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Prediction and interpretation of shear strength in rectangular reinforced concrete walls under axial load using GP-optimized XGBoost

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Abstract: This study investigates the applicability of machine learning models for predicting the shear strength of rectangular reinforced concrete (RC) walls subjected to axial load. A comprehensive experimental database consisting of 456 wall specimens was compiled, including geometric parameters, reinforcement ratios, material properties, and axial load effects. Four supervised learning models Decision Tree (DT), Random Forest (RF), CatBoost, and Extreme Gradient Boosting (XGBoost) were first evaluated using default hyperparameters. Although RF achieved the best testing performance ($R^2 = 0.910$, RMSE = 137.40 kN), XGBoost showed greater consistency between validation and testing results ($R^2 = 0.884$ – 0.900 ; RMSE = 136.03–141.31 kN). Considering both predictive accuracy and generalization stability, XGBoost was selected for further optimization using Gaussian Process (GP)-based Bayesian optimization. The optimized model achieved improved accuracy ($R^2 = 0.914$, RMSE = 131.11 kN), indicating enhanced generalization capability. Comparison with conventional design provisions such as ACI 318-19 shows that the machine learning model provides lower mean error and reduced dispersion, particularly for walls with large geometric aspect ratios. SHAP analysis reveals that geometric parameters (wall length l_w , height h_w , and thickness t_w), reinforcement ratios (horizontal ρ_h and longitudinal ρ_L), and axial load P are dominant factors governing shear strength. Notably, the XGBoost model captures the combined influence of longitudinal and transverse reinforcement, whereas ACI 318-19 primarily considers horizontal reinforcement through the shear component V_s and does not explicitly account for longitudinal reinforcement contribution. The results highlight the superiority of machine learning in modeling complex nonlinear interactions among design parameters and demonstrate the strong potential of GP-optimized XGBoost for structural design and assessment of RC walls.

Keywords: RC walls, shear strength, XGBoost, Gaussian Process, SHAP.

1. Introduction

Reinforced concrete (RC) walls are essential structural components in buildings, functioning not only as primary load-bearing members but also as key elements that transfer vertical and lateral actions to the foundation system. Due to the complementary mechanical properties of concrete and steel reinforcement, the high compressive resistance of concrete and the strong tensile capacity of steel, RC walls can provide high strength, stiffness, and overall stability [1], [2]. In low-rise structures, RC walls are commonly adopted as conventional load-bearing walls. In mid and high rise buildings, their role expands as shear walls, where RC wall frame systems effectively reduce story drift and enhance global stability under wind and earthquake demands [3].

Despite their widespread use, accurate prediction of RC wall shear capacity remains challenging because wall behavior is governed by nonlinear material response, cracking evolution, and complex interaction among axial load, flexure, and shear. Classical experimental and analytical studies have shown that failure modes and shear-transfer mechanisms are strongly affected by wall geometry, reinforcement detailing, and boundary conditions. For example, the seminal work by Paulay and Priestley [3] emphasized the interaction between flexural and diagonal cracking mechanisms in seismic wall behavior. Lefas, Kotsovos, and Ambraseys [4] reported that slenderness and reinforcement configuration substantially alter the shear response and governing failure mode, especially when wall aspect ratio increases. Thomsen and Wallace [5] further clarified the relationship between wall shape, loading patterns, and failure mechanisms, supporting improvements in nonlinear modeling approaches. In addition, Bazant and Planas [6] developed fracture-related concepts for quasi-brittle materials that underpin improved prediction of shear cracking and energy dissipation in concrete. From a practical standpoint, RC walls are expected to maintain stable performance in

extreme loading conditions, where stiffness and ductility demands are critical for global system stability [5].

Current design standards, including ACI 318-19 [7], Eurocode 2 (EN 1992-1-1:2004) [8], and TCVN 5574:2018 [9], provide simplified formulations and detailing provisions for the design and assessment of RC walls. These code-based approaches are widely used to estimate the shear strength of RC walls based on key material and geometric parameters. Although these code-based methods are convenient for design, they often rely on simplified assumptions (e.g., linearized stress distribution or decomposed resistance components) and may not fully capture the nonlinear coupled influence of geometry, axial load level, and reinforcement interactions, especially for walls with large geometric ratios or under demanding load combinations [1]. Consequently, researchers have explored more advanced approaches (e.g., softened strut-and-tie concepts and nonlinear FE analysis), but these methods can be computationally expensive and not straightforward for routine design implementation.

In the last decade, artificial intelligence and machine learning (ML) have emerged as promising alternatives for modeling complex nonlinear structural behavior. ML models can learn direct mappings from input design variables to response quantities without assuming an explicit functional form. For RC walls, a growing body of studies has demonstrated the feasibility of ML for shear strength prediction and failure-mode classification. Chen et al. and Nguyen et al. [10], [11] used artificial neural networks for shear-related prediction tasks in short wall systems. Feng et al. [12] developed an XGBoost-based model for predicting shear capacity of squat RC walls and reported high predictive accuracy. Chou et al. [13] compared multiple ML techniques across experimental datasets and highlighted the robustness of boosting-based models. For interpretability and explicit formula discovery, Gondia et al. [14] employed genetic programming

to derive usable expressions for design practice. Hybrid optimization strategies have also been explored; Keshtegar et al. [15] combined ML with meta-heuristic optimization to enhance prediction performance. In parallel, classification-oriented studies such as Mangalathu et al. and Zhang et al. [16], [17] demonstrated strong performance of ensemble/boosting methods for identifying wall

failure modes. Alshboul et al. developed a gene expression programming-based regression model for predicting the shear strength of slender RC beams without stirrups [18]. And some research on applying machine learning to analyze the performance of shear wall structures, and other structures such as flat floors, steel pipe columns, high beams, etc. [19 - 24]

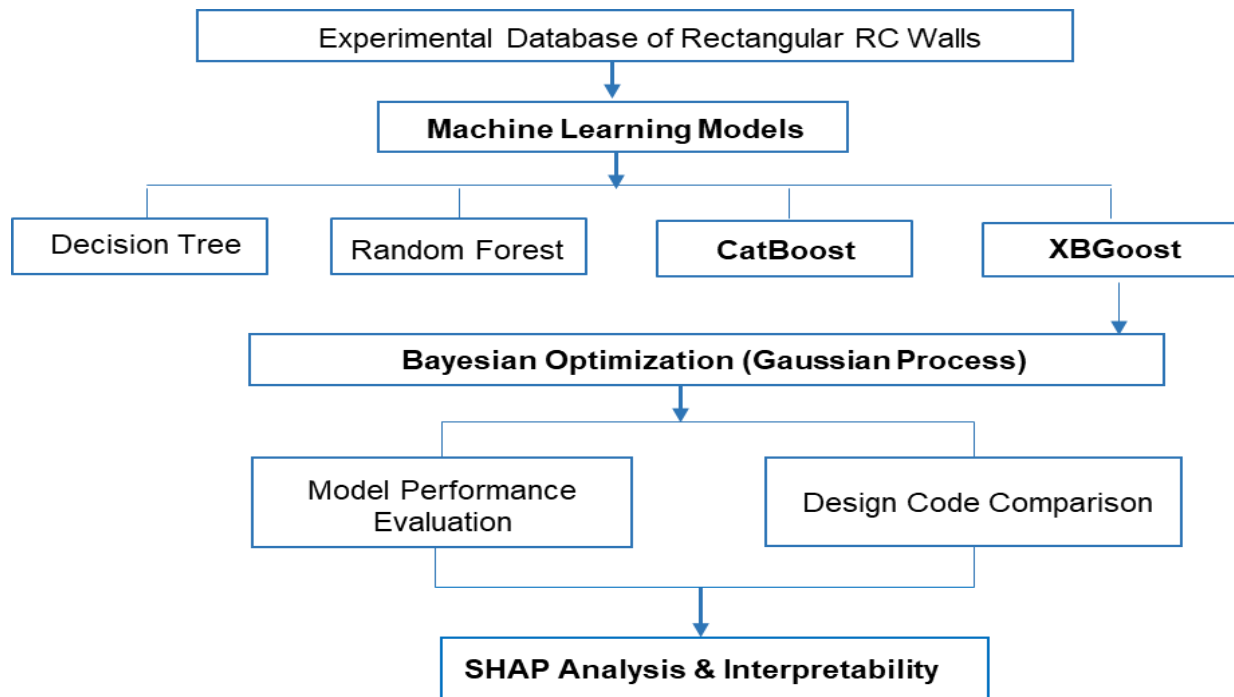


Fig. 1. Outlines of the current research

Despite these advances, several limitations remain before ML models can be considered design-ready tools for RC walls. (i) Many studies focus on specific wall categories (e.g., squat walls or flanged walls) and may not generalize to rectangular wall datasets under varying axial load conditions [10], [12]. (ii) Data heterogeneity and limited benchmark frameworks complicate fair comparison between ML models and design standards such as ACI 318-19 [7]. (iii) More importantly, several high-performing ML models remain “black-box” in engineering practice; thus, robust interpretability and mechanics-consistent explanations are required to enhance trust and facilitate code calibration [16], [17]. (iv) Finally, hyperparameter tuning strategy strongly influences boosting model performance, yet systematic optimization (e.g., Bayesian optimization with

Gaussian Process) is not consistently integrated with interpretability and code benchmarking in RC wall studies.

Motivated by the identified research gaps, this study develops a comprehensive machine learning (ML) framework for predicting the shear strength of rectangular reinforced concrete (RC) walls subjected to axial load, based on a curated and standardized experimental database. The proposed framework integrates three core components: (1) a systematic comparison of ensemble-based learning models to identify the most suitable predictive algorithm; (2) Bayesian hyperparameter optimization using a Gaussian Process to enhance model robustness and generalization capability; and (3) SHAP-based interpretability analysis to quantify the relative influence of key design variables and to elucidate

nonlinear interactions among geometric parameters, reinforcement characteristics, and axial load effects.

Furthermore, the performance of the optimized ML model is benchmarked against established design provisions and analytical models, including ACI 318-19 (Building Code Requirements for Structural Concrete) [7]; ASCE/SEI 43-05 [25] and the Wood (1990) [26] model, in order to assess its practical applicability within structural design practice.

The overall workflow and methodological structure of the present research are illustrated in Fig.1 (Outlines of the Current Research).

2. Data Description

A comprehensive and reliable experimental database forms the foundation for developing robust machine learning (ML) models for structural prediction. In this study, a dataset consisting of 456 rectangular reinforced concrete (RC) wall specimens subjected to combined lateral shear and axial compression was compiled from previously published experimental investigations, including S.L. Wood [26], Massone and Melo [27], Ning and Li [28], C. Sittipunt et al. [29], Park et al. [30], Teng and Chandra [31], Massone et al. [32], Wang et al. [33], Vallenat et al. [34], Hirosawa et

al. [35], Barda et al. [36], and Paulay et al. [37]. These specimens represent a broad spectrum of geometric configurations, reinforcement detailing, material strengths, and axial load levels, providing a sufficiently diverse parameter space for training and validating predictive models.

A typical experimental configuration of RC wall testing included in the database is illustrated in Fig. 2. As shown, the input variables can be categorized into four primary groups: (i) geometric parameters, (ii) material properties, (iii) reinforcement characteristics, and (iv) applied axial load. The geometric parameters include wall height h_w , wall length l_w , and wall thickness t_w . The material property is represented by the concrete compressive strength f_{ck} . Reinforcement variables consist of the web longitudinal reinforcement ratio ρ_v and its yield strength f_{yv} , the web horizontal reinforcement ratio ρ_h and its yield strength f_{yh} , and the boundary longitudinal reinforcement ratio ρ_L with its yield strength f_{yL} . The axial load applied to the wall is denoted by P . The output variable of interest is the experimentally measured shear strength V_{exp} . The detailed statistical characteristics of all variables are summarized in Table 1.

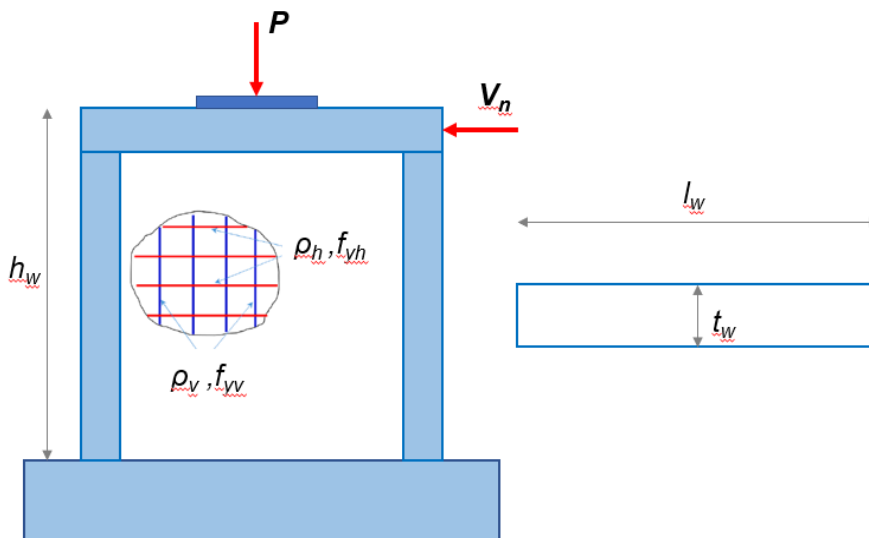


Fig. 2. The image illustrates a typical experimental configuration for a reinforced concrete wall

The statistical distributions of the input and output variables are presented in Fig. 3. The

dataset exhibits substantial variability across geometric dimensions. Wall height ranges from

150 mm to 6401 mm, and wall length from 254 mm to 3960 mm, with a majority of specimens concentrated between approximately 500 mm and 2500 mm. Wall thickness varies between 30 mm and 360 mm, typically falling within 80–200 mm. The concrete compressive strength f_{ck} ranges from 12.3 MPa to 130.8 MPa, covering both normal-strength and high-strength concrete. Reinforcement ratios ρ_v and ρ_h are predominantly below 2%, consistent with common engineering practice, while steel yield strengths range from approximately 200 MPa to 980 MPa, reflecting the use of different reinforcement grades. The applied axial load P ranges from 0 to 2429 kN, with most specimens subjected to compression levels below 800 kN. The experimental shear strength V_{exp} ranges from 15.35 kN to 3136 kN and shows a right-skewed distribution, highlighting the nonlinear nature of shear resistance and its strong dependence on geometry and boundary conditions. The linear correlation matrix shown in Fig. 4 provides insight into the relationships among variables. The experimental shear strength V_{exp} demonstrates strong positive correlations with wall length ($r=0.73$) and wall thickness ($r=0.71$), and moderate correlations with axial load ($r=0.36$)

and horizontal reinforcement yield strength ($r=0.36$). These trends are consistent with structural mechanics principles, as larger geometric dimensions and increased axial compression generally enhance shear capacity. In contrast, reinforcement ratios (ρ_v, ρ_h, ρ_L) exhibit relatively weak to moderate linear correlations with V_{exp} , suggesting that their effects may involve nonlinear interactions or multivariate dependencies.

Interdependencies among certain input variables are also observed, such as between wall thickness and wall length, and between longitudinal and horizontal reinforcement yield strengths. These relationships reflect design consistency within experimental programs and highlight the necessity of multivariate modeling approaches. Overall, the correlation analysis indicates that while geometric parameters and axial load have clear linear associations with shear strength, the influence of material and reinforcement variables may be more complex. This observation supports the application of ML techniques capable of capturing nonlinear and high-dimensional interactions beyond traditional linear formulations.

Table 1. Features of shear strength database for RC walls

Variable	Unit	Minimum	Maximum	Mean	Standard Deviation	Variable Type
h_w	mm	150.00	6401.00	1726.99	1255.63	input
l_w	mm	254.00	3960.00	1301.96	661.70	input
t_w	mm	30.00	360.00	125.38	71.57	input
f_{ck}	MPa	12.30	130.80	32.55	15.89	input
ρ_v	%	0.00	6.24	0.94	0.92	input
f_{yv}	MPa	0.00	770.00	415.02	115.43	input
ρ_h	%	0.00	3.67	0.64	0.536	input
f_{yh}	MPa	0.00	770.00	416.91	116.68	input
ρ_L	%	0.27	10.58	3.91	2.155	input
f_{yL}	MPa	222.10	980.00	519.663	154.25	input
P	kN	0.00	2429.00	245.796	393.44	input
V_{exp}	kN	15.35	3136.00	445.145	457.011	output

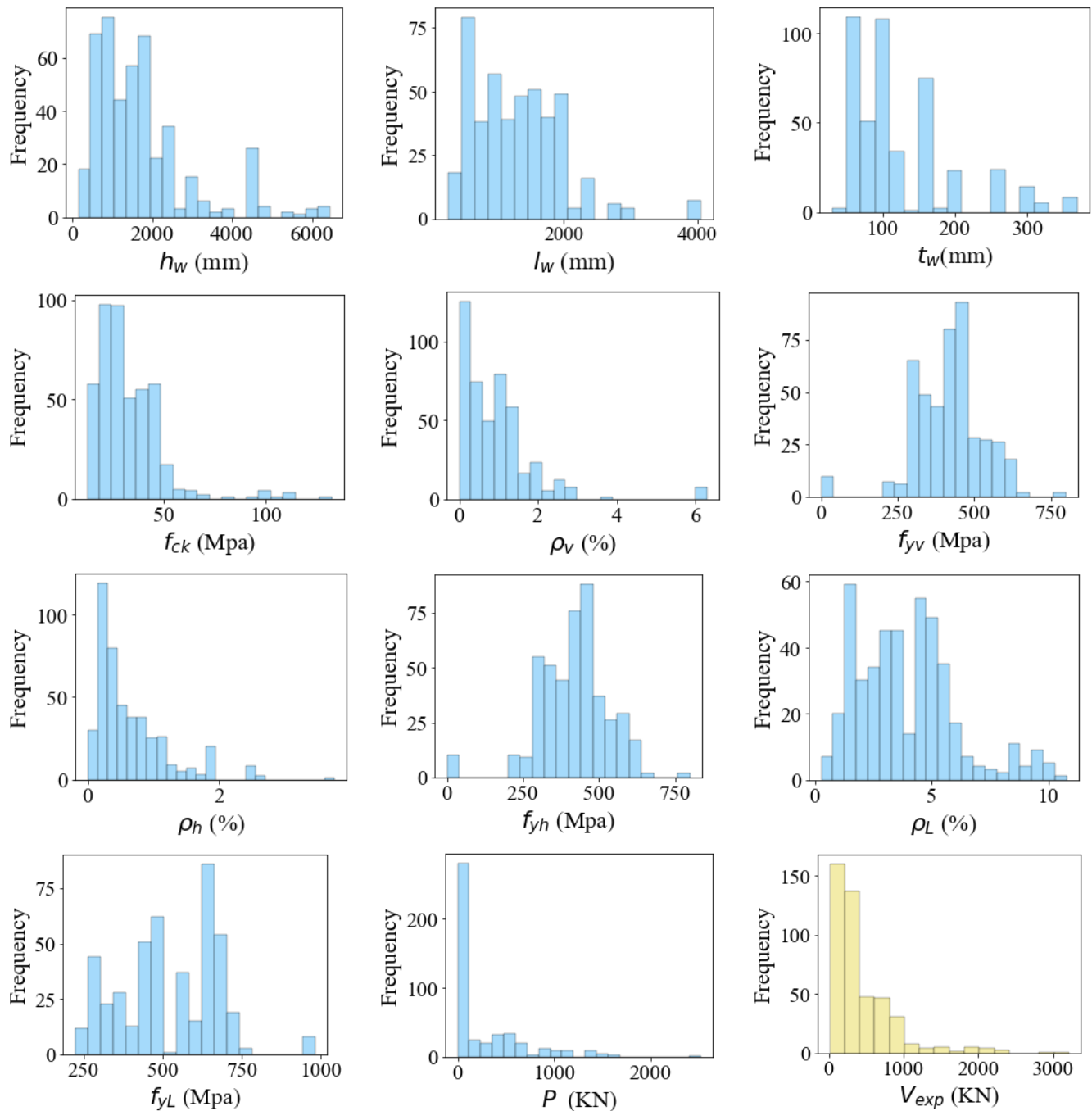


Fig. 3. Distribution graph of input and output parameters

In summary, the assembled database spans a wide and representative range of structural parameters, providing a reliable basis for developing and validating ML-based predictive models for the shear strength of rectangular RC walls under axial load.

3. Methodology

This study proposes a machine learning (ML) framework to predict the shear strength of rectangular reinforced concrete (RC) walls

subjected to axial load. Based on the curated experimental database, four tree-based algorithms were selected for systematic evaluation: Decision Tree (DT), Random Forest (RF), CatBoost, and XGBoost. These models have demonstrated strong performance in structural engineering prediction problems and nonlinear regression tasks.

Initially, the four models were trained and tested using default hyperparameters to establish

a consistent performance baseline. Subsequently, the best-performing model was further optimized using Bayesian Optimization based on Gaussian Process (GP). Bayesian Optimization is an efficient probabilistic method for hyperparameter tuning,

particularly suitable for computationally expensive models, as it constructs a surrogate model and iteratively searches for optimal configuration [38], [39]. This procedure enhances model stability and generalization capability.

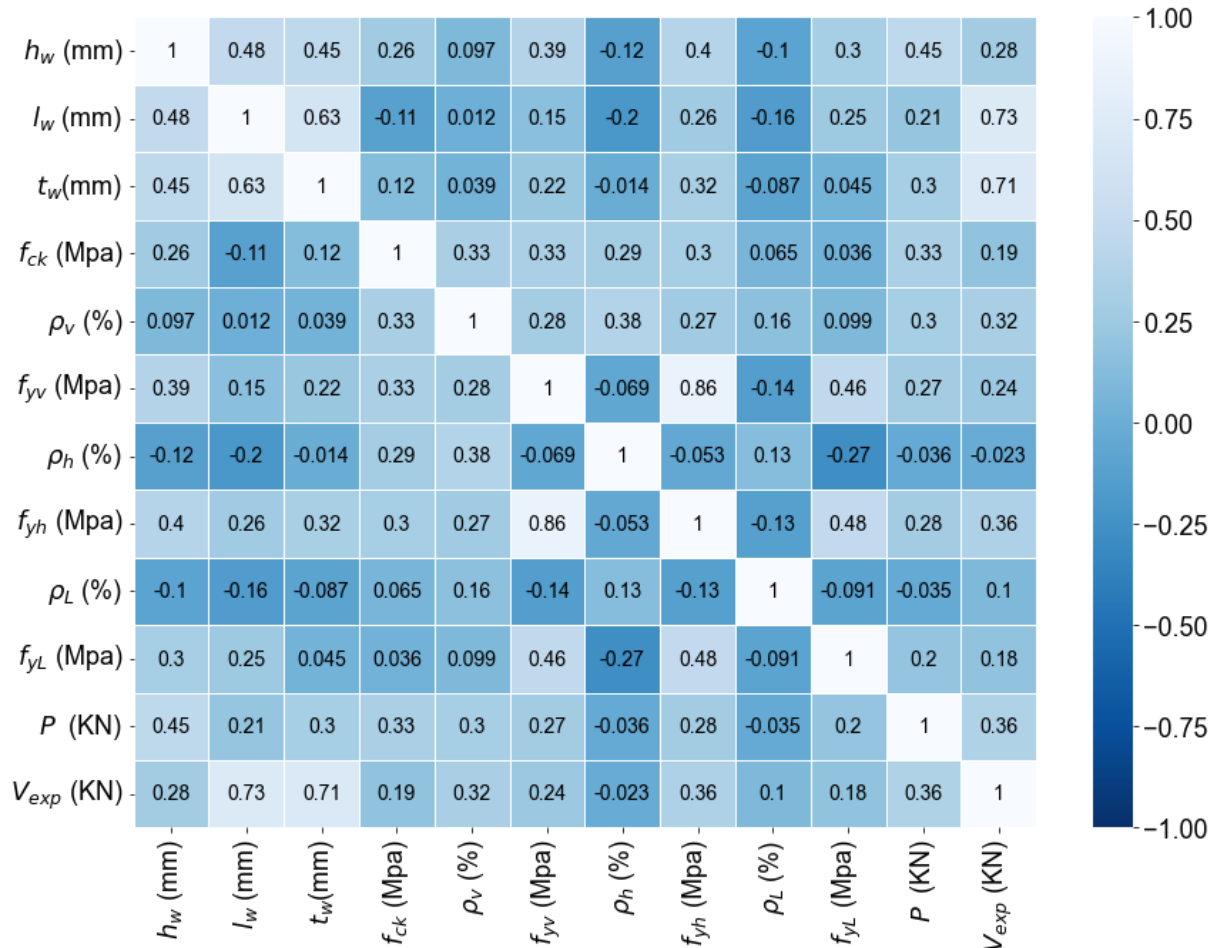


Fig. 4. Correlation matrix between parameters in a dataset

To improve interpretability, the SHapley Additive exPlanations (SHAP) method was applied to the optimized XGBoost model. Grounded in cooperative game theory, SHAP assigns each feature a contribution value representing its marginal influence on the model prediction [40]. In structural engineering applications, SHAP has proven effective in identifying dominant parameters and clarifying complex nonlinear relationships between input features and structural responses [41], [42]. The interpretability analysis therefore bridges data-driven prediction with mechanics-based understanding.

3.1. Machine Learning Algorithms

Decision Tree (DT) is a supervised learning

method that partitions the feature space into hierarchical decision rules. It is intuitive and interpretable but may exhibit high variance [43].

Random Forest (RF) is an ensemble learning algorithm that constructs multiple decision trees using bootstrap aggregation and random feature selection, thereby improving robustness and reducing overfitting [44].

CatBoost is a gradient boosting algorithm developed to enhance stability and reduce prediction bias through ordered boosting and symmetric tree structures. It has shown strong performance in regression tasks involving structured data [45].

XGBoost (Extreme Gradient Boosting) is an

advanced gradient boosting framework incorporating regularization, efficient tree pruning, and parallel computation. Owing to its strong generalization ability and computational efficiency, XGBoost has been widely adopted in engineering prediction problems [46].

3.2. Performance Evaluation Metrics

To assess predictive performance, four statistical indices were employed: Mean Absolute Error (MAE), Root Mean Square Error (RMSE), Mean Square Error (MSE), and the coefficient of determination (R^2). These metrics are commonly used in structural engineering regression problems.

$$MAE = \frac{1}{N} \sum_{j=1}^N |p_j - p_{t,j}| \quad (1)$$

$$RMSE = \sqrt{\frac{1}{N} \sum_{j=1}^N (p_j - p_{t,j})^2} \quad (2)$$

$$MSE = \frac{1}{N} \sum_{j=1}^N (p_j - p_{t,j})^2 \quad (3)$$

$$R^2 = 1 - \frac{\sum (p_j - p_{t,j})^2}{\sum (p_j - \bar{p})^2} \quad (4)$$

where p_j and $p_{t,j}$ denote experimental and predicted shear strengths, respectively, and N is the total number of samples.

3.3. Semi-Empirical Code-Based Models for Benchmarking

To evaluate the reliability of the ML framework, predictions were benchmarked against three mechanics-based semi-empirical formulations: ACI 318-19 [7], ASCE/SEI 43-05 [25], and Wood (1990) [26].

The ACI 318-19 [7] formulation expresses nominal shear strength as:

$$V_n = (\alpha_c \lambda \sqrt{f_{ck}} + \rho_h f_{yh}) A_{cv} \quad (5)$$

This model accounts for concrete and horizontal reinforcement contributions but does not explicitly incorporate axial load effects.

The ASCE/SEI 43-05 [25] model evaluates

shear capacity as:

$$V_n = v_n d t_w \quad (6)$$

where the shear stress v_n incorporates axial load, aspect ratio, and equivalent reinforcement ratio, thus providing a more comprehensive mechanics-based formulation.

The Wood (1990) [26] model expresses shear strength based on shear-friction reinforcement:

$$V_n = \frac{A_{vf} f_{yv}}{4} \quad (7)$$

Although axial load effects are implicitly considered, the upper bound imposed in this formulation may lead to conservative predictions.

By benchmarking the ML predictions against these established models, the study aims to assess whether data-driven approaches can achieve improved accuracy while maintaining consistency with structural mechanics principles.

4. Machine Learning Implementation and Results

4.1. Implementation of Machine Learning Models

The four selected machine learning models, Decision Tree (DT), Random Forest (RF), CatBoost, and XGBoost, were implemented using the Scikit-learn framework in Python together with the official CatBoost and XGBoost libraries. The dataset was randomly divided into a training set (80%) and a testing set (20%) to ensure an unbiased evaluation of model performance.

To obtain a reliable estimate of generalization capability, a 10-fold cross-validation procedure was applied to the training dataset. Specifically, the training data were partitioned into ten subsets; in each fold, nine subsets were used for training and one for validation. The final performance was computed as the average of the ten validation results. This procedure reduces variance in performance estimation and provides a more representative measure of predictive robustness.

All models were first evaluated using default hyperparameters to establish a consistent baseline

for comparison. The cross-validation results were primarily used for model selection and hyperparameter optimization, whereas the independent testing dataset was used for the final evaluation of model generalization capability.

4.2. Model Performance with Default Hyperparameters

The comparative performance results are illustrated in Fig. 5, which presents the evaluation

metrics across the training, validation, and testing phases. For the independent testing dataset, all four models achieved R^2 values higher than 0.85, indicating that the selected machine learning algorithms were able to capture the main variability of the shear strength of RC walls. However, clear differences were observed in terms of overfitting tendency, prediction error, and generalization stability.

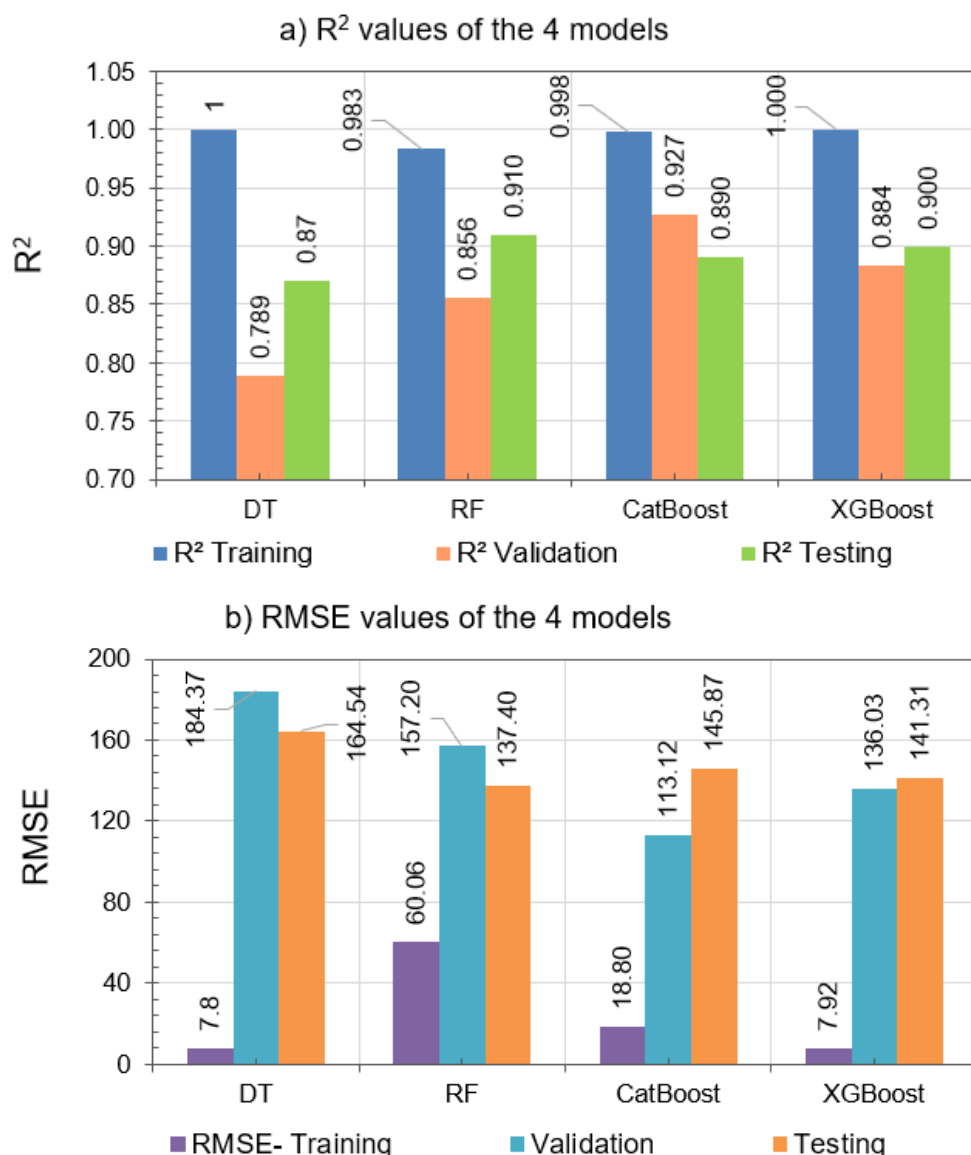


Fig. 5. Chart comparing the performance metrics of machine learning models

The Decision Tree (DT) model achieved perfect training performance ($R^2 = 1.00$) and very low training RMSE, demonstrating its strong ability to fit the training data. However, the validation R^2 decreased to 0.789 and the validation RMSE increased markedly, indicating a clear overfitting

tendency. Although the testing R^2 remained acceptable, the large discrepancy between training and validation performance suggests limited robustness.

Random Forest (RF) improved substantially compared with DT, achieving a testing R^2 of 0.910

and a testing RMSE of 137.40 kN. Nevertheless, the difference between validation and testing performance remained noticeable, suggesting that its predictive stability was still less consistent than that of the boosting-based models.

Among the boosting algorithms, CatBoost achieved the highest validation R^2 of 0.927 and the lowest validation RMSE of 113.12 kN, showing strong fitting capability during cross-validation. However, its testing R^2 decreased to 0.890 and its testing RMSE increased to 145.87 kN, indicating a relatively larger gap between validation and testing performance.

In contrast, XGBoost showed a more balanced behavior across the validation and testing phases. Although its testing R^2 of 0.900 was

slightly lower than that of RF and its testing RMSE was not the lowest among all models, the discrepancy between validation and testing performance was relatively small. Specifically, the R^2 values of XGBoost were 0.884 for validation and 0.900 for testing, while the RMSE values were 136.03 kN and 141.31 kN, respectively. This small difference indicates more stable generalization behavior and higher predictive reliability on unseen data.

Therefore, XGBoost was selected for subsequent hyperparameter optimization based on the combined consideration of predictive accuracy and consistency between validation and testing performance, rather than solely on the testing-set metrics.

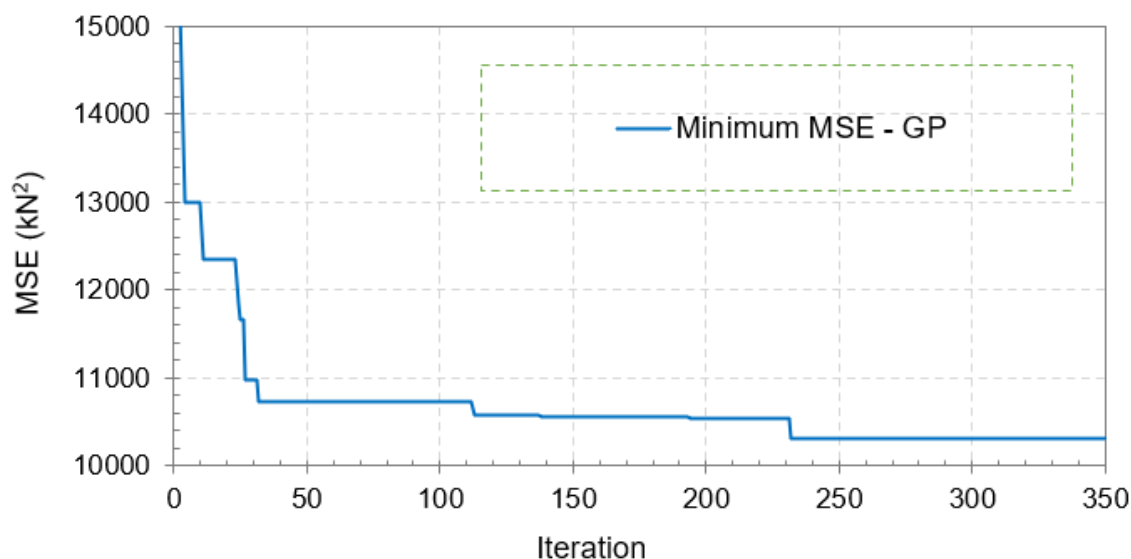


Fig. 6. Optimizing hyperparameters based on the MSE index of the validation set

4.3. Hyperparameter Optimization of XGBoost

The convergence behavior of the optimization process is shown in Fig. 6, where the validation MSE is plotted against the number of iterations. The objective was to minimize MSE over 350 iterations. As illustrated in Fig. 6, the optimization curve gradually converged and stabilized after approximately 230 iterations, indicating that the global optimum had been effectively identified.

The minimum validation MSE achieved through GP-based optimization was 10,308.40 kN^2 . The corresponding optimal hyperparameter

configuration is summarized in Table 2, which lists the search ranges and the selected optimal values for each parameter. The optimized configuration includes:

Compared with default settings, the optimized model demonstrates improved generalization capability and controlled model complexity. Model overfitting was mitigated through regularization terms, subsampling strategy, shallow tree depth, and validation-based Bayesian optimization. The optimized XGBoost model is subsequently adopted for interpretability analysis and benchmarking against semi-empirical design

formulations in the following sections.

4.4. Performance Improvement after Hyperparameter Optimization

The effectiveness of hyperparameter tuning using Gaussian Process-based Bayesian

Optimization is illustrated in Fig. 7, which compares the performance of the default XGBoost model and the optimized XGBoost model (denoted as XGBoost.Opt) across the training, validation, and testing datasets.

Table 2. Hyperparameter optimization for the XGBoost model using the Bayesian optimization method - Gaussian process

Optimal method -	Hyperparameter	Range	Optimal value
Bayesian Optimization - Gaussian process (GP)	'n_estimators'	100 - 1000	1000
	'max_depth'	3 - 9	3
	'learning_rate'	0.05 - 0.30	0.1399
	'booster'	'gbtree', 'dart'	'dart'
	'gamma'	0.01 - 0.50	0.5
	'subsample'	0.60 - 0.90	0.6
	'colsample_bytree'	0.60 - 0.90	0.9
	'reg_lambda'	- 50	22

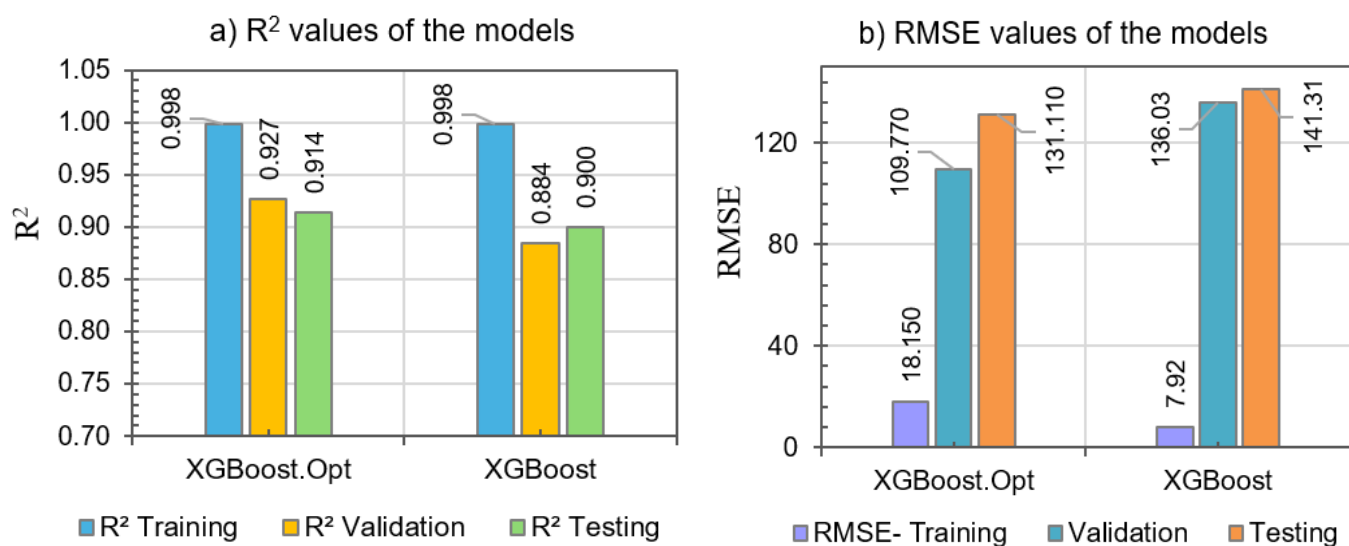


Fig. 7. Comparing the learning outcomes of the XGBoost model between default parameters and optimized parameters using the GP method with different training, validation, and verification sets

As shown in Fig. 7(a), the optimized model consistently achieves higher R² values in all three phases. In particular, the training R² reaches 0.998, while the testing R² increases to 0.914. This improvement indicates that the optimized model not only captures the input-output relationship more effectively but also maintains strong generalization capability when evaluated on unseen data. The comparison of RMSE values, presented in Fig. 7(b), further confirms this

enhancement. The optimized model exhibits a noticeable reduction in prediction error across all datasets. On the testing dataset, RMSE decreases from 141.31 kN (default configuration) to 131.113 kN after optimization. This reduction reflects improved prediction accuracy and increased robustness of the model. These results emphasize the critical role of hyperparameter tuning in maximizing model performance and controlling generalization error.

To further visualize predictive capability, Fig. 8 presents scatter plots comparing predicted versus experimental shear strength for the optimized XGBoost model. As observed in Fig. 8(a), the training data points closely align with the identity line ($x = y$), demonstrating excellent agreement between predictions and experimental values. The high training R^2 (0.998) and low RMSE (18.151 kN) confirm that the model effectively learns the underlying nonlinear relationships within the dataset. For the testing dataset, shown in Fig. 8(b), data dispersion increases as expected, yet most points remain within the $\pm 10\%$ and $\pm 20\%$ error bands. The testing R^2 of 0.914 indicates

reliable generalization performance on unseen data. Importantly, no systematic bias is observed in the prediction trend, suggesting balanced model behavior across low and high shear strength ranges.

Overall, Fig. 7 and Fig. 8 demonstrate that Gaussian Process-based hyperparameter optimization significantly enhances both predictive accuracy and stability of the XGBoost model. The optimized model achieves a desirable balance between model complexity and generalization capability, supporting its practical applicability for shear strength prediction of rectangular RC walls under axial load.

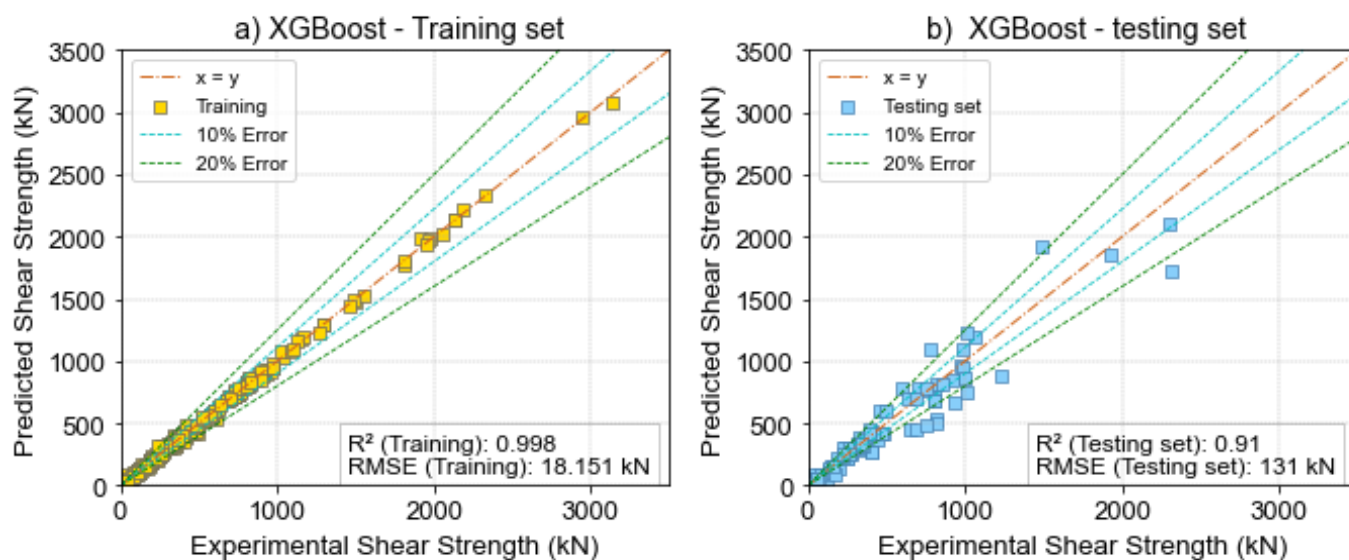


Fig. 8. The shear strength prediction results of the XGBoost model were optimized using the Gaussian Process method

5. Feature Importance Analysis Using SHAP

To further interpret the predictive mechanism of the optimized XGBoost model, SHapley Additive exPlanations (SHAP) were employed. SHAP is a game-theory-based interpretability framework that quantifies the marginal contribution of each input variable to the model output [44]. Unlike traditional feature importance measures, SHAP provides both global importance ranking and local explanations at the individual prediction level, enabling a deeper understanding of the decision-making mechanism of complex nonlinear models.

Fig. 9 presents the SHAP summary plot and the relative feature importance derived from the

optimized XGBoost model. Overall, geometric parameters dominate the prediction of shear strength. In particular, wall length l_w (26.6%) and wall thickness t_w (22.9%) exhibit the highest SHAP contributions, followed by wall height h_w (9.3%). These results indicate that the effective shear-resisting area and the global geometric configuration play primary roles in determining the shear capacity of rectangular RC walls.

Reinforcement-related parameters also demonstrate noticeable influence. The boundary longitudinal reinforcement ratio ρ_L (8.0%), horizontal reinforcement ratio ρ_h (7.8%), and horizontal reinforcement yield strength f_{yh} (6.3%)

contribute significantly to the prediction. These variables are directly associated with shear-transfer mechanisms, including truss action, confinement effects, and crack control during diagonal tension failure. The axial load P also exhibits an important contribution (7.7%), confirming the coupled interaction between axial compression and shear resistance. In contrast, concrete compressive strength f_{ck} (3.5%) shows comparatively lower importance, suggesting that geometry and reinforcement configuration play more dominant roles within the investigated database. Other variables, including web reinforcement ratio ρ_v (3.1%), web reinforcement yield strength f_{yv} (2.6%), and boundary reinforcement yield strength f_{yL} (2.2%), show moderate to lower influence. The SHAP-based feature importance results are generally consistent with the linear correlation trends presented in Fig. 4. Specifically, wall length l_w and wall thickness t_w exhibit the strongest positive correlations with the experimental shear strength V_{exp} , with correlation coefficients of 0.73 and 0.71, respectively. Correspondingly, these two variables also possess the highest SHAP importance values. Similarly, wall height h_w and axial load P show moderate

positive correlations with V_{exp} and are associated with moderate SHAP contributions. This consistency indicates that the optimized XGBoost model successfully captures the dominant physical trends already observable from the statistical correlation analysis. At the same time, the SHAP results reveal that several reinforcement-related variables, despite exhibiting relatively weak linear correlations with V_{exp} in Fig. 4, still contribute meaningfully to the model prediction. This observation suggests that their effects are governed not only by direct linear relationships but also by nonlinear interactions and coupled effects with geometry and loading conditions. When compared with the shear strength formulation in ACI 318-19 [7], the ML model exhibits partial consistency in that geometric parameters and concrete strength remain fundamental contributors. However, an important difference emerges regarding the role of longitudinal reinforcement. While ACI 318-19 primarily considers horizontal reinforcement through the shear reinforcement component V_s , the XGBoost model indicates that both longitudinal and horizontal reinforcement contribute significantly to shear resistance.

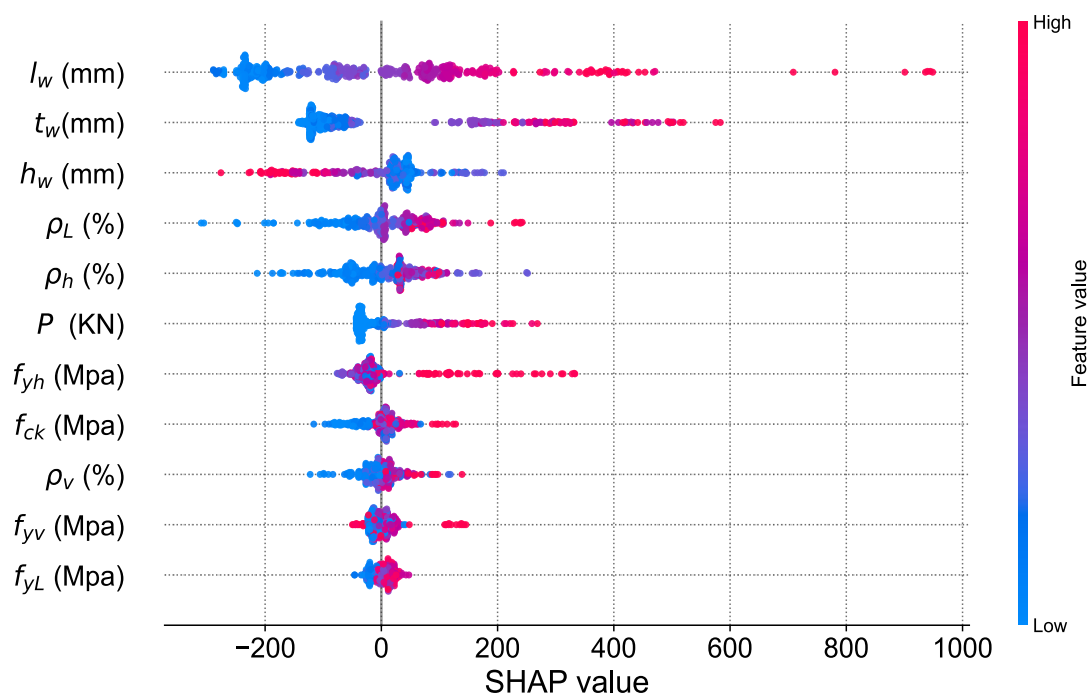
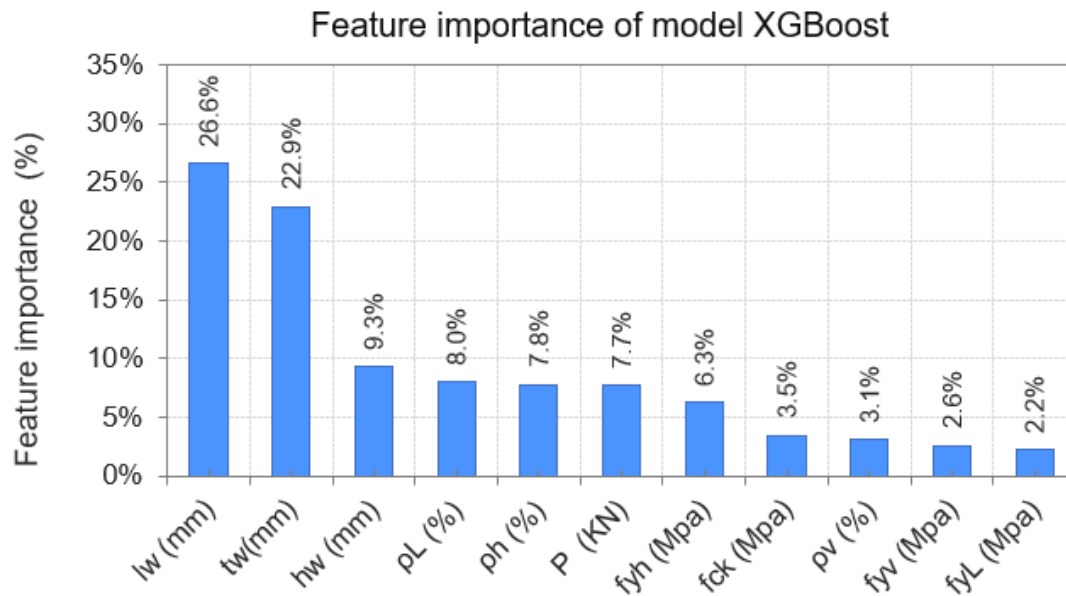


Fig. 9. SHAP summary plot and the relative importance of features in the XGBoost model

**Fig. 9.** (continued)

This finding suggests that the combined interaction between longitudinal reinforcement, transverse reinforcement, geometric configuration, and axial load plays a more critical role in actual wall behavior than explicitly reflected in current semi-empirical formulations. Therefore, the SHAP analysis highlights the capability of ML models to capture complex nonlinear dependencies that may not be fully represented in traditional code equations.

Overall, Fig. 9 demonstrates that the optimized XGBoost model not only achieves high predictive accuracy but also provides physically interpretable insights consistent with structural mechanics principles, while revealing additional nonlinear interaction effects beyond conventional linear correlation analysis and semi-empirical design approaches.

6. Performance of Machine Learning Models versus Current Design Provisions

Table 3. Comparing the performance of ML models and mechanical models

Models	V_{predic} to V_{exp} ratio				
	Minimum	Maximum	Mean	Standard Deviation	Coefficient of Variation (COV %)
ACI 318 - 19	0.219	4.742	1.191	0.744	62.48
ASCE/SEI 43-05	0.325	4.953	1.484	0.765	51.55
Wood 1990	0.240	4.830	0.971	0.604	62.18
XGBoost	0.244	2.013	1.018	0.126	12.37

To evaluate the predictive reliability of the optimized XGBoost model in practical engineering contexts, its performance was benchmarked against three widely adopted semi-empirical shear strength models. These include two models specified in current design standards — ACI 318-19 (Chapter 11) [7] and ASCE/SEI 43-05 [25] and one well-established research-based model proposed by Wood (1990) [26].

All four models were applied to predict the shear strength of the 456 rectangular RC wall specimens collected in this study, covering a wide range of height-to-length ratios and reinforcement configurations.

The statistical comparison between predicted and experimental shear strengths is summarized in Table 3, while the distribution of the prediction-to-experiment ratios is illustrated in Fig.

10. The evaluation metrics include the mean ratio, standard deviation (St.D.), maximum (Max.), minimum (Min.), and coefficient of variation (COV%).

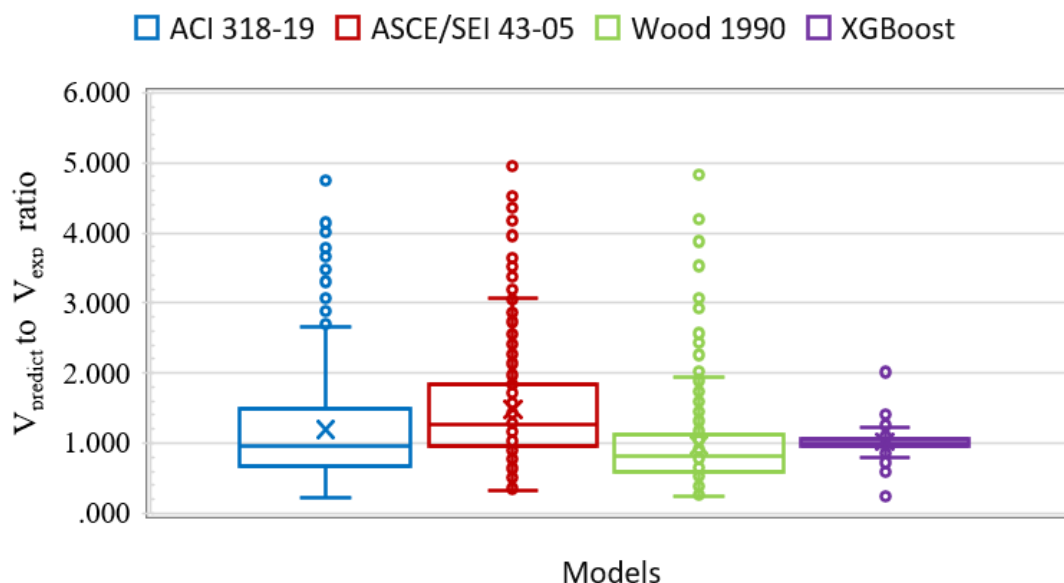


Fig. 10. Results of shear resistance prediction using mechanical model and XGBoost model

The results clearly indicate that the semi-empirical models exhibit substantial dispersion and larger prediction errors compared to XGBoost. Specifically, the maximum prediction-to-experiment ratios reach 4.953 for ASCE/SEI 43-05, 4.830 for Wood (1990), and 4.742 for ACI 318-19, demonstrating significant overestimation in certain cases. In contrast, the XGBoost model shows a maximum ratio of only 2.013 and an average prediction ratio close to unity, indicating balanced predictions without systematic bias.

Furthermore, the standard deviation and COV values of the code-based models are significantly higher than those of XGBoost. For instance, ASCE/SEI 43-05 presents a standard deviation of 0.765 and a COV of 51.55%, whereas the optimized XGBoost model yields a much lower standard deviation of 0.126 and a COV of 12.37%. These statistics demonstrate the superior consistency and reliability of the ML-based approach.

A more detailed comparison is presented in Fig. 11, which illustrates the variation of prediction ratios with respect to the geometric parameter h_w/l_w . As shown in Fig. 11(a)–(c), the traditional

semi-empirical models exhibit increasing scatter as the height-to-length ratio increases, particularly for slender walls. Many predictions fall outside the ± 1 standard deviation band, indicating limited accuracy for walls with diverse geometric configurations. In contrast, the XGBoost model (Fig. 11(d)) shows a highly concentrated distribution around the mean ratio across the entire range of h_w/l_w . Most data points remain within the ± 1 standard deviation bounds, regardless of geometric variation. This behavior highlights the ability of XGBoost to capture nonlinear interactions between geometry, reinforcement, and axial load effects more effectively than simplified design formulations.

Overall, the comparative analysis presented in Table 3 and Fig. 10 and Fig. 11 demonstrates that the optimized XGBoost model significantly outperforms current semi-empirical design equations in terms of accuracy, stability, and generalization. The results suggest that data-driven ML models have strong potential to complement or enhance existing code-based shear strength predictions for rectangular RC walls under axial load.

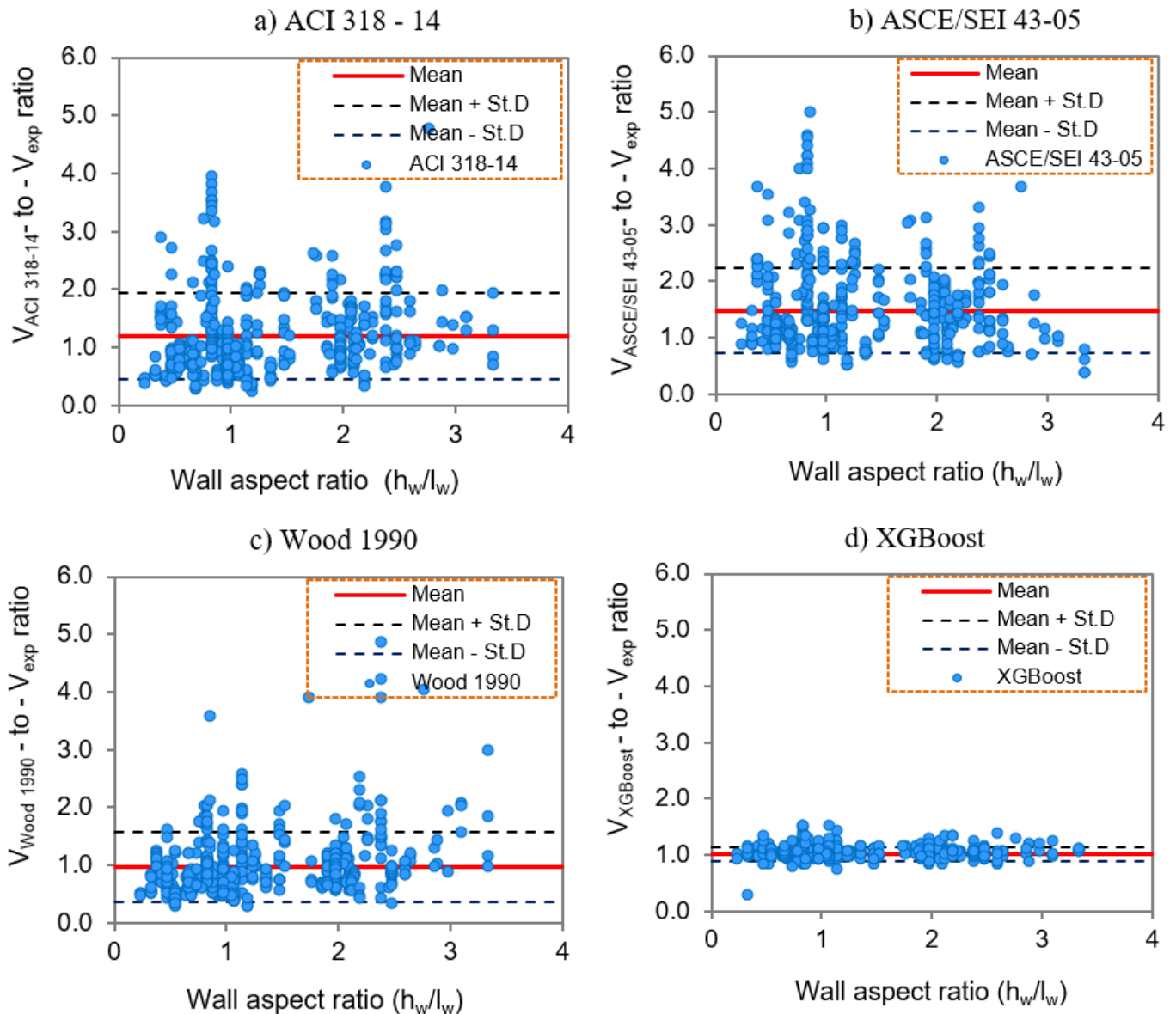


Fig. 11. Shear strength was predicted by the following mechanically based models: a) ACI 318-19; b) ASCE/SEI 43-05; c) Wood 1990; and d) XGBoost model at different h_w/l_w ratios

7. Discussion: Mechanical Interpretation and Design Implications

The SHAP-based interpretation and comparative evaluation with current design provisions provide important mechanical insights into the shear behavior of rectangular RC walls under axial load. The dominance of geometric parameters, particularly wall length l_w and wall thickness t_w , confirms that the effective shear-resisting area and sectional stiffness fundamentally govern shear capacity. From a mechanics perspective, increasing l_w enlarges the shear transfer zone and internal lever arm, while

increasing t_w directly enhances the gross shear area A_{cv} , thereby increasing the concrete contribution V_c . In addition, the significant contribution of boundary longitudinal reinforcement ratio ρ_L , revealed by SHAP analysis, highlights a key aspect not explicitly emphasized in ACI 318-19. While current code formulations primarily account for horizontal reinforcement through the shear reinforcement term V_s , the ML results indicate that longitudinal reinforcement also plays a meaningful role by improving confinement, delaying diagonal crack propagation, and enhancing axial-shear interaction mechanisms.

The moderate yet consistent influence of axial load P aligns with structural mechanics principles, as axial compression enhances shear resistance through frictional effects and confinement but introduces nonlinear behavior that is simplified in conventional formulations. The comparison with ACI 318-19, ASCE/SEI 43-05, and Wood (1990) further demonstrates that traditional semi-empirical equations exhibit substantial dispersion, particularly for walls with higher h_w/l_w ratios, whereas the optimized XGBoost model maintains stable prediction accuracy across varying geometric configurations. These findings suggest that shear resistance in RC walls is governed by a coupled axial–flexural–shear mechanism involving nonlinear interactions among geometry, reinforcement, and axial load, rather than by a purely additive $V_c + V_s$ formulation. From a practical standpoint, the results indicate that data-driven ML models can serve as effective complementary tools to existing design provisions, offering improved prediction reliability and potential calibration guidance for future refinement of empirical coefficients in shear strength equations.

8. Conclusion

This study developed and validated a machine learning framework for predicting the shear strength of rectangular reinforced concrete (RC) walls under axial load, based on a curated database of 456 experimental specimens. The following conclusions can be drawn:

Comparative performance of ML models: Among the four investigated models (Decision Tree, Random Forest, CatBoost, and XGBoost), the boosting-based algorithms demonstrated superior predictive capability and generalization performance. XGBoost was selected for further optimization due to its competitive accuracy and stability.

Effectiveness of Gaussian Process optimization: Bayesian Optimization based on Gaussian Process significantly improved the predictive performance of XGBoost. The optimized

model achieved a testing R^2 of 0.914 and reduced RMSE from 141.93 kN (default) to 131.11 kN. The coefficient of variation of prediction ratios was reduced to 12.37%, indicating high reliability and low dispersion.

Interpretability and mechanical consistency: SHAP analysis revealed that geometric parameters (wall length and thickness) are the dominant factors governing shear strength, followed by reinforcement ratios and axial load. The findings confirm consistency with structural mechanics principles while highlighting nonlinear interactions not fully represented in current code equations.

Comparison with existing design provisions: The optimized XGBoost model outperformed ACI 318-19, ASCE/SEI 43-05, and Wood (1990) models in terms of accuracy, stability, and dispersion. Semi-empirical formulations exhibited significant scatter, particularly for walls with higher height-to-length ratios, whereas the ML model maintained stable predictions across varying geometric configurations.

Implications for design practice: The results demonstrate that data-driven ML models can serve as effective complementary tools for shear strength prediction and reliability assessment of RC walls. The integration of ML-based insights may support future refinement of empirical coefficients in design standards.

Future research may expand the database to include walls with different cross-sectional shapes, higher slenderness ratios, and varying failure modes. Hybrid modeling approaches that combine mechanics-based formulations with ML-driven calibration are also recommended to enhance transparency and code applicability.

Declaration of Generative AI

The authors used ChatGPT (OpenAI) solely to refine the language and improve the readability of the manuscript. The authors developed and verified all scientific analyses, interpretations, and

conclusions and take full responsibility for the final content.

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