-layer, fully connected architecture, including one input layer, two hidden layers, and one output layer. The number of nodes in the input layer is determined by the feature

variable dimension, and the number of output layer nodes is set to 1 node according to the prediction target.

The hidden layer is the core of ANN and comprises several neurons. Within each neuron, the input variables are calculated to obtain the output variables and connected to each other through a modifiable weighted interconnection. The main parameters of the model are the number of hidden layers and the number of neuron nodes in each layer, which are determined through multiple training and learning [31]. The number of corresponding nodes with the best performance is taken as the number of hidden layer units. In terms of network training, the Adam optimization algorithm is adopted for parameter optimization. The main training parameters are set as follows: the maximum number of training iterations is 1000, the initial learning rate is 0.01, and the target minimum error is 1×10^{-6} .

The output of neuron i in the hidden layer can be expressed as Equation (1).

$$y = F(\sum_{i=1}^n w_{ij}x_i + c) \quad (1)$$

where $x_i (i = 1, 2, 3, \dots, n)$ is the input value of the i -th neuron; w_{ij} is the connection weight from the i -th neuron to the j -th neuron; c is the threshold of this neuron; F is the activation function; and y is the output of the artificial neuron.

This study employs the hyperbolic tangent sigmoid function ($\tanh$) as the activation function for the hidden layer. This function exhibits two key advantages: ① its differentiable nature enables effective implementation of backpropagation algorithms, and ② its zero-centered output characteristic accelerates gradient descent convergence compared to conventional sigmoid functions. The specific expression is shown in Equation (2).

$$f(x) = \tanh(x) = \frac{1 - e^{-x}}{1 + e^{-x}} \quad (2)$$

(2) Extreme Gradient Boosting (XGBoost)

XGBoost is a typical ML algorithm for the newly established boosting integrated learning model, which helps to avoid overfitting and optimize computing power. It is realized by minimizing the objective function. Furthermore, a regularization term is added on the basis of the gradient boosting tree, while maintaining the fastest processing speed possible. The goal of the XGBoost algorithm is to make the predicted value y_{pi} close to the real value y_{ei} . After m iterations, the target function Z can be denoted as follows:

$$Z^{(m)} = \sum_{i=1}^n l(y_{ei}, y_{pi}^{m-1} + g_m(x_i)) + \Omega(g_m) + C \quad (3)$$

where $l(y_{ei}, y_{pi}^{m-1})$ is the loss function used to evaluate the accuracy of y_{pi}^{m-1} ; $g_m(x_i)$ is the predicted value of the regression tree; $\Omega(g_m)$ is the regularization term; and C is a norm function. By using the second-order Taylor expansion, it can be simplified as Equation (4).

$$Z^{(m)} = \sum_{i=1}^n l\left(q_i g_m(x_i) + \frac{1}{2} h_i g_m^2(x_i)\right) + \Omega(g_m) \quad (4)$$

In the formula, $q_i = l'(y_{ei}, y_{pi}^{m-1})$ and $h_i = l''(y_{ei}, y_{pi}^{m-1})$.

3. Dataset Description

3.1. Input and Output Variables

This study systematically collected experimental data from the FRP-SRCB literature published between 2002 and 2024 [19,32–89] to establish a new ML model experimental

database. The specific dataset of FRP-SRCB specimens is shown in the Supplementary Materials. The data collection process was conducted as follows: (1) Literature retrieval was performed using keywords such as “FRP-strengthened concrete beams” and “shear behavior” across databases including Web of Science, Scopus, and China National Knowledge Infrastructure (CNKI). (2) Data screening is based on the following criteria: ① complete material properties and geometric parameters must be provided; ② the failure mode of the test beam must be clearly reported. ③ The data must include the initial test data or extractable precise chart data. (3) Finally, 455 sets of valid experimental data samples were obtained.

Based on existing research, the factors influencing the shear bearing capacity of FRP-SRCB include the properties and dosage of FRP materials, in addition to the same factors as ordinary RC beams such as beam section dimensions, steel strength, and reinforcement ratio. Therefore, the selected input parameters of the bearing capacity prediction model include the beam width b , the beam effective height d , the shear span ratio λ , the yield strength of longitudinal tensile reinforcement f_y , the reinforcement ratio of the tensile steel bar ρ_l , the yield strength of hoop reinforcement f_{yv} , the reinforcement ratio of the stirrup ρ_v , the compressive strength of concrete f_c , the tensile strength of FRP material f_f , the elastic modulus E_f , the distribution rate ρ_f , the strengthening configuration (SC) (FW, U, and SB), and the bonding angle α . The model output is the shear bearing capacity V_u .

The distribution rate ρ_f of FRP material is calculated as follows:

$$\rho_f = 2nt_f w_f / bs_f \quad (5)$$

where n is the number of adhesive layers of FRP material; t_f is the thickness of FRP material; w_f is the width of FRP material; and s_f is the center-to-center spacing of FRP material.

Table 1 reveals the statistical feature of the input and output parameters in the dataset, and Figure 2 demonstrates the correlation between input parameters and the shear capacity of FRP-SRCB. It can be observed that the dataset has a large level of discretization, a wide scope of values, and a uniform distribution of parameters. Therefore, it can offer a dependable data foundation for the establishment of a data-driven shear capacity prediction model.

Table 1. Statistical characteristics of FRP-strengthened sample set parameters.

Classification	Parameter	Minimum	Maximum	Median	Mean	Standard Deviation
Input parameter	b (mm)	75.00	406.00	150.00	173.34	56.15
	d (mm)	123.00	660.00	260.00	273.53	91.33
	λ	0.94	4.88	2.80	2.61	0.77
	f_y (MPa)	311.22	625.10	500.00	494.11	61.40
	ρ_l (%)	0.75	7.54	2.50	2.91	1.50
	f_{yv} (MPa)	240.00	740.00	363.30	429.64	152.83
	ρ_v (%)	0	0.84	0.11	0.16	0.18
	f_c (MPa)	13.30	71.00	34.70	35.47	11.03
	E_f (GPa)	5.30	392.00	233.60	210.38	96.56
	f_f (MPa)	110.00	4900.00	3450.00	3064.34	1352.38
	ρ_f (%)	0.02	2.80	0.18	0.37	0.51
	α (°)	45.00	90.00	90.00	84.76	14.45
Output parameter	V_u (kN)	45.90	888.00	187.50	224.25	141.49

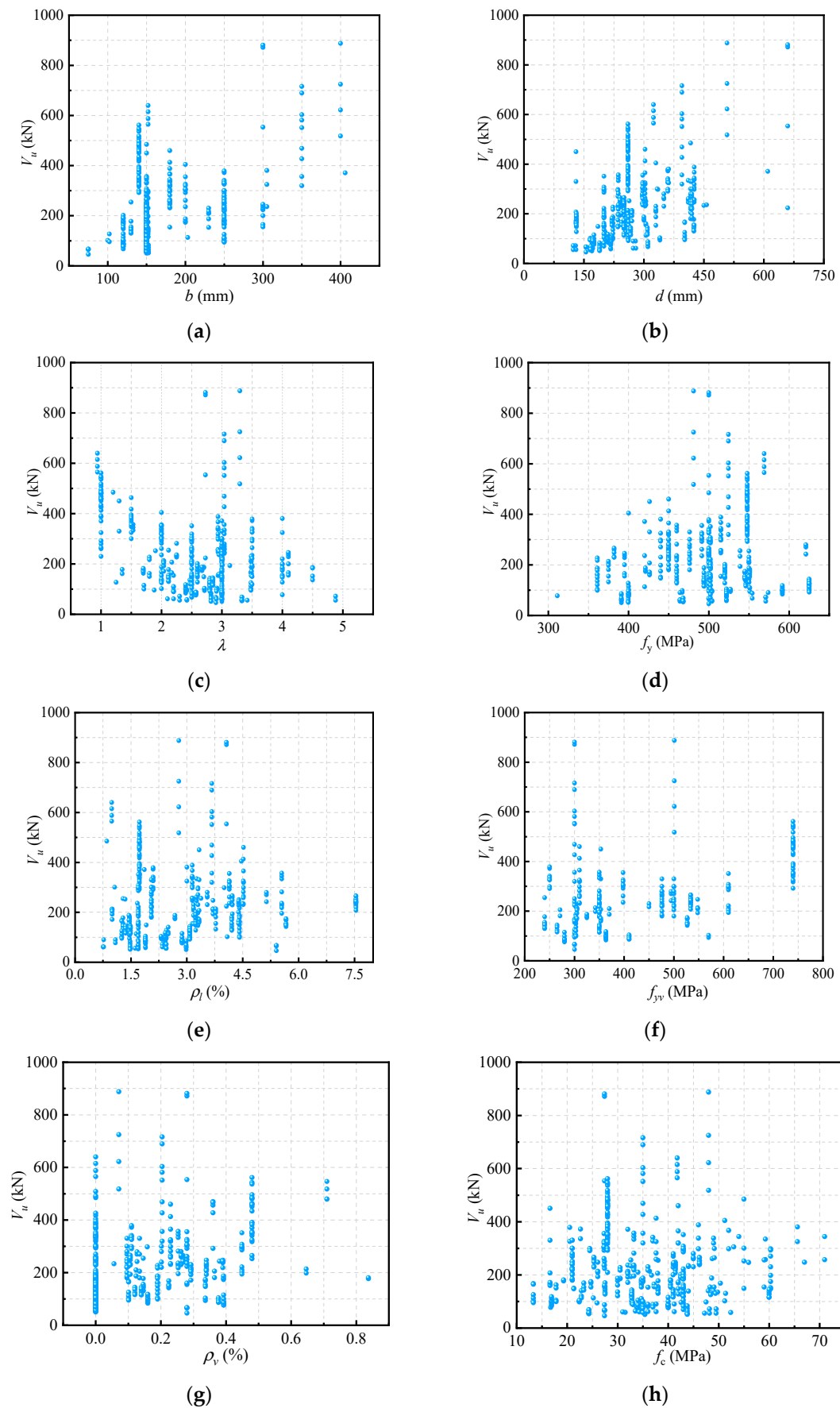


Figure 2. Cont.

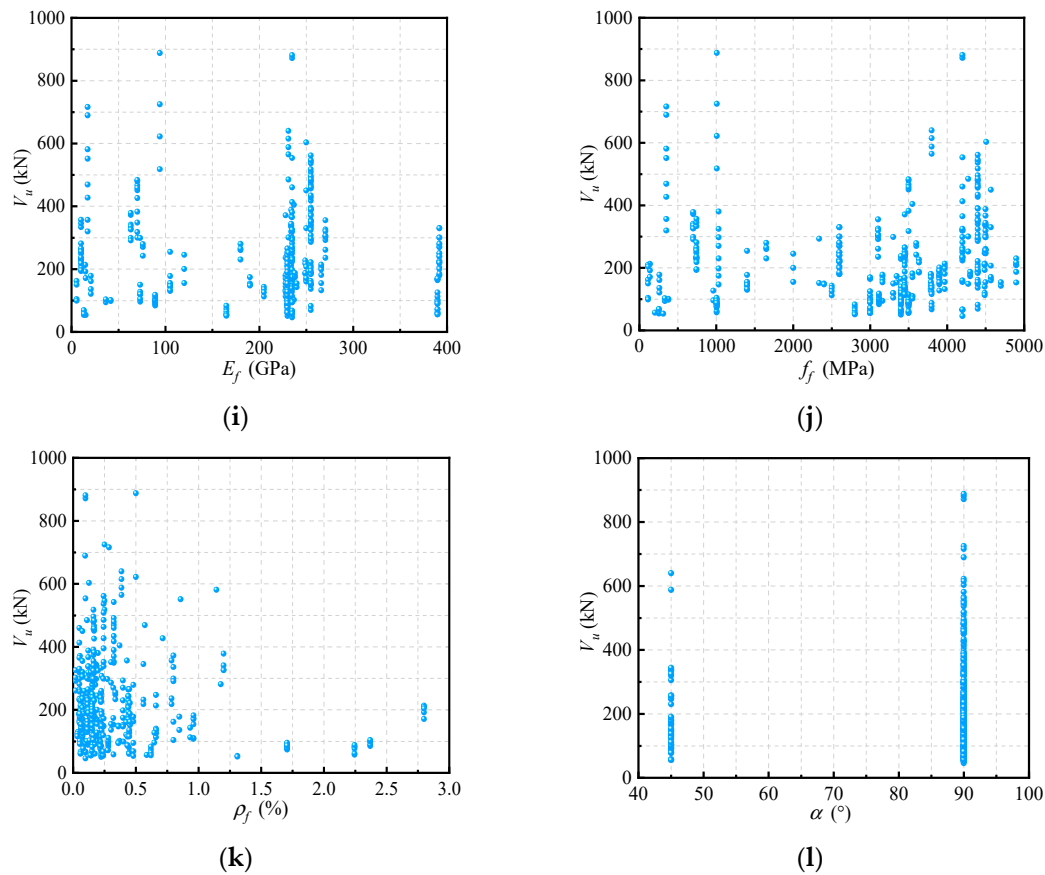


Figure 2. Relationship between shear capacity and input characteristic parameters after FRP reinforcement: (a) relationship between b and V_u ; (b) relationship between d and V_u ; (c) relationship between λ and V_u ; (d) relationship between f_y and V_u ; (e) relationship between ρ_l and V_u ; (f) relationship between f_{yv} and V_u ; (g) relationship between ρ_v and V_u ; (h) relationship between f_c and V_u ; (i) relationship between E_f and V_u ; (j) relationship between f_f and V_u ; (k) relationship between ρ_f and V_u ; (l) relationship between α and V_u .

3.2. Correlation Analysis

To avoid inputting similar features and over-fitting problems, this paper uses Pearson correlation coefficient (Equation (6)) to ensure the validity of the selected parameters for prediction. Figure 3 shows the correlation thermal map obtained according to the variables in the sample data, which provides the correlation coefficients among the variables. The shaded red and blue represent the positive and negative correlations, respectively. The color depth and proportion on the side represent the gradient of correlation strength from ± 1 to 0. It can be noticed that the correlation coefficient r between the input variables varies from -0.49 to 0.74 . In general, an r -value below 0.8 indicates that there is no multicollinearity problem in the variable [90,91], suggesting that there is no significant correlation between the selected features. Furthermore, it can be observed that the shear capacity V_u has a relatively high positive correlation with the beam width b and the beam effective height d (the correlation coefficients are 0.48 and 0.41). Conversely, the correlation coefficients of the rest variables are comparatively weak. As a whole, the connection between the shear capacity and the 13 input variables is not a straightforward multivariate linear relationship and it is not appropriate to use a simple explicit equation to quantify the shear capacity of

FRP-SRCB. Therefore, it is necessary to build the nonlinear mapping relationship between the shear bearing capacity of FRP-SRCB and each input variable by ML.

$$r = \frac{\sum_{i=1}^n (x_i - \bar{x})(y_i - \bar{y})}{\sqrt{\sum_{i=1}^n (x_i - \bar{x})^2} \sqrt{\sum_{i=1}^n (y_i - \bar{y})^2}} \quad (6)$$

where r is Pearson correlation coefficient; x_i and y_i are the two characteristic parameters of the i th specimen, respectively; $\bar{x}$ and $\bar{y}$ represent the sample mean of the two characteristic parameters; and n represents the total number of specimens in the sample set.

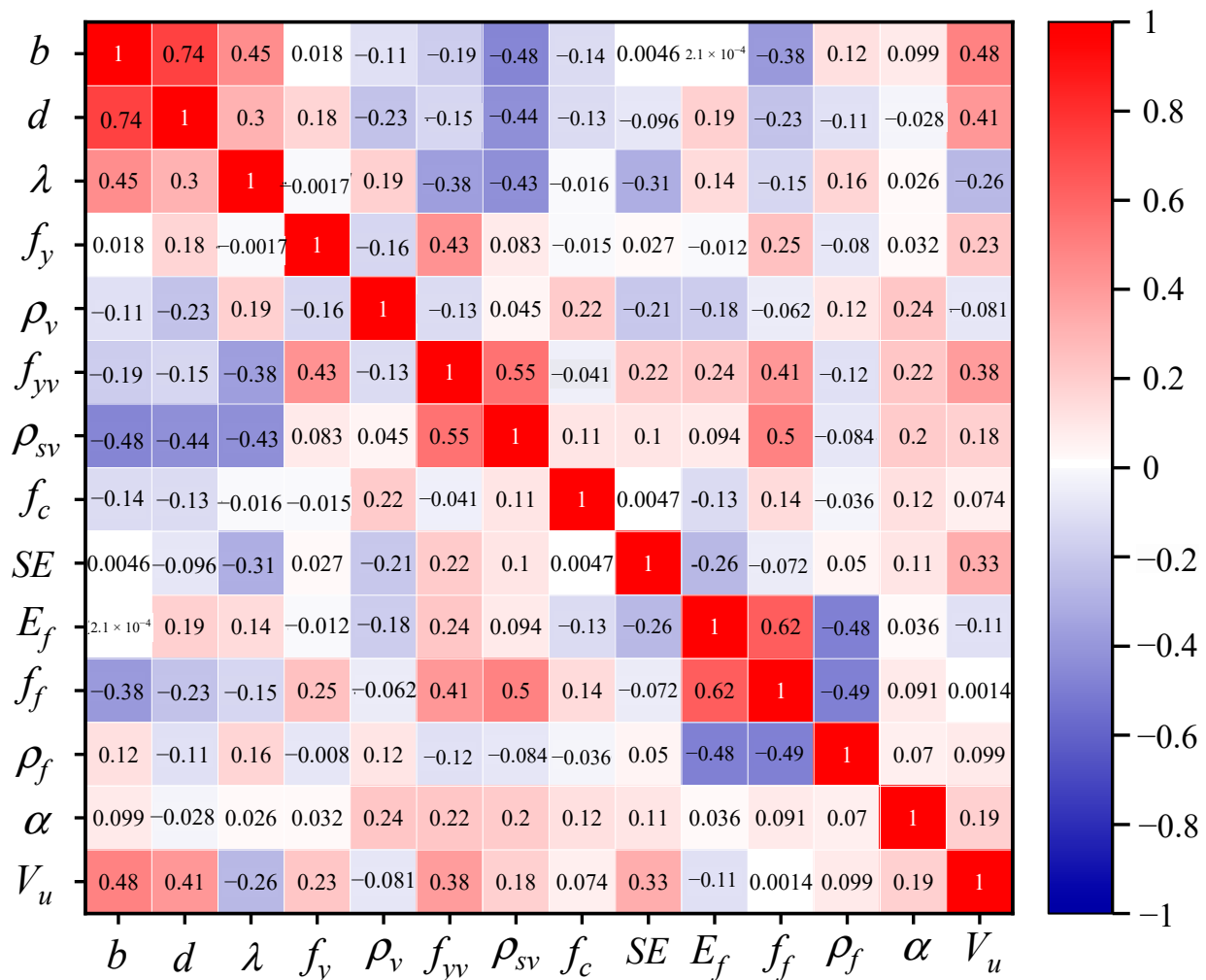


Figure 3. Pearson correlation coefficient matrix diagram between single characteristic parameters.

3.3. Model Training Process

To realize the prediction of FRP-SRCB shear capacity, the 13 physical parameters are determined as inputs. Based on 455 sets of test databases and two ML algorithms, a reliable ML prediction model is obtained through training, optimization, and validation of the ML model. The detailed implementation process is illustrated in Figure 4.

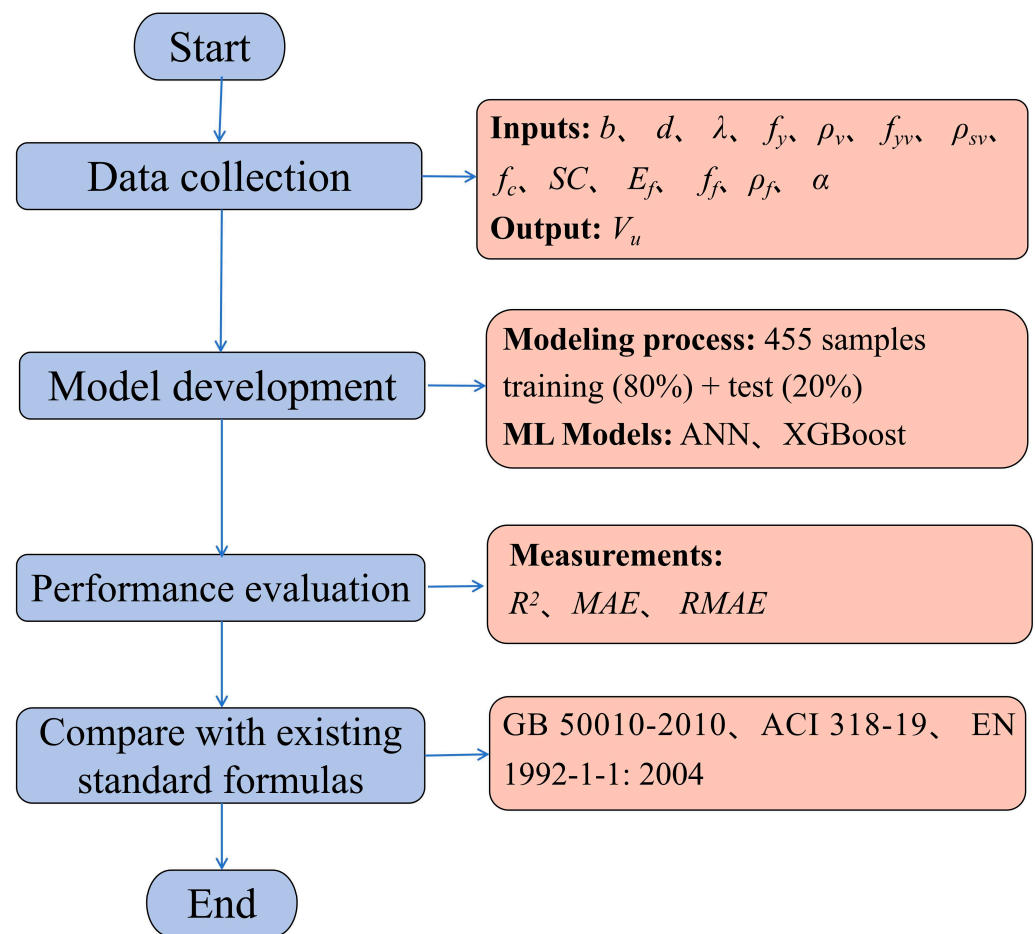


Figure 4. Prediction process of FRP-SRCB shear capacity based on ML.

The dataset needs to be normalized and preprocessed to avoid the dimensional difference in different feature data resulting in inconsistent feature weights. The 13 input feature parameters are dimensionless and scaled to [0, 1] to eliminate the influence of variable dimensions and ensure that the feature values have balanced weights. The normalization formula is as follows:

$$\tilde{x} = \frac{x - x_{\min}}{x_{\max} - x_{\min}} \quad (7)$$

where x is the input variable; $x_{\max}$ and $x_{\min}$ are the maximum and minimum values of the input variable; and $\tilde{x}$ is the standardized input variables. For the sorted dataset (455 groups), it is randomly classified into the training set (364 groups) and the test set (91 groups) in an 80/20 ratio. The training dataset is utilized for training ANN and XGBoost models and the predictive stability of ML models is estimated using evaluation indicators. The model's performance is estimated using the test dataset, and further analysis and discussion are based on the obtained R^2 , MAE , and $RMSE$ values.

3.4. Evaluation Indicators

To quantify the performance of ANN and XGBoost models in the prediction of FRP-SRCB shear capacity, three commonly used regression evaluation indicators are adopted, namely determination coefficient R^2 , mean absolute error (MAE), and root mean square error ($RMSE$), as shown in Equations (8)–(10). These indicators provide a comprehensive

understanding of model performance by assessing the magnitude and direction of the error between predicted and actual values.

$$R^2 = 1 - \frac{\sum_{i=1}^n (y_{ei} - y_{pi})^2}{\sum_{i=1}^n (y_{ei} - y_m)^2} \quad (8)$$

$$MAE = \frac{1}{n} \sum_{i=1}^n |y_{ei} - y_{pi}| \quad (9)$$

$$RMSE = \sqrt{\frac{1}{n} \sum_{i=1}^n (y_{ei} - y_{pi})^2} \quad (10)$$

where y_{ei} , y_{pi} , and y_m are the test value, predicted value, and mean value of the sample, respectively; and n is the number of datasets. The higher the R^2 , the smaller the MAE and $RMSE$, indicating that the model has better predictive accuracy, with smaller deviations between predicted values and true values.

4. Model Performance

Table 2 lists the R^2 , MAE , and $RMSE$ of the ANN and XGBoost models obtained using the training and test datasets. It can be further observed that the training set and test set R^2 of the XGBoost algorithm are 0.999 and 0.879, respectively, showing improvements of 13.52% and 0.23% compared to the ANN model, implying that the XGBoost model is higher than the ANN model in the degree of sample data fitting. The MAE and $RMSE$ of the XGBoost algorithm on the training set are 1.096 and 1.438, respectively, representing reductions of 96.27% and 97.04% compared to the ANN model. The MAE and $RMSE$ of the XGBoost algorithm on the test set are 31.872 and 40.898, respectively, which are 12.29% and 19.40% lower than those of the ANN model. This indicates that the XGBoost model has the smallest discrepancy between the predicted and actual values, with significantly better prediction accuracy than the ANN model. It is further confirmed that the prediction performance of the integrated ML model is better than that of the single learning model in the two models. This is because the working principle of integrated learning improves the generalization ability and robustness of the learner by incorporating the prediction results of various base learners. Its excellent prediction performance has been demonstrated in multiple studies [92–94].

Table 2. Performance evaluation indicators of developed ML model.

Dataset	Model	R^2	MAE	$RMSE$
Training set	ANN	0.880	29.433	48.635
	XGBoost	0.999	1.096	1.438
Test set	ANN	0.877	36.337	50.741
	XGBoost	0.879	31.872	40.898

To facilitate the comparison of the prediction effect between the models, a diagonal solid line ($X = Y$) representing a prediction accuracy of 100% and a dotted line (with slopes of 1.2 and 0.8) indicating the relative prediction error within $\pm 20\%$ are plotted on the correlation scatter plots of the two models, respectively. The more centralized the data points along the diagonal solid line, the higher the prediction accuracy of the model. Conversely, the farther away from the diagonal solid line, the lower the prediction accuracy. Figure 5 illustrates the scatter plot of the regression prediction results of the two models.

Compared with the ANN model, more data points of FRP-SRCB shear strength prediction based on the XGBoost model are concentrated within the error limit of $\pm 20\%$, and its proportion within this range is significantly higher. Whether for the training set or for the test set, the results of the XGBoost model are better than those of the ANN model. The scatter plot is closer to the diagonal of $X = Y$, indicating that the test value is closer to the true value. This shows that the prediction model of FRP-SRCB shear capacity based on the XGBoost algorithm performs better in the samples, and it can be found that the integrated learning method demonstrates obvious advantages.

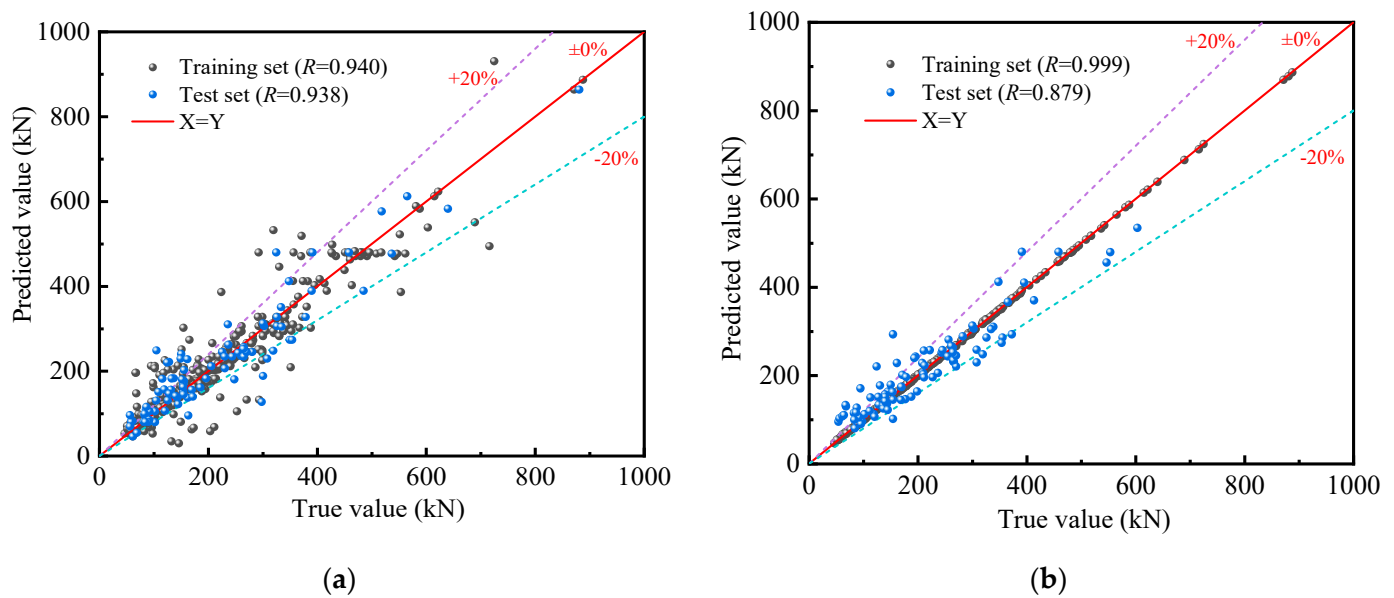


Figure 5. ML model prediction fitting results: (a) ANN model; (b) XGBoost model.

Figure 6 illustrates the comparison between the predicted value and the experimental value of the FRP-SRCB shear capacity prediction model using two ML algorithms (ANN and XGBoost). The error plot describes the difference between the predicted value and the actual value as the vertical distance from the zero line, which is called the residual ($Y_{pre} - Y_{exp}$). This method simplifies the assessment of the proximity between the predicted and actual values because the residual plot is closely aligned with the zero line, depicting that the prediction is accurate. It can be noticed from Figure 6 that the single model (ANN) exhibits a wide distribution of residual values, ranging from -221.21 kN to 213.16 kN, and the prediction performance is poor. However, compared with the performance of the ANN model on the test set, the prediction performance of the ANN model on the training set is deficient. On the other hand, the residual value range of the integrated model (XGBoost) is smaller than that of the single model, ranging from 90.54 kN to 193.36 kN, indicating that its prediction performance is better. More complex functional terms can be employed to capture the relationship between independent and dependent variables in the integrated model, thereby predicting the true values more reliably. Therefore, the error between the true value and the predicted value of the integrated model is apparently smaller than that of the single model.

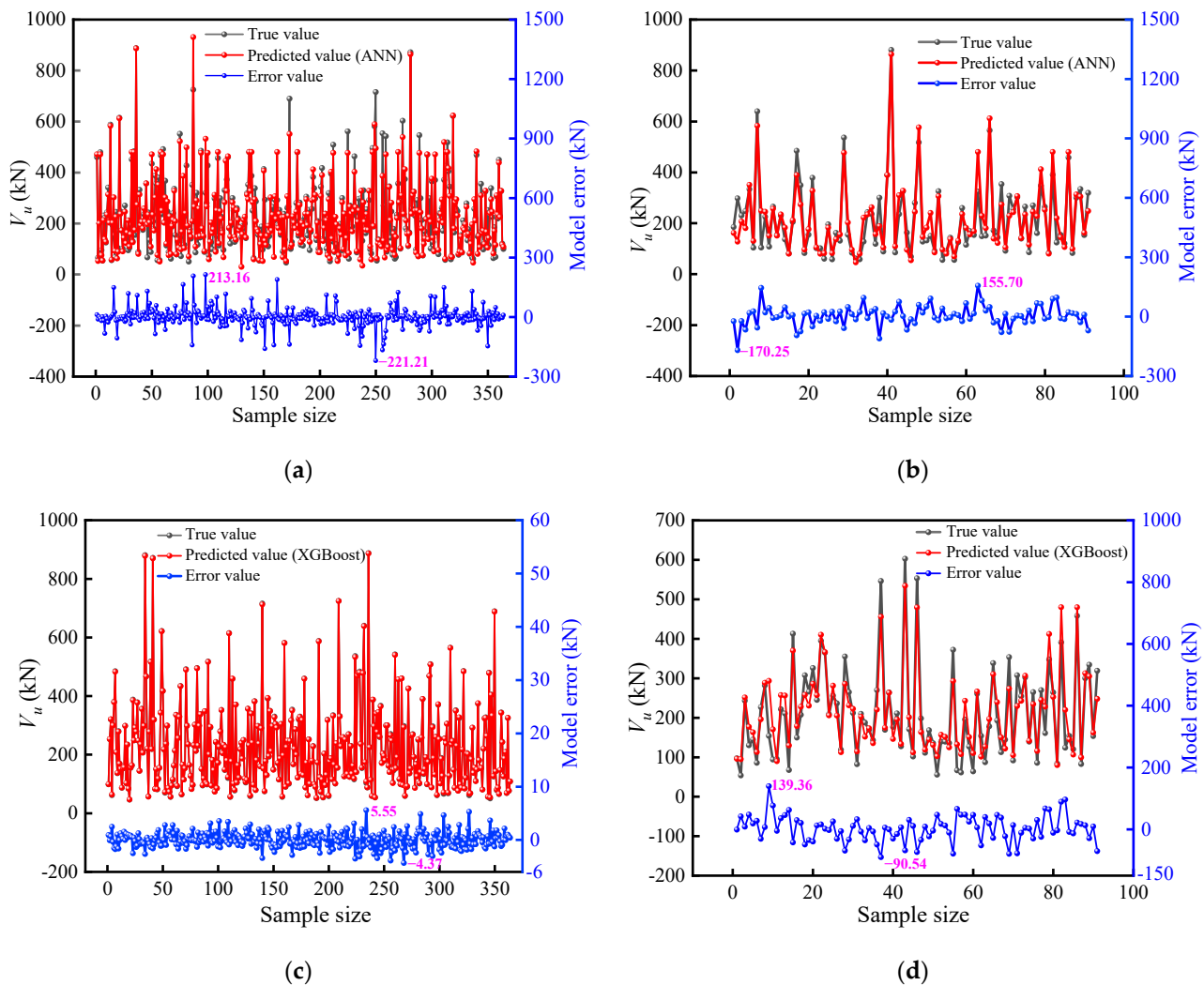


Figure 6. Comparison results of ML model prediction: (a) ANN training set; (b) ANN test set; (c) XGBoost training set; (d) XGBoost test set.

5. Comparative Analysis with Existing Design Codes

To further validate the proposed ML-based prediction model and demonstrate its superiority. This section compares the calculation models from three national design codes with the ANN and XGBoost models.

5.1. Overview of Design Code Models

Through the experimental study of concrete beams strengthened with externally bonded FRP, it was found that the mechanism of FRP is similar to that of stirrups. With the increase in load, the stress of FRP changes little before the cracking of the inclined section of the beam. However, after the emergence of the inclined crack, the stress of the FRP intersecting with the inclined crack suddenly increases. FRP not only bears part of the shear force, but also effectively inhibits the expansion of the inclined crack, as well as significantly improving the biting force between the aggregates in the concrete at the main inclined crack of the inclined section of the beam. Therefore, for the inclined section shear capacity V_u of the externally bonded FRP-SRCB, the contribution value of the externally bonded FRP material to the shear capacity is added based on the ordinary RC beam shear

capacity formula, as displayed in Equation (11). Table 3 shows the shear capacity calculation expressions from the design codes of China, the United States, and Europe.

$$V_u = V_{cs} + V_f = V_c + V_s + V_f \quad (11)$$

where V_u is the shear capacity of FRP-SRCB; V_{cs} is the shear capacity of reinforced beam diagonal section concrete and stirrups; and V_f is the shear capacity of reinforced beam diagonal section fiber cloth.

Table 3. Design specification formulas for various countries.

Specifications	V_{cs}	V_f
Chinese code GB 50010-2010 [95]	Without web reinforcement $V = \alpha_{cv} \beta_h \beta_\rho f_t b d$ With web reinforcement $V_{cs} = V_c + V_s = \alpha_{cv} f_t b d + f_{yv} \frac{A_{sv}}{s} d$	$V_f = \frac{\Psi_{vb} f_f A_f h_f}{s_f} = \frac{\Psi_{vb} f_f 2 n t_f w_f h_f}{s_f}$
American code ACI 318-19 [96]	$V_n = V_c + V_s$ $V_c = \begin{cases} 8 \lambda \rho_l^{1/3} \sqrt{f'_c} b d & A_v \geq A_{v,min} \\ 8 \lambda \lambda_s \rho_l^{1/3} \sqrt{f'_c} b d & A_v \leq A_{v,min} \end{cases}$ $V_c \leq 5 \lambda \sqrt{f'_c} b d$ $\frac{A_{v,min}}{s} = \text{MAX} \left[0.75 \sqrt{f'_c} \frac{b}{f_{yt}}, 50 \frac{b}{f_{yt}} \right]$ $\lambda_s = \sqrt{\frac{2}{1+d/10}} \leq 1$ $V_s = \frac{A_v f_{yt} d}{s}$	$V_f = \psi_f V_f^0$ $V_f^0 = \frac{A_f f_{fe} (\sin \alpha + \cos \alpha) d_f}{s_f}$ $A_f = 2 t_f w_f$ $f_{fe} = E_f \varepsilon_{fe}$ $\varepsilon_{fe} = \begin{cases} 0.004 \leq 0.75 \varepsilon_{fu} & \text{FW} \\ k_v \varepsilon_{fu} \leq 0.004 & \text{U or SB} \end{cases}$ $k_v = \frac{k_1 k_2 L_e}{11900 \varepsilon_{fu}}$ $f_{fe} = E_f \varepsilon_{fe}$ $\varepsilon_{fe} = \begin{cases} 0.004 \leq 0.75 \varepsilon_{fu} & \text{FW} \\ k_v \varepsilon_{fu} \leq 0.004 & \text{U or SB} \end{cases}$ $k_v = \frac{k_1 k_2 L_e}{11900 \varepsilon_{fu}}$ $k_1 = \left(\frac{f_c}{27} \right)^3$ $k_2 = \begin{cases} \frac{d_f - L_e}{d_f} & \text{U} \\ \frac{d_f - 2L_e}{d_f} & \text{SB} \end{cases}$ $L_e = \frac{23300}{(n t_f E_f)^{0.58}}$
European code EN 1992-1-1:2004 [97]	Without web reinforcement $V_{Rd,c} = C_{Rd,c} k (100 \rho_l f_{ck})^{1/3} b d$ $k = 1 + \sqrt{\frac{200}{d}} \leq 2.0$ $C_{Rd,c} = 0.18 / \gamma_c$ With web reinforcement $V_{Rd,s} = \frac{A_{sw} f_{yw} z}{s} (\cot \theta + \cot \alpha) \sin \alpha$	$V_f = 0.9 \varepsilon_{fe} E_f \rho_f b d (1 + \cot \alpha) \sin \alpha$ For FW $\varepsilon_{fe} = 0.17 \left(\frac{f'_c}{E_f \rho_f} \right)^{2/3} \varepsilon_{fu}$ For U or SB $\varepsilon_{fe} = \min \left[0.65 \left(\frac{f'_c}{E_f \rho_f} \right)^{0.56} \times 10^{-3}, 0.17 \left(\frac{f'_c}{E_f \rho_f} \right)^{2/3} \varepsilon_{fu} \right]$

Notation: α_{cv} Shear capacity coefficient of concrete. For the component under uniform load, 0.7 is taken; and for the independent beam under concentrated load, $\alpha_{cv} = 1.75 / (\lambda + 1)$. When $\lambda < 1.5$, 1.5 is taken; when $\lambda > 3$, 3.0 is taken.

β_h The influence coefficient of cross-sectional height, $\beta_h = (800/d)^{1/4}$. When $d \leq 800\text{mm}$, 800 is taken; when $d > 2000\text{mm}$, 2000 is taken.

β_ρ The influence coefficient of longitudinal tensile steel reinforcement ratio, $\beta_\rho = 0.7 + 20\rho$. ρ is the longitudinal tensile steel reinforcement ratio.

f_t Design value of concrete axial tensile strength.

Table 3. Cont.

Specifications	V_{cs}	V_f
f_{yv}	Design value of stirrup tensile strength.	
A_{sv}	Stirrup area configured in the same section.	
s	Stirrup spacing along the member length direction.	
Ψ_{vb}	The reduction coefficient of shear capacity is calculated according to Table 4. When the shear span ratio λ is in the middle, it is calculated according to the internal interpolation method.	
h_f	The vertical distance from the upper end of FRP to the center of the longitudinal bar.	
f'_c	Compressive strength of concrete cylinder.	
λ_s	Size effect correction factor.	
ψ_f	The reduction factor related to the pasting form. For side pasting and U-pasting form, $\psi_f = 0.85$; For the full-pasting form, $\psi_f = 0.95$.	
α	The angle between FRP and beam axis.	
f_{fe}	The effective stress of FRP.	
ε_{fe}	The effective strain of FRP.	
ε_{fu}	The ultimate tensile strain of FRP.	
k_1, k_2, k_v	The correction factor, which is related to concrete strength, FRP bonding scheme, FRP-concrete interface bonding and FRP effective bonding length.	
f_{ywd}	Design value of yield strength of shear reinforcement.	
v_1	The strength reduction factor of shear-fractured concrete, which is calculated by $v_1 = 0.6(1 - f_{ck}/250)$.	
θ	The angle between the concrete pressure bar and the longitudinal pressure bar.	
α_{cw}	Considering the stress state coefficient in the compression chord. In the case of no prestress, the specification is recommended $\alpha_{cw} = 1.0$.	
f_{cd}	Design value of concrete compressive strength.	
z	The internal force arm of the cross-section, which can be approximated as $z = 0.9d$.	

Table 4. Values of shear strength reduction factor.

Strip Anchoring Method	Shear Span Ra-tio $\lambda \leq 1.5$	Uniform Load or Shear Span Ratio $\lambda > 1.5$
Ring hoop or self-locking U-shaped hoop	0.68	1
Rubber anchor or steel anchor U-shaped hoop	0.6	0.88
General U-shaped hoop with fabric laminates	0.5	0.75

5.2. Comparison of Calculation Results of Different Design Codes

To better assess the accuracy of the prediction of FRP-SRCB shear capacity in each design code formula, evaluation indexes (average value, standard deviation, and coefficient of variation) for the ratio of the predicted value to the test value (V_{pre}/V_{exp}) are introduced in the data analysis, as displayed in Table 5. The average value of V_{pre}/V_{exp} of ACI is 0.64, the standard deviation is 0.33, and the coefficient of variation is 0.51. This indicates that this code has a small degree of dispersion in predicting bearing capacity, but the prediction is too conservative. The main reason is that in this design code, the shear capacity of RC beams only considers the shear resistance of stirrups while ignoring the effect of the concrete and shear span ratio on the shear capacity. The factors that can provide shear capacity are not fully included, as the predicted value of the bearing capacity is significantly smaller than the experimental value. However, the V_{pre}/V_{exp} average values of Chinese standard (GB) and European standard (EN) are both greater than 1, which are 1.57 and 1.56, respectively. The standard deviations are 1.13 and 1.26, and the coefficients of variation are 0.72 and 0.81, indicating that the calculation results of these two design codes have a large deviation and the relative fluctuation of data is large. The main reason is that most of the RC

beam shear capacity models in China belong to semi-empirical and semi-theoretical models. Compared with the three national standard models, the average values of V_{pre}/V_{exp} of the ANN model and XGBoost model are close to 1, which are 1.05 and 1.02, respectively. The standard deviations are 0.29 and 0.14, and the coefficient of variation are 0.27 and 0.13. This indicates that the calculated results of these two models are closest to the test values. Moreover, the dispersion of the calculated results is minimal, and it can be illustrated that these two models are more exact in predicting the shear capacity of FRP-SRCB, which further explains the accuracy and effectiveness of the ML model.

Table 5. An analysis of the ratio of the calculated value to the experimental value of different specifications.

Models/Specifications	AVE	SD	COV
ANN Model	1.05	0.29	0.27
XGB Model	1.02	0.14	0.13
GB 50010-2010	1.57	1.13	0.72
ACI 318-19	0.64	0.33	0.51
EN 1992-1-1:2004	1.56	1.26	0.81

Note: AVE, SD, and COV represent the average value, standard deviation, and coefficient of variation in the ratio of the predicted value to the experimental value, respectively.

To further evaluate the safety of the shear capacity of the three design codes and two models, $V_{pre}/V_{exp} = 1$ is used as the dividing line, as shown in the blue dotted line in Figure 7. The number of RC beam specimens in the safety area (the calculated value of shear capacity is lower than the test value of shear capacity, that is, $V_{pre}/V_{exp} < 1$) and the non-safety area (the calculated value of shear capacity is higher than the test value of shear capacity, that is, $V_{pre}/V_{exp} > 1$) in Figure 7 are counted. The proportion of specimens that meet the requirements of the shear capacity calculation formula of each design code is obtained. It can be noticed from Figure 7a that most data points of V_{pre}/V_{exp} calculated based on Chinese and European design codes are located above the dividing line of $V_{pre}/V_{exp} = 1$. The proportion of specimens in the safe area is relatively small, which are 35.82% and 47.03%, respectively, indicating that the prediction of shear capacity of these two design codes is dangerous and cannot meet the safety requirements of FRP-SRCB. Most of the data points of V_{pre}/V_{exp} calculated based on the American code are concentrated below the dividing line of $V_{pre}/V_{exp} = 1$. The proportion of specimens in the safe area of shear capacity prediction is 87.25% of the total specimens, illustrating that the prediction of shear capacity of this code is conservative. Although it meets the safety needs of FRP-SRCB shear capacity, the prediction of shear bearing capacity is too conservative.

It can be noticed from Figure 7b that the distributions of the ANN model and XGBoost model based on the ML algorithm for shear capacity prediction are mostly concentrated at the edge of the dividing line $V_{pre}/V_{exp} = 1$, and the distribution region is relatively concentrated. The proportion of specimens in the safe region is 49.67% and 48.35%, respectively. Compared with the standard formula, the predicted value of the ANN model and the XGBoost model introduced in this paper has a smaller error with the true value of the test and has certain generalization performance and applicability. The predicted value of the standard formula has a large error with the true value of the test, indicating that the standard formula has certain limitations. The reason may be the following: (1) There are various factors affecting the shear capacity of FRP-SRCB, and only a few main factors are considered in the standard formulas. (2) Most of the design codes are semi-empirical and semi-theoretical formulas, which are limited by the number of specimens. The ML model adopted in this paper considers 13 different variables, and the size of the samples is large, which can fully consider the influence of diverse factors and obtain accurate prediction results.

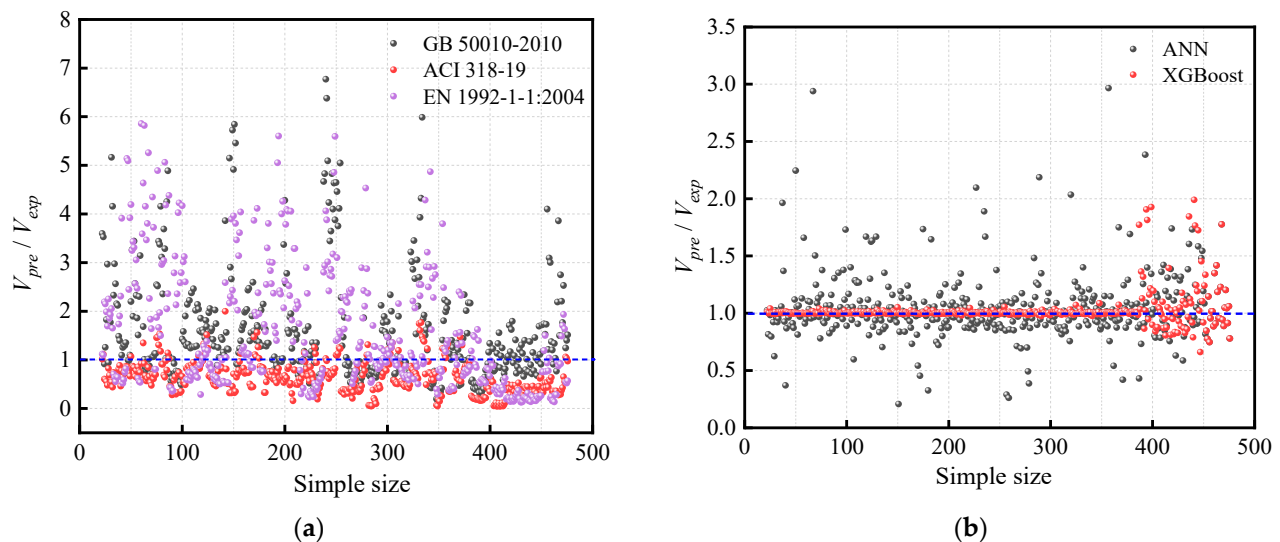


Figure 7. Analysis of prediction results: (a) different code formulas; (b) ANN and XGBoost models.

6. Conclusions

This study presents an innovative application of ML techniques to develop high-precision prediction models with strong generalization capabilities, effectively overcoming the limitations of traditional semi-empirical formulas in analyzing multi-factor coupling effects. Based on Pearson correlation analysis, the nonlinear correlation law between the shear bearing capacity of FRP-SRCB and key parameters was quantitatively revealed, thereby opening a new theoretical perspective for the research of FRP reinforcement. The main conclusions are as follows:

- (1) Pearson correlation analysis shows that the shear capacity V_u of FRP-SRCB has a relatively high positive correlation with the beam width b and the beam effective height d (correlation coefficients are 0.48 and 0.41), while the correlation coefficients with the other variables are low.
- (2) The intelligent prediction model for FRP-SRCB shear capacity was established by using the database to train the ML algorithm. The results show that the two ML models established perform well in shear capacity prediction. In general, the performance of the integrated model (XGBoost) is better than that of the single model (ANN), showing favorable accuracy.
- (3) The prediction results of three national standard formulas are compared with the ANN and XGBoost algorithms. The results reveal that the accuracy of the standard formula is limited and the variability is large. On the contrary, ML models greatly improve the prediction precision compared with traditional standard formulas. The variation coefficients of the ratio of the predicted value the actual value the ANN model and the XGBoost model are 27% and 13%, respectively, while the coefficient of variation in the standard model is more than 50%.
- (4) Future research should incorporate additional experimental data under extreme conditions (such as ultra-high-strength concrete components or specimens with large shear/span ratio) to enhance the generalization ability of the model. Moreover, integrating mechanism models (such as modified compression field theory) with ML algorithms to develop hybrid models that combine high accuracy with strong interpretability should be considered. This approach not only expands the application boundaries of ML in the engineering field but also provides an innovative solution for the intelligent evaluation of structural performance.

Supplementary Materials: The following supporting information can be downloaded at: <https://www.mdpi.com/article/10.3390/buildings15111908/s1>, Table S1: The specific dataset of FRP-SRCB specimens.

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