

Article

Machine-Learning-Based Predictive Models for Punching Shear Strength of FRP-Reinforced Concrete Slabs: A Comparative Study

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Abstract: This study is focused on the punching strength of fiber-reinforced polymer (FRP) concrete slabs. The mechanical properties of reinforced concrete slabs are often constrained by their punching shear strength at the column connection regions. Researchers have explored the use of fiber-reinforced polymer reinforcement as an alternative to traditional steel reinforcement to address this limitation. However, current codes poorly calculate the punching shear strength of FRP-reinforced concrete slabs. The aim of this study was to create a robust model that can accurately predict its punching shear strength, thus improving the analysis and design of composite structures with FRP-reinforced concrete slabs. In this study, 189 sets of experimental data were collected, and six machine learning models, including linear regression, support vector machine, BP neural network, decision tree, random forest, and eXtreme Gradient Boosting, were constructed and evaluated based on goodness of fit, standard deviation, and root-mean-square error in order to select the most suitable model for this study. The optimal model obtained was compared with the models proposed by codes and the researchers. Finally, a model explainability study was conducted using SHapley Additive exPlanations (SHAP). The results showed that random forests performed best among all machine learning models and outperformed existing models suggested by codes and researchers. The effective depth of the FRP-reinforced concrete slabs was the most important and proportional to the punching shear strength. This study not only provides guidance on the design of FRP-reinforced concrete slabs but also informs future engineering practice.



Citation: Xu, W.; Shi, X. Machine-Learning-Based Predictive Models for Punching Shear Strength of FRP-Reinforced Concrete Slabs: A Comparative Study. *Buildings* **2024**, *14*, 2492. <https://doi.org/10.3390/buildings14082492>

Academic Editor: José Filipe Miranda Melo

Received: 4 July 2024

Revised: 4 August 2024

Accepted: 5 August 2024

Published: 12 August 2024



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Keywords: punching shear strength; fiber-reinforced polymer; reinforced concrete slabs; machine learning; SHapley Additive exPlanations

1. Introduction

The use of reinforced concrete in combination with composite structures has become increasingly popular. Reinforced concrete slabs, as a crucial component in modern building structures, not only bear the load of the building but also exemplify the seamless integration of material science and structural engineering [1–4]. In the composite material system of reinforced concrete, high-strength steel and durable concrete work together to resist external forces, ensuring the safety and stability of the structure [5–7]. Reinforced concrete slabs are widely used in flooring, roofing, and special structures such as staircases and bridge slabs, owing to their unique mechanical properties and ease of construction [8–11].

To enhance the punching shear strength of reinforced concrete slabs, various techniques such as enclosed loops, bent steel reinforcements, and shear connectors have been widely implemented. Recently, there has been a surge in scholarly attention toward using fiber-reinforced polymers (FRPs) as a reinforcing medium in concrete slabs, aiming to improve their capacity to resist punching shear forces. This innovative approach addresses some of the limitations associated with traditional steel reinforcement. The use of FRPs in concrete slabs represents a significant advancement in construction materials technology, providing enhanced durability and performance in structural applications. Researchers

have conducted numerous studies and experiments to investigate the behavior and benefits of FRP-reinforced concrete slabs under various loading conditions. These efforts have led to a deeper understanding of how to effectively incorporate FRPs into concrete structures, optimizing their strength and longevity [12–16]. Compared with traditional concrete slabs, FRP-reinforced slabs offer several advantages, including being lightweight, having excellent corrosion resistance, high strength, insulation properties, and fatigue resistance. These characteristics make them particularly suitable for building structures with specific requirements, such as a high load-bearing capacity, enhanced corrosion resistance, or electrical insulation, and they have promising prospects for broader application [17,18].

Various models have been proposed by both codes and researchers to estimate the punching shear strength of concrete slabs reinforced with FRP. CSA, JSCE, and ACI have proposed punching shear strength prediction models considering the effect of loading area dimensions, effective depth, and concrete strength [19–21]. In addition, Deifalla [17] proposed a punching shear strength prediction model based on critical shear crack theory. These models have significantly advanced the study of FRP-reinforced concrete slabs. However, the complex structure of these slabs, coupled with the interplay of multiple parameters, makes it challenging to accurately predict their punching shear strength using existing mathematical models. The applicability of these models remains limited, as their coefficients of variation are large compared with experimental values, indicating a need for further refinement. In addition, Badra et al. [18] constructed a predictive model for the punching strength of FRP-reinforced concrete slabs using ANN and SVM. Although the accuracy of this model is better than that of the codes' and Deifalla's model, its coefficient of variation is large (0.25 for ANN and 0.2 for SVM), which makes it difficult to guarantee the reliability of the application and lacks explainability. Based on this, a predictive model for punching shear strength of FRP-reinforced concrete slabs with higher accuracy and explainability is required to be proposed.

In recent years, ensemble learning has gained popularity in structural engineering due to its superior performance compared with single learning methods and its enhanced explainability [22,23]. For instance, Khodadadi et al. [10] introduced a pioneering machine learning approach for predicting the compressive strength of Carbon-Fiber-Reinforced Polymer-Confined Concrete (CFRP-CC) specimens. Utilizing a Particle Swarm Optimization-Categorical Boosting (PSO-CatBoost) algorithm, their model, based on an extensive database of 916 experimental outcomes from 105 scholarly articles, demonstrated superior predictive performance compared with six contemporary machine learning models and six empirical models. Their approach uniquely incorporated SHapley Additive exPlanations (SHAP) and Permutation Feature Importance (PFI) methodologies to elucidate feature importance, establishing a new benchmark in CFRP-CC predictive modeling. Taffese et al. [24] collected 170 sets of data, used CatBoost to predict the ultimate moment of UHPC-strengthened beams, and conducted a feature importance study based on SHAP. Sapkota et al. [25] collected 226 data sets, used five ensemble learning models to predict the effective stiffness of rectangular reinforced concrete columns, and used SHAP to study the sensitivity between input and output parameters. Pal et al. [26] predicted a slump of fiber-reinforced concrete containing waste rubber and recycled aggregates based on 464 data sets using 12 models, including single and ensemble learning. The results showed that XGBoost performed best among all the models. Alyami et al. [27] predicted the compressive strength of concrete containing rice husk based on 348 data sets using three ensemble models and one single model. They carried out an interpretable study of the model using SHAP. The results showed that the ensemble model outperformed the single model, and SHAP explained the key indicators affecting the compressive strength.

This research explored the application of artificial intelligence algorithms in predicting the punching shear strength of concrete slabs reinforced with FRP materials. Advanced machine learning techniques were employed, building upon previous studies, with a particular emphasis on model interpretability. Methodologies such as SHAP and importance and sensitivity analyses were utilized to clarify the ML results. Specifically, 189 sets of experi-

mental data were collected, and six machine learning models, including linear regression, support vector machine, BP neural network, decision tree, random forest, and eXtreme Gradient Boosting, were constructed and evaluated based on goodness of fit, standard deviation, and root-mean-square error in order to select the most suitable model for this study. The optimal model obtained was compared with the models proposed by codes and the researchers. Finally, a model explainability study was conducted using SHapley Additive exPlanations (SHAP). The developed ML model was compared against existing formulas. Ultimately, the study identified the paramount variables influencing punching shear capacity and formulated enhanced predictive equations with improved accuracy.

The follow-up study consists of the following sections: Section 2 is the database construction, including statistical analysis and distribution of features. Section 3 is the model construction and evaluation, including the selection of models most applicable to this study, the evaluation of the codes and the researcher's model, and the interpretable study of the features. The last section is the conclusion, which evaluates the codes and the researcher's model and specifies the machine learning model that is most applicable to this study.

2. Database Construction

2.1. Parametric Study

Researchers have analyzed the parameters affecting the punching shear strength of FRP-reinforced concrete slabs through a number of experiments. Ahmad and Banthia et al. showed that the punching strength of FRP-reinforced concrete slabs decreased with increasing concrete strength. Bank and Ospina found that the punching strength increased with increasing FRP reinforcement ratio. Louka and El-gendy investigated the relationship between the modulus of elasticity and the punching strength, and the results showed that a positive relationship between the modulus of elasticity and the punching strength. Bouguerra's study showed that the punching strength increased with an increase in loading area dimensions. In addition, Bouguerra and Tom's study showed that the punching strength increased with an increase in effective depth.

2.2. Data Collection

In conjunction with the researcher's findings in Section 2.1 and taking into account the collectability of data, an aggregation of 189 experimental data sets was compiled from a thorough examination of 36 distinct research endeavors [12–16,28–57], including key input variables: loading area shape (A, B), loading area dimensions (b, c), effective depth (d), concrete strength (f'_c), FRP Young's modulus (E), FRP reinforcement ratio (ρ); and output variable: punching shear strength (V). The statistical analysis of the data is shown in Table 1. The distribution of the data is shown in Figure 1.

Table 1. Statistical characterization of features.

	A	B	b	c	d	f'_c	ρ	E
Unit	mm	mm	mm	mm	mm	MPa	%	GPa
skew	−0.43	−0.28	0.69	−0.97	0.94	3.43	1.74	1.31
max	3000	4000	635	300	284	179	3.76	230
min	300	300	25	25	45	22.2	0.18	28.4
mean	1960.90	1735.77	300.95	212.20	131.43	45.78	0.94	79.91

As can be seen in Figure 1, the distribution of the features is wide but uneven across the intervals.

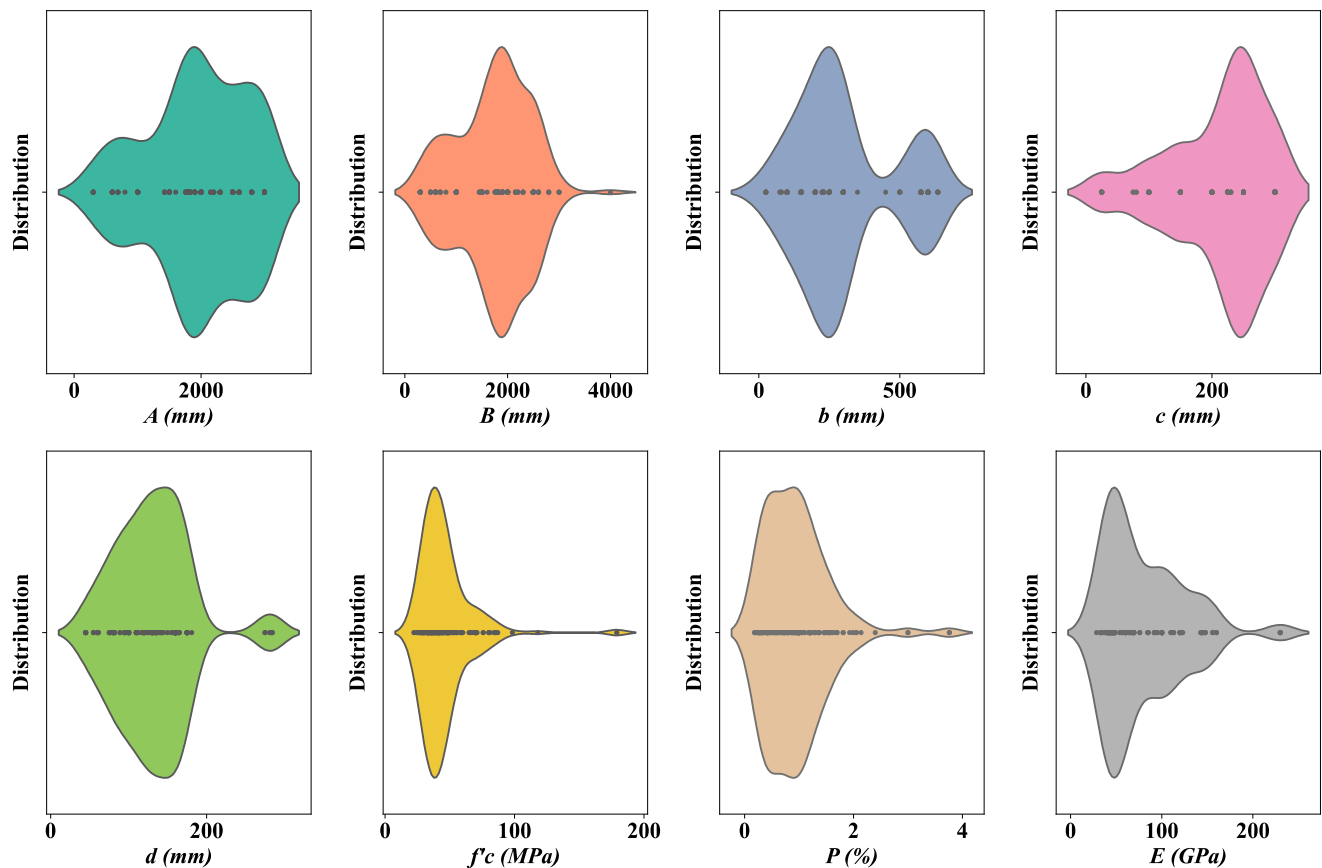


Figure 1. Distribution of parameters.

3. Model Construction and Evaluation

3.1. Modeling

The 189 sets of data collected in Section 2.2 were used for model construction, of which 80% of the data were used as the training set and 20% as the test set. Six machine learning algorithms, linear regression (LR), support vector machine (SVM), BP neural network (BPNN), decision tree (DT), random forest (RF), and eXtreme Gradient Boosting (XGBoost), were used to construct the machine learning model. The reason for choosing these models is that the above six models have been widely used, and LR, SVM, and BP are the early classical machine learning models. DT, RF, and XGBoost, on the other hand, are all tree-based models; XGBoost was proposed in 2016 and is widely used due to its excellent performance on different data sets. All the above models were run on Python. The hyperparameters for each machine learning were obtained using grid search and five-fold cross-validation. Grid search is a method to find the best model hyperparameters by traversing different parameter combinations. Five-fold cross-validation is a commonly used method for model evaluation, and its principle is shown in Figure 2. The data set is partitioned into five equally sized segments, where four portions serve as the training dataset, and the residual segment constitutes the test set. The iteration process is repeated five times to get the average of the five sets of model performance evaluation results, which can be more accurate in evaluating model performance.



Figure 2. Five-fold cross-validation.

3.2. Machine Learning Model Evaluation

The comparison of the predicted and experimental values of each machine learning model is shown in Figure 3. The performance evaluation metrics are shown in Table 2.

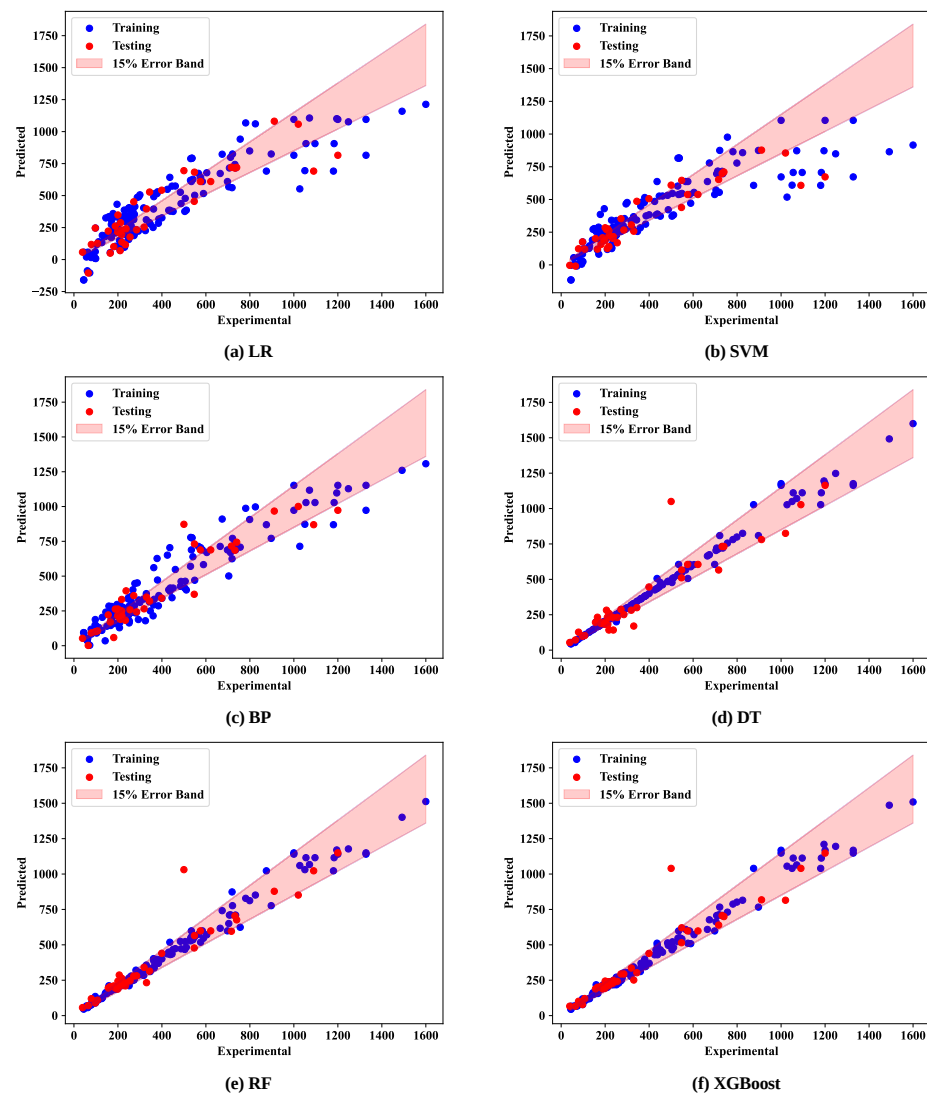


Figure 3. Predicted values of machine learning models.

Table 2. Performance of machine learning models.

	Training			Test		
	R ²	SD	RMSE	R ²	SD	RMSE
LR	0.81	91.34	143.76	0.8	90.81	131.81
SVM	0.75	132.25	166.53	0.79	105.94	134.81
BP	0.89	106.98	107.13	0.87	104.89	105.34
DT	0.98	35.15	37.27	0.86	93.1	109.34
RF	0.98	37.35	46.30	0.89	86.75	99.24
XGBoost	0.98	34.55	42.67	0.88	88.61	100.34

3.3. Codes' and Researcher's Model Evaluation

The existing models for calculating the punching shear strength of FRP-reinforced concrete slabs are shown in Table 3.

Figure 4 illustrates the comparative performance of the model developed within this research against existing models.

Table 3. Existing models.

Ref.	Formula	Symbols
JSCE	$V = \beta_d \beta_\rho \beta_r f_{Pcd} b_{0.5d} d$	$\beta_d = \left(\frac{1000}{d}\right)^{\frac{1}{4}} \leq 1.5 \beta_\rho = (100 \rho E / E_s)^{\frac{1}{3}} \leq 1.5 \beta_r$ $= 1 + \frac{1}{\left(1 + \frac{0.25 b_{0.5d}}{d}\right)} f_{Pcd} = 0.2 \sqrt{f'_c} \leq 1.2 b_{0.5d} = 4(c + d)$
CSA		$V = b_{0.5d} d \begin{cases} 0.028(1 + \frac{2}{\beta_c} (E \rho f'_c)^{\frac{1}{3}}) \\ 0.147 (E \rho f'_c)^{\frac{1}{3}} \left(0.19 + \alpha_s \frac{d}{b_{0.5d}}\right) \\ 0.056 (E \rho f'_c)^{\frac{1}{3}} \end{cases}$ $\beta_c = 1, \alpha_s = 4$ $b_{0.5d} = 4(c + d)$
ACI	$V = 0.8 \sqrt{f'_c} k d b_{0.5d}$	$k = \sqrt{2 \rho n + (\rho n)^2} - \rho n n = 4750 \sqrt{f'_c} b_{0.5d} = 4(c + d)$
ECSC	$\psi = 0.28 \frac{r_s}{d} \frac{f_f}{E} \left(\frac{V}{V_{flex}}\right)^{0.4}$	$V_{flex} = 2 \pi m_R \frac{r_s}{r_q - r_c}, m_R = d^2 \rho f_f \left(1 - \frac{\rho f_f}{2 f'_c \left(\frac{30}{f'_c}\right)^{\frac{1}{3}}}\right)$

As can be seen in Figure 4, the goodness of fit of both the codes and the researcher's model is below 0.8. In addition, the coefficient of variation between the calculated and experimental values of their models is more than 60%. However, the RF model constructed in this study has a very high goodness of fit and coefficients of variation within 20%, which is much better than existing models.

3.4. Model Explainability

From Section 3.2, it can be seen that RF performs the best among all machine learning models, and therefore, an explainable study of the model is performed using RF. The explainability of the model is performed through SHAP, a method for interpreting machine learning models that combines Shapley values from game theory and local interpretive techniques to provide global and local interpretations of model predictions. The global explainability of RF is shown in Figures 5 and 6, and the local explainability is shown in Figure 7 using the SHAP force plot. It is important to note that in these figures, yellow indicates a positive impact, and green indicates a negative impact.

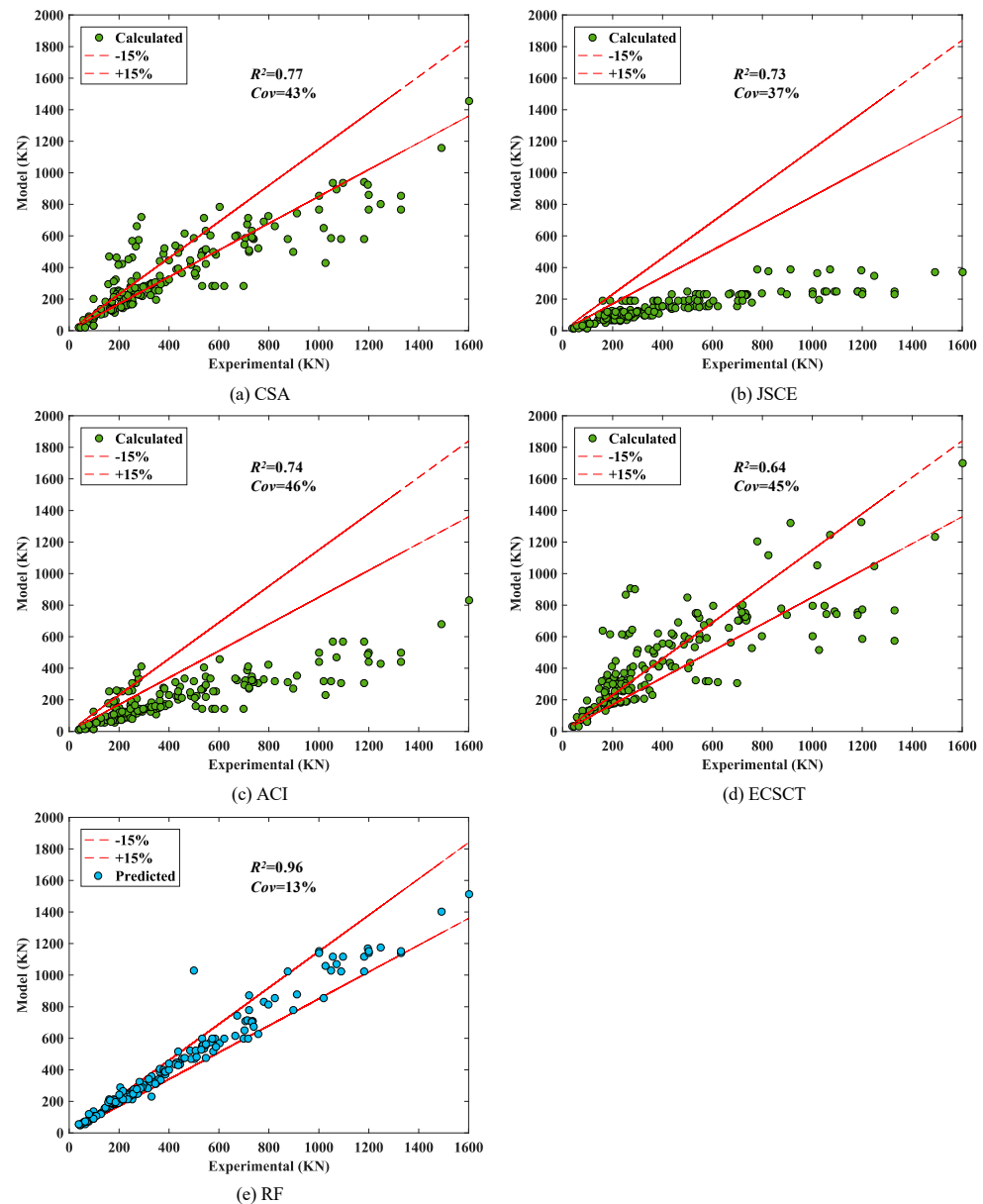


Figure 4. Model evaluation.

Figure 5 analyzes the importance of the parameters in terms of the entire data set. As can be seen in Figure 5, overall, effective depth (d) had the greatest impact on punching shear strength, while FRP Young's modulus (E) and loading area dimensions (c) had a lesser impact on punching shear strength. Figure 6, on the other hand, provides a sensitivity analysis of the parameters from the perspective of the entire dataset. Taking the first four parameters with higher importance as an example, it can be seen from Figure 6 that all four parameters with higher importance had a positive effect on the punching shear strength, i.e., the punching shear strength improved as d , b , B , and ρ increased.

Figures 5 and 6 analyze the importance and sensitivity of the parameters from a global point of view. However, the parameters' importance and sensitivity tended to differ for different samples. Figure 7 gives the predicted overlay for two different samples. The former sample is from Bouguerra [16], and the latter is from Hussein [57].

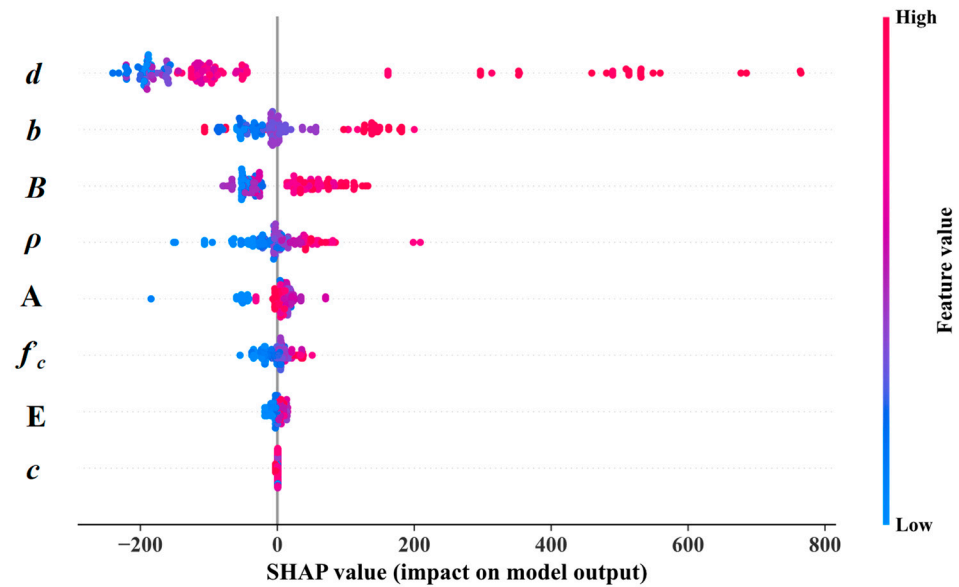


Figure 5. Importance study of parameters.

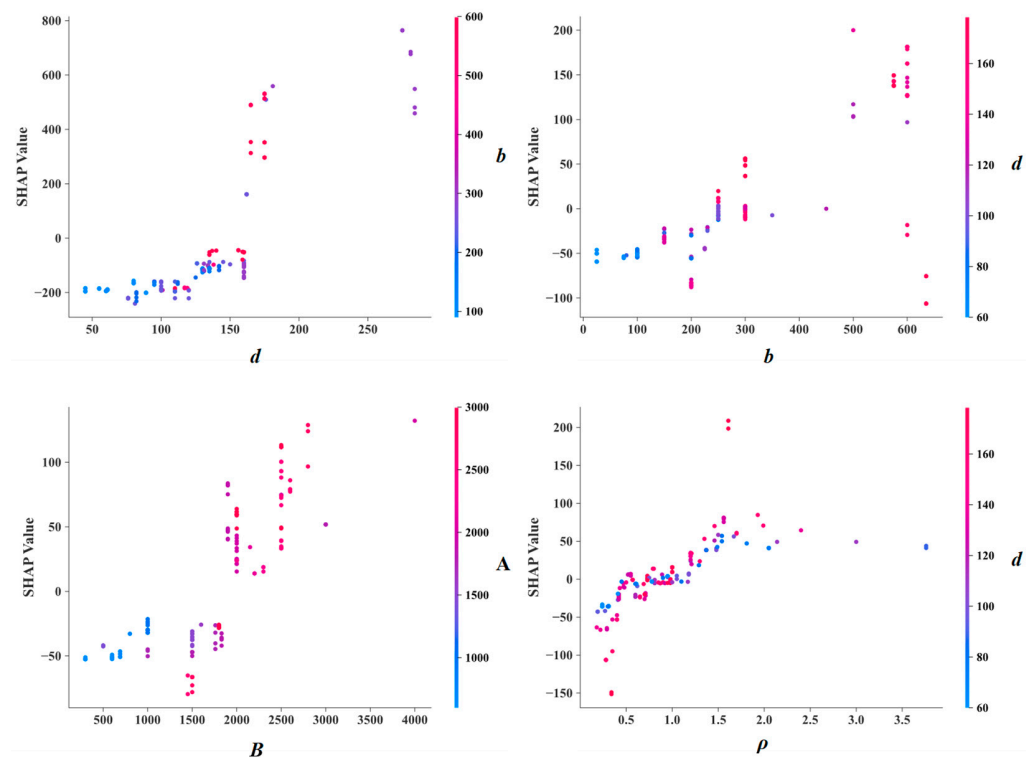


Figure 6. Sensitivity study of parameters.

Figure 7 demonstrates that the importance and sensitivity of features to punching shear strength are different in different samples. For example, for the two samples mentioned above, ρ was inversely related to punching shear strength in the first sample and the opposite in the second sample. Similarly, E had a positive effect on punching shear strength in the first sample but a negative effect in the second sample. It is important to note that even though the effects of the features were not exactly the same in both samples, RF predicted them both better. The experimental value of the first sample was 181 KN, and the model predicted 190.21 KN with an error of 5.08%. The second sample had an experimental value of 218 KN, and the model predicted 219.567 KN with an error of 0.72%.

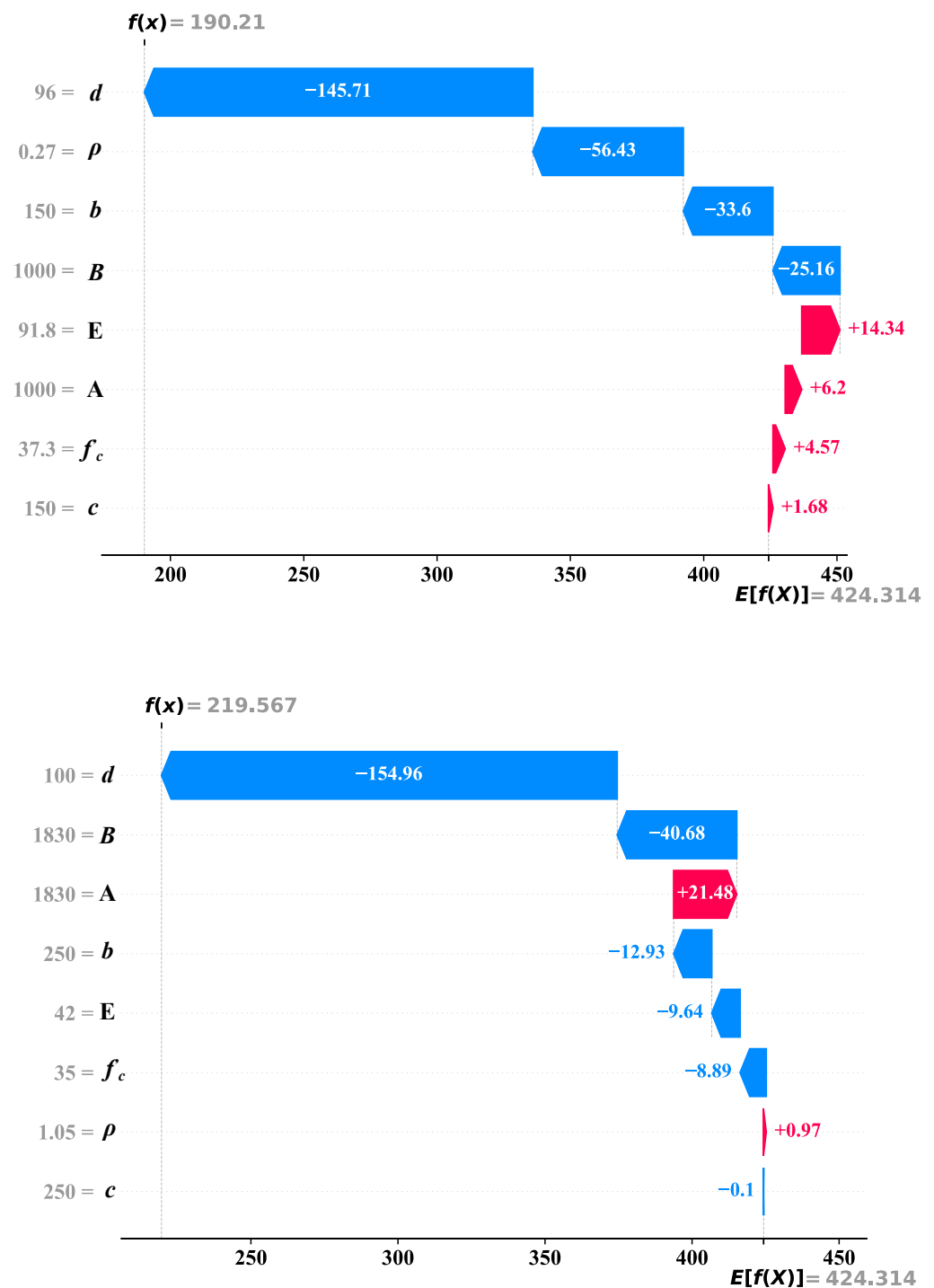


Figure 7. SHAP waterfall plot.

4. Conclusions

In this study, a punching shear strength prediction model for FRP-reinforced RC slabs was constructed using six machine learning algorithms, and an explainable study of the model was carried out using SHapley Additive exPlanations (SHAP). The following conclusions were obtained:

- (1) SVM performs worst among all models, and tree-based models (DT, RF, XGBoost) performed significantly better than LR, SVM, and BP on training and test sets. RF is the most suitable model for predicting the punching shear strength of FRP-reinforced

RC slabs. Among all the machine learning models, its performance was the most balanced on the training and test sets.

- (2) The existing codes and the models suggested by researchers for calculating the punching shear strength of FRP-reinforced concrete slabs had low goodness of fit (below 0.8) and coefficients of variation exceeding 60%, which are not conducive to practical engineering applications. The RF prediction model constructed in this study had a high goodness of fit (0.96) and a low coefficient of variation (13%).
- (3) The effective depth (d) of the FRP-reinforced concrete slabs was the most important and proportional to the punching shear strength. FRP Young's modulus (E) and loading area dimensions (c) had less influence on punching shear strength and had a more complex relationship with punching shear strength.

The conclusions on the significance and sensitivity of the features obtained in this study can be used as a reference for code revision and engineering design of FRP-reinforced concrete slabs. However, this study is data-driven and does not incorporate knowledge of the mechanics of FRP-reinforced concrete slabs, and further refinement of the model with professional knowledge is required in the future.

Author Contributions: Conceptualization, methodology, software, validation, writing—original draft, writing, W.X.; supervision, funding acquisition, writing, X.S. All authors have read and agreed to the published version of the manuscript.

Funding: This research received no external funding.

Data Availability Statement: The original contributions presented in the study are included in the article, further inquiries can be directed to the corresponding author.

Conflicts of Interest: The authors declare no conflict of interest.

Nomenclature

A and B	Slab dimensions
b and c	Loading area dimensions
d	Effective depth
f'_c	Concrete compressive strength
ρ	Flexure reinforcement ratio
E_f	Young's modulus of FRP longitudinal reinforcements
E_s	Young's modulus of steel reinforcements
$b_{0.5d}/d$	Ratio between failure surface and depth
r_s	The distance between the centerline of the loading area and the inflection point
V_{flex}	The two-way shear for flexure failure
r_q	The distance between the centerline of the loading area and the loading point
r_c	The distance between the centerline and the edge of the loading area
m_R	The resisting slab flexure strength
f_f	The stress of the FRP longitudinal reinforcements at failure due to concrete crushing

References

- Hafez, H.; Malchiodi, B.; Tošić, N.; Drewniok, M.; Purnell, P.; de la Fuente, A. Decarbonization potential of steel fibre-reinforced limestone calcined clay cement concrete one-way slabs. *Constr. Build. Mater.* **2024**, *435*, 136847. [\[CrossRef\]](#)
- Zhao, X.; Sun, J.; Zhao, H.; Jia, Y.; Fang, H.; Wang, J.; Yao, Y.; Wei, D. Experimental and mesoscopic modeling numerical researches on steel fiber reinforced concrete slabs under contact explosion. In *Structures*; Elsevier: Amsterdam, The Netherlands, 2024; Volume 61.
- Chen, Z.; Yu, J.; Nong, Y.; Yang, Y.; Zhang, H.; Tang, Y. Beyond time: Enhancing corrosion resistance of geopolymer concrete and BFRP bars in seawater. *Compos. Struct.* **2023**, *322*, 117439. [\[CrossRef\]](#)
- Tang, Y.; Wang, Y.; Wu, D.; Chen, M.; Pang, L.; Sun, J.; Feng, W.; Wang, X. Exploring temperature-resilient recycled aggregate concrete with waste rubber: An experimental and multi-objective optimization analysis. *Rev. Adv. Mater. Sci.* **2023**, *62*, 20230347. [\[CrossRef\]](#)
- Al-Darzi, S.Y. The effect of using shredded plastic on the behavior of reinforced concrete slab. *Case Stud. Constr. Mater.* **2022**, *17*, e01681. [\[CrossRef\]](#)

6. Djamai, Z.I.; Le Nguyen, K.; Larbi, A.S.; Salvatore, F.; Cai, G. PCM-modified textile-reinforced concrete slab: A multiscale and multiphysics investigation. *Constr. Build. Mater.* **2021**, *293*, 123483. [\[CrossRef\]](#)
7. Zakaria, D.; Deifalla, A.; Mousa, E.; Elrahman, A.A. Two-way shear full behavior of reinforced concrete flat slabs under membrane tensile forces. *Case Stud. Constr. Mater.* **2023**, *18*, e01912. [\[CrossRef\]](#)
8. Hassanli, R.; Youssf, O.; El-Naqeeb, M.H.; Yekrangnia, M.; Elchalakani, M.; Ghanbari-Ghazijahani, T.; Bazli, M. Investigation of punching shear performance in concrete slabs reinforced with GFRP and synthetic fibers: An experimental study. *Eng. Struct.* **2024**, *311*, 118215. [\[CrossRef\]](#)
9. Yan, J.; Su, J.; Xu, J.; Hua, K.; Lin, L.; Yu, Y. Explainable machine learning models for punching shear capacity of FRP bar reinforced concrete flat slab without shear reinforcement. *Case Stud. Constr. Mater.* **2024**, *20*, e03162. [\[CrossRef\]](#)
10. Han, T.; Liang, S.; Zhu, X.; Wang, W.; Yang, J. An investigation of the flexural behaviour of large-span prestressed and steel-reinforced concrete slabs. *Sci. Rep.* **2023**, *13*, 10710. [\[CrossRef\]](#) [\[PubMed\]](#)
11. Ors, D.M.; Ramadan, M.; Maree, A.M.F.; Zaher, A.H.; Afifi, A.; Ebid, A.M. Machine learning base models to predict the punching shear capacity of posttensioned UHPC flat slabs. *Sci. Rep.* **2024**, *14*, 3969. [\[CrossRef\]](#) [\[PubMed\]](#)
12. Khodadadi, N.; Roghani, H.; Harati, E.; Mirdarsoltany, M.; De Caso, F.; Nanni, A. Fiber-reinforced polymer (FRP) in concrete: A comprehensive survey. *Constr. Build. Mater.* **2024**, *432*, 136634. [\[CrossRef\]](#)
13. Banthia, N.; Al-Asaly, M.; Ma, S. Behavior of concrete slabs reinforced with fiber-reinforced plastic grid. *J. Mater. Civ. Eng.* **1995**, *7*, 252–257. [\[CrossRef\]](#)
14. Bank, L.C. Punching shear behavior of pultruded FRP grating reinforced concrete slabs. In *Non-Metallic (FRP) Reinforcement for Concrete Structures: Proceedings of the Second International RILEM Symposium*; CRC Press: Boca Raton, FL, USA, 1995; Volume 29.
15. Louka, H.J. Punching Behaviour of a Hybrid Reinforced Concrete Bridge Deck. Master's Thesis, University Manitoba, Winnipeg, MB, Canada, 1999.
16. Bouguerra, K.; Ahmed, E.; El-Gamal, S.; Benmokrane, B. Testing of full-scale concrete bridge deck slabs reinforced with fiber-reinforced polymer (FRP) bars. *Constr. Build. Mater.* **2011**, *25*, 3956–3965. [\[CrossRef\]](#)
17. Deifalla, A. Punching shear strength and deformation for FRP-reinforced concrete slabs without shear reinforcements. *Case Stud. Constr. Mater.* **2022**, *16*, e00925. [\[CrossRef\]](#)
18. Alkhatib, S.; Deifalla, A. Punching shear strength of FRP-reinforced concrete slabs without shear reinforcements: A reliability assessment. *Polymers* **2022**, *14*, 1743. [\[CrossRef\]](#)
19. CSA. *Design and Construction of Building Structures with Fiber Reinforced Polymers (CAN/CSA S806-12)*; CSA: Rexdale, ON, Canada, 2012.
20. JSCE. *Recommendation for Design and Construction of Concrete Structures Using Continuous Fiber Reinforcing Materials*; Concrete Engineering Series 23; Machida, A., Ed.; JSCE: Tokyo, Japan, 1997; p. 325.
21. ACI-440; Guide for the Design and Construction of Concrete Reinforced with FRP Bars (ACI 440.1R-15). ACI: Farmington Hills, MI, USA, 2015.
22. Dabiri, H.; Faramarzi, A.; Dall'asta, A.; Tondi, E.; Micozzi, F. A machine learning-based analysis for predicting fragility curve parameters of buildings. *J. Build. Eng.* **2022**, *62*, 105367. [\[CrossRef\]](#)
23. Cheng, M.C.; Bonopera, M.; Leu, L.J. Applying random forest algorithm for highway bridge-type prediction in areas with a high seismic risk. *J. Chin. Inst. Eng.* **2024**, *47*, 597–610. [\[CrossRef\]](#)
24. Taffese, W.Z.; Zhu, Y.; Chen, G. Ensemble-learning model based ultimate moment prediction of reinforced concrete members strengthened by UHPC. *Eng. Struct.* **2024**, *305*, 117705. [\[CrossRef\]](#)
25. Sapkota, S.C.; Das, S.; Saha, P. Optimized machine learning models for prediction of effective stiffness of rectangular reinforced concrete column sections. In *Structures*; Elsevier: Amsterdam, The Netherlands, 2024; Volume 62.
26. Pal, A.; Ahmed, K.S.; Mangalathu, S. Data-driven machine learning approaches for predicting slump of fiber-reinforced concrete containing waste rubber and recycled aggregate. *Constr. Build. Mater.* **2024**, *417*, 135369. [\[CrossRef\]](#)
27. Alyami, M.; Nassar, R.-U.; Khan, M.; Hammad, A.W.; Alabduljabbar, H.; Nawaz, R.; Fawad, M.; Gamil, Y. Estimating compressive strength of concrete containing rice husk ash using interpretable machine learning-based models. *Case Stud. Constr. Mater.* **2024**, *20*, e02901. [\[CrossRef\]](#)
28. Węglarczyk, S. Kernel density estimation and its application. In *ITM Web of Conferences*; EDP Sciences: Les Ulis, France, 2018; Volume 23.
29. Wakjira, T.G.; Ebead, U.; Alam, M.S. Machine learning-based shear capacity prediction and reliability analysis of shear-critical RC beams strengthened with inorganic composites. *Case Stud. Constr. Mater.* **2022**, *16*, e01008. [\[CrossRef\]](#)
30. Rahman, A.H.; Kingsley, C.Y.; Kobayashi, K. Service and ultimate load behavior of bridge deck reinforced with carbon FRP grid. *J. Compos. Constr.* **2000**, *4*, 16–23. [\[CrossRef\]](#)
31. Hassan, T.; Abdelrahman, A.; Tadros, G.; Rizkalla, S. Fibre reinforced polymer reinforcing bars for bridge decks. *Can. J. Civ. Eng.* **2000**, *27*, 839–849. [\[CrossRef\]](#)
32. Zaghloul, A. Punching Shear Strength of Interior and Edge Column-Slab Connections in CFRP Reinforced Flat Plate Structures Transferring Shear and Moment. Ph.D. Thesis, Carleton University, Ottawa, ON, Canada, 2007.
33. El-Ghandour, A.W.; Pilakoutas, K.; Waldron, P. Punching shear behavior of fiber reinforced polymers reinforced concrete flat slabs: Experimental study. *J. Compos. Constr.* **2003**, *7*, 258–265. [\[CrossRef\]](#)

34. Ospina, C.E.; Alexander, S.D.; Cheng, J.R. Punching of two-way concrete slabs with fiber-reinforced polymer reinforcing bars or grids. *Struct. J.* **2003**, *100*, 589–598.
35. Zaghoul, A.E.; Razaqpur, A.G. Punching shear behavior of CFRP reinforced concrete flat plates. In Proceedings of the International Conference on Composites in Construction, Cosenza, Italy, 16–19 September 2003.
36. Hussein, A.; Rashid, I.; Benmokrane, B. Two-way concrete slabs reinforced with GFRP bars. In Proceedings of the 4th International Conference on Advanced Composite Materials in Bridges and Structures, Calgary, AB, Canada, 20–23 July 2004.
37. Jacobson, D.A.; Bank, L.C.; Oliva, M.G.; Russell, J.S. Punching shear capacity of double layer FRP grid reinforced slabs. In Proceedings of the 7th International Conference on Fiber Reinforced Plastics for Reinforced Concrete Structures, Kansas City, MO, USA, 1 October 2005; ACI, Specs. Publication: Farmington Hills, MI, USA, 2005. SP. 230–49. pp. 857–876.
38. El-Gamal, S.; El-Salakawy, E.; Benmokrane, B. Behavior of concrete bridge deck slabs reinforced with fiber-reinforced polymer bars under concentrated loads. *ACI Struct. J.* **2005**, *102*, 727.
39. Zhang, Q.; Marzouk, H.; Hussein, A. A preliminary study of high-strength concrete two-way slabs reinforced with GFRP bars. In Proceedings of the 33rd CSCE Annual Conference: General Conference and International History Symposium, Toronto, ON, Canada, 2–4 June 2005.
40. El-Tom, E. Behavior of Two-Way Slabs Reinforced with GFRP Bars. Ph.D. Thesis, Memorial University of Newfoundland, St. John's, NL, Canada, 2007.
41. Zaghoul, E.E.R.; Mahmoud, Z.I.; Salama, T.A. Punching behavior and strength of two-way concrete slabs reinforced with glass fiber reinforced polymer (GFRP) rebars. In Proceedings of the Structural Composites for Infrastructure Applications, Hurghada, Egypt, 23–25 May 2008; pp. 1–16.
42. El-Gamal, S.; El-Salakawy, E.; Benmokrane, B. Influence of reinforcement on the behavior of concrete bridge deck slabs reinforced with FRP bars. *J. Compos. Constr.* **2007**, *11*, 449–458. [[CrossRef](#)]
43. Lee, J.H.; Yoon, Y.S.; Cook, W.D.; Mitchell, D. Improving punching shear behavior of glass fiber-reinforced polymer reinforced slabs. *ACI Struct. J.* **2009**, *106*, 427.
44. Zhu, H.; Zhang, Y.; Gao, D.; Xiao, Z. Deformation behavior of concrete two-way slabs reinforced with BFRP bars subjected to eccentric loading. In *Advances in FRP Composites in Civil Engineering: Proceedings of the 5th International Conference on FRP Composites in Civil Engineering (CICE 2010), Beijing, China, 27–29 September 2010*; Springer: Berlin/Heidelberg, Germany, 2011.
45. Min, K.H.; Yang, J.M.; Yoo, D.Y.; Yoon, Y.S. Flexural and punching performances of FRP and fiber reinforced concrete on impact loading. In *Advances in FRP Composites in Civil Engineering: Proceedings of the 5th International Conference on FRP Composites in Civil Engineering (CICE 2010), Beijing, China, 27–29 September 2010*; Springer: Berlin/Heidelberg, Germany, 2011.
46. Zhu, H.T.; Wang, Y.Z.; Li, J.Z. Plastic analysis on punching shear capacity of two-way BFRP rebar reinforced concrete slabs under central concentrated load. *J. Zhengzhou Univ.* **2012**, *33*. [[CrossRef](#)]
47. Nguyen-Minh, L.; Rovňák, M. Punching shear resistance of interior GFRP reinforced slab-column connections. *J. Compos. Constr.* **2013**, *17*, 2–13. [[CrossRef](#)]
48. Hassan, M.; Ahmed, E.; Benmokrane, B. Punching-shear strength of normal and high-strength two-way concrete slabs reinforced with GFRP bars. *J. Compos. Constr.* **2013**, *17*, 04013003. [[CrossRef](#)]
49. El-gendy, M.; El-Salakawy, E. Punching shear behaviour of GFRP-RC slab-column edge connections. In Proceedings of the Seventh International Conference on FRP Composites in Civil Engineering, Vancouver, BC, Canada, 20–22 August 2014; pp. 1–6.
50. Tharmarajah, G.; Taylor, S.E.; Cleland, D.J.; Robinson, D. Corrosion-resistant FRP reinforcement for bridge deck slabs. In Proceedings of the Institution of Civil Engineers, Bridge Engineering 168 September 2015 Issue BE3; Thomas Telford Ltd.: London, UK, 2015; pp. 208–217.
51. Mostafa, A. Punching Shear Behavior of GFRP-RC Slab-Column EdgeConnections with High Strength Concrete and Shear Reinforcement. Master's Thesis, Manitoba University, Winnipeg, MB, Canada, 2016. Volume 51.
52. Fareed, E.; Ahmed, E.A.; Benmokrane, B. Experimental testing of concrete bridge-deck slabs reinforced with Basalt-FRP reinforcing bars under concentrated loads. *J. Bridge Eng.* **2016**, *21*, 04016029.
53. Gouda, A.; El-Salakawy, E. Punching shear strength of GFRP-RC interior slab-column connections subjected to moment transfer. *J. Compos. Constr.* **2016**, *20*, 04015037. [[CrossRef](#)]
54. Oskouei, A.V.; Kivi, M.P.; Araghi, H.; Bazli, M. Experimental study of the punching behavior of GFRP reinforced lightweight concrete footing. *Mater. Struct.* **2017**, *50*, 256. [[CrossRef](#)]
55. Hussein, A.H.; El-Salakawy, E.F. Punching shear behavior of glass fiber-reinforced polymer-reinforced concrete slab-column interior connections. *Acids Struct. J.* **2020**, *115*. [[CrossRef](#)]
56. Hemzah, S.A.; Al-Obaidi, S.; Salim, T. Punching shear model for normal and high-strength concrete slabs reinforced with CFRP or steel bars. *Jordan J. Civ. Eng.* **2019**, *13*, 1–19.
57. Huang, Z.; Zhao, Y.; Zhang, J.; Wu, Y. Punching shear behavior of concrete slabs reinforced with CFRP grids. *Structures* **2020**, *26*, 617–625. [[CrossRef](#)]

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