Journal of Turkish

Operations Management

Assessing column stability: a comparative study of machine learning regression models for shear strength prediction

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Article Info

Article History:
Received: 06.12.2023
Revised: 22.03.2024
Accepted: 07.04.2024

Keywords

Machine Learning, Random Forest, Reinforced concrete, Regression, Shear Strength

Abstract

This research presents a comprehensive investigation into the accurate estimation of shear strength in rectangular reinforced concrete columns through advanced machine learning (ML) models. The study addresses the intricate challenge posed by shear strength complexity, which is crucial for evaluating column stability and ensuring structural integrity. Building upon a substantial dataset comprising 545 experimental observations sourced from diverse literature, this research establishes a robust foundation for predictive modeling. Four distinct ML regression models, Random Forest, Decision Tree, XGBoost, and LightGBM, are meticulously evaluated for their performance. The evaluation employs established metrics, including R^2, RMSE, MAE, and MAPE to quantify their predictive capabilities. The outcomes highlight the models' robustness in capturing nuanced variations in shear strength, with impressive R^2 values ranging from 93.6% to 93.9%, showcasing their exceptional ability to elucidate intricate shear behaviors. Furthermore, comparative analysis indicates the slightly superior performance of the Random Forest over the Decision Tree, highlighting the efficacy of ensemble methods in this context. Extending the exploration to include XGBoost and LightGBM, the study showcases their potential as accurate shear strength predictors. The performance of the models is validated through scatter plots and error distribution plots, confirming accurate shear strength predictions across various scenarios. This research significantly advances structural engineering methodologies by demonstrating the potential of ML to enhance shear strength estimation accuracy. The findings not only underscore the exceptional performance of ML models but also provide valuable insights into their comparative effectiveness, paving the way for enhanced structural assessments in columns.

1. Introduction

Reinforced concrete (RC) columns are crucial structural elements in the field of civil engineering, providing essential support and stability to buildings and infrastructures worldwide (Özyüksel Çiftçioğlu & Naser, 2022). These columns are designed to withstand a variety of forces, including compression, bending, and shear. Although significant research has been conducted to accurately predict their behavior under various loading conditions, one particular aspect that requires the utmost attention is the accurate estimation of shear strength in RC columns (Park et al., 2012; Zhou & Liu, 2010).

Shear strength plays a pivotal role in determining the overall structural integrity and safety of RC columns. Unlike compression and bending forces, which are relatively more predictable, shear forces exert complex effects on these columns, making their accurate estimation a formidable challenge. Shear failure can occur suddenly and catastrophically, leading to the collapse of the entire structure. Therefore, a precise prediction of shear strength is of paramount importance to ensure structural reliability and avoid potential disasters (Wong & Kuang, 2014).

The implications of underestimating or overestimating the shear strength of the RC columns are profound. If the shear strength is underestimated, it could lead to inadequate reinforcement or a lack of appropriate design measures. This, in turn, increases the risk of premature shear failure, compromising structural stability, and posing a threat to the safety of occupants. However, overestimating shear strength can result in an overly conservative design, leading to unnecessary material and financial costs. Therefore, achieving an accurate prediction of shear strength is essential not only for safety but also to optimize construction practices and resource allocation.

The challenges in accurately estimating shear strength arise from the intricate interplay between various factors influencing the behavior of RC columns. These factors include concrete strength, reinforcement detailing, column dimensions, loading conditions, and boundary constraints. Researchers and engineers face the ongoing task of developing reliable models and techniques to capture complex shear behavior and accurately estimate the shear strength of RC columns.

Machine learning (ML) has emerged as a promising approach to address the challenges associated with accurately estimating shear strength in RC columns. ML techniques leverage the power of data-driven analysis and computational algorithms to uncover intricate patterns and relationships within complex systems (Babaee Tirkolaee et al., 2020; Khalilpourazari et al., 2020; Khalilpourazari & Hashemi Doulabi, 2022; Moslemi et al., 2021). In the realm of civil engineering, ML offers a unique opportunity to improve our understanding of shear behavior by integrating a multitude of influencing factors and their interactions. Using historical data on RC column performance and behavior under diverse loading conditions, ML models can learn from this information and make generalizations accordingly. This allows them to make predictions about shear strength that go beyond the limitations of traditional analytical methods (Emam et al., 2021; Zavvar Sabegh et al., 2014). ML algorithms, such as decision trees, support vector machines, neural networks, and ensemble methods, can be trained on datasets comprising various column geometries, material properties, loading scenarios, and failure modes. The models can then capture intricate nonlinear relationships that might be challenging to express through conventional equations (Khalilpourazari & Pasandideh, 2016). One of the significant advantages of using ML for shear strength estimation is its adaptability to changing conditions and new data. As new research findings and experimental data become available, ML models can be updated and refined, continuously improving their accuracy (Hashemi Doulabi & Khalilpourazari, 2023; Khalilpourazari & Doulabi, 2021; Mohammadi & Khalilpourazari, 2017; Naser & Ciftcioglu, 2022; Naser & Çiftçioğlu, 2023; Özyüksel Çiftçioğlu, 2023).

Traditional methods often fail when confronted with the intricate and multifaceted nature of shear strength in RC columns. The variation in material properties, geometric configurations, and loading conditions poses challenges that traditional approaches struggle to address comprehensively. This inadequacy not only highlights the limitations of conventional methods but also creates a void in the literature on robust and universally applicable models for shear strength prediction. The gap in the literature becomes increasingly evident when considering the diverse scenarios and configurations encountered in real-world applications. Conventional methods, relying on simplified assumptions and empirical equations, may lack the flexibility and adaptability required to capture the intricate interplay of factors influencing shear strength in RC columns. As a result, there is a compelling need for advanced methodologies that can surpass the limitations of traditional approaches and offer more accurate and versatile predictions. This research seeks to address this gap in the literature by introducing ML as a powerful tool for shear strength prediction in RC columns.

Integration of ML into the realm of civil engineering leads to a significant change in the approach to estimating shear strength in RC columns. It allows for a more holistic and data-driven understanding of this complex phenomenon, enabling more accurate predictions and better-informed design decisions. As researchers and practitioners continue to bridge the gap between traditional engineering principles and modern data-driven techniques, the potential to optimize structural safety, construction practices, and resource allocation remains a compelling prospect.

2. Database

A comprehensive compilation of 545 experimental data sets on rectangular RC columns has been meticulously gathered from the literature (A. & O., 1984; Ahn & Shin, 2007; Belkacem et al., 2019; Dinh et al., 2019; Eom et al., 2014; Ghannoum et al., 2012; Goksu et al., 2014; Ho, 2012; Hugo et al., 2016; Hwang & Yun, 2004; Karbasi Arani et al., 2013, 2014; Lam et al., 2003; Y.-A. Li et al., 2014; Y. Li et al., 2018; Marefat et al., 2006; Melo et al., 2015; Shi et al., 2021; Woods et al., 2007; J. Zhang et al., 2020; Y. Zhang et al., 2019). The investigation requires the provision of ten crucial input parameters, including geometric dimensions, bar specifications, material properties, and axial load (P), to accurately estimate the shear strength of RC columns *(Vmax)*. The geometric dimensions encompass the height of the column (L), the width of the cross-section (B), and the length of the cross-section (H). Reinforcement details constitute the longitudinal reinforcement ratio (ρl), the transverse reinforcement bar ratio (ρh), and the spacing of transverse reinforcements (s), all of which significantly influence the capacity of the column to resist shear forces. Incorporating the properties of the material is of utmost importance, and we take into account the yield strength of both longitudinal (fyl) and transverse (fyw) reinforcing bars, as well as the compressive strength of the concrete (fc). These characteristics of the material directly affect the overall performance and structural integrity of the RC columns under varying load conditions. The descriptive statistics for the variables are presented in Table 1, covering the minimum, maximum, mean, and standard deviation values.

Table 1. Descriptive statistics of the dataset

	L	B	H	ρl	ρh	s	fc	fyl	fyw	P	$Vmax$
min	225.00	108.50	100.00	0.20	0.01	20.00	20.00	77.06	215.00	0.00	13.34
max	3000.00	610.00	610.00	4.50	4.00	457.20	141.00	745.00	1470.00	5491.75	982.00
mean	1285.87	284.20	301.00	2.15	0.95	101.41	49.12	447.90	496.88	1135.67	228.61
st dv	651.85	109.51	115.65	0.70	0.94	78.54	27.37	79.71	226.32	1083.46	175.22

Figure 1 illustrates a visual representation of the colormap correlation matrix. This matrix effectively portrays the relationships between variables within the dataset. Notably, the colors red and blue denote strong positive and negative correlations, respectively. The correlation matrix distinctly reveals that variables B (cross-section), H (cross-section length), and P (axial load) exhibit a significant correlation coefficient of +0.6 in relation to the shear strength of the RC columns. Furthermore, it should be noted that the variable fc (compressive strength of concrete) has a negative correlation coefficient of -0.1 with compressive strength.

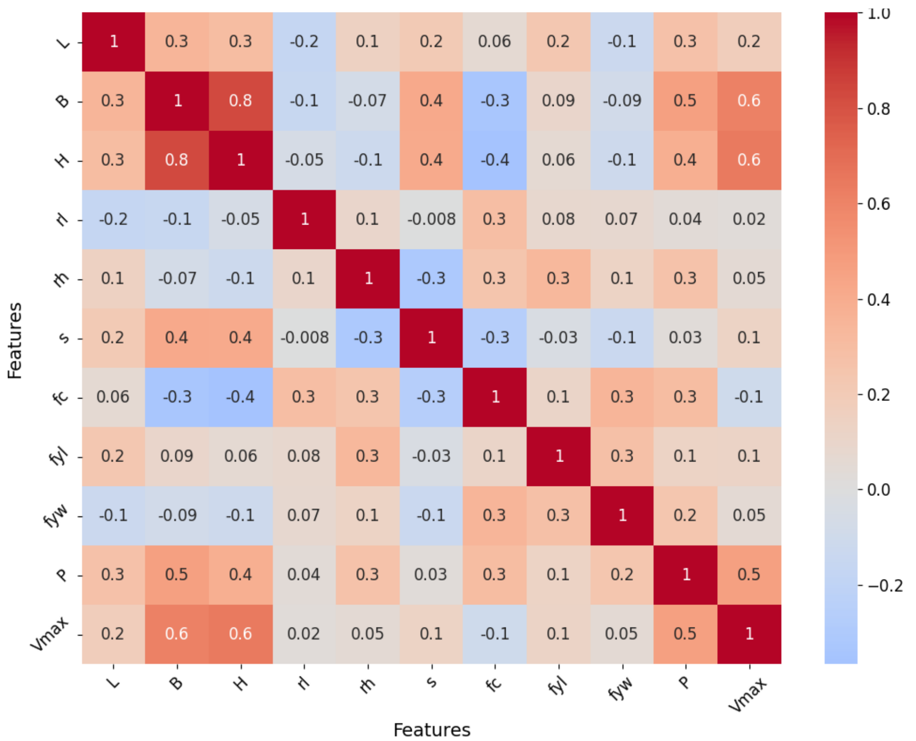

Figure 1. Correlation matrix of variables in the dataset

3. Methodology

3.1. Random Forest

Random Forest (RF) is a powerful and widely used ensemble learning technique in the field of ML (Breiman, 2001). It is renowned for its robustness, versatility, and excellent predictive performance in both classification and regression tasks. RF has gained popularity due to its ability to handle complex data sets and mitigate issues like overfitting. The method is an extension of the DT algorithm, and it combines multiple individual decision trees to form a more accurate and reliable predictor. The fundamental principle behind RF lies in aggregating the predictions of multiple decision trees, thereby forming a forest of trees. Each tree in the forest is trained on a random subset of the data, and at each split, a random subset of features is considered. This randomness introduces diversity among the trees, reducing overfitting and enhancing the generalization ability of the model. During the prediction phase, the final output is determined by averaging (in regression) or voting (in classification) the outputs of individual trees, resulting in a more robust and accurate prediction. In the classification context, RF constructs multiple decision trees during the training phase (Liu et al., 2021; X. Zhang et al., 2021). Each decision tree is built on a random subset of the training data, and at each split, a random subset of features is considered. During inference, each decision tree in the forest independently predicts the class label for a given input, and the final class is determined by majority voting. On the other hand, RF is equally adept at solving regression problems. In regression tasks, the algorithm assembles multiple decision trees just as in the classification setting, but the predictions from each individual tree are averaged instead of voting. Consequently, the final prediction is the mean of the results from all decision trees. This averaging process ensures that the RF regression model can capture complex nonlinear relationships between features and the target variable while also mitigating the effects of outliers and noise. RF finds extensive applications in various engineering domains. In civil engineering, it can help predict structural integrity, soil stability, etc. The proficiency of the algorithm in handling high-dimensional data and accommodating intricate non-linear relationships renders it an invaluable instrument for addressing intricate engineering challenges and augmenting decision-making endeavors within diverse industrial contexts.

3.2. Decision Tree

The Decision Tree (DT) algorithm is a widely employed and interpretable ML technique that serves as a powerful tool for classification and regression tasks (Quinlan, 1986). Its fundamental principle lies in partitioning the feature space into a hierarchical structure of nodes, where each node represents a decision based on a particular feature, leading to subsequent splits until the leaf nodes produce the final predictions. Decision trees are extensively utilized due to their ability to handle categorical and numerical data, their ease of interpretability, and their ability to capture nonlinear relationships between features (Naser, 2021; Rajakarunakaran et al., 2022). The construction of a DT starts with selecting the most informative feature of the dataset to create the root node. The subsequent nodes are generated by iteratively choosing the best feature and its optimal split point, which maximizes information gain or minimizes impurity. Information gain measures the reduction in uncertainty after a split, whereas impurity refers to the homogeneity of the target values within a node. The recursive partitioning process continues until predefined termination conditions are met, such as reaching a specified depth or having a minimum number of data points in a leaf node. To avoid overfitting, techniques such as pruning or setting a minimum number of samples per leaf are commonly used. Decision trees find wide-ranging applications in engineering disciplines due to their versatility and comprehensibility. Their capability to handle large datasets and effectively model complex systems has positioned Decision Trees as a valuable asset in the engineering domain, enabling informed decision-making and problem-solving across various sectors.

3.3. Extreme Gradient Boosting

Extreme Gradient Boosting (XGBoost) is a state-of-the-art ML algorithm renowned for its exceptional predictive capabilities (Chen & Guestrin, 2016). XGBoost has gained widespread popularity in both academia and industry due to its outstanding performance across a diverse array of tasks, including regression, classification, and ranking (Nguyen-Sy et al., 2020; Nguyen et al., 2021). The efficacy of the algorithm comes from its ability to blend the advantages of boosting and gradient descent, enabling it to handle complex high-dimensional data with remarkable accuracy and efficiency. XGBoost operates by building an ensemble of weak learners, typically decision trees, in a sequential manner. Each subsequent tree aims to correct the errors of the previous ones, progressively refining the predictions. The algorithm employs a combination of regularization techniques, such as regularization L1 and L2, to avoid overfitting and improve generalization. Additionally, it employs a novel "gradient boosting" strategy to minimize a cost function by iteratively fitting weak learners to the negative gradient of the loss function. This technique facilitates optimizing the performance of the model by minimizing prediction errors. In the realm of engineering, XGBoost has found extensive applications across various domains. Its speed and adaptability enable engineers to effectively handle large-scale datasets and complex relationships, making XGBoost an indispensable tool to solve intricate engineering challenges and improve decision-making processes in diverse engineering applications.

3.4. Light Gradient Boosting Machine

Light Gradient Boosting Machine (LightGBM) is a gradient-boosting framework that has gained remarkable popularity in the field of ML due to its efficiency and high performance (Ke et al., 2017). It is based on the concept of gradient boosting, which involves sequentially adding weak learners (typically decision trees) to improve the accuracy of the model. What sets LightGBM apart is its focus on optimizing both training speed and memory consumption, making it well-suited for handling large-scale datasets and computationally intensive tasks. The core idea behind LightGBM lies in its novel approach to tree construction and leaf-wise growth strategy. Unlike traditional depth-first tree growth, LightGBM adopts a leaf-wise approach, where it selects the leaf node with the maximum decrease in the loss function during each tree expansion. This technique significantly reduces the number of nodes and the depth of the tree, thereby reducing computation time and memory usage (Ma et al., 2022). Additionally, LightGBM employs a histogram-based method to quantize feature values into discrete bins, further accelerating the training process. The algorithm also offers various regularization techniques, such as L1 and L2 regularization, to prevent overfitting and enhance generalization. LightGBM finds wide applications in various engineering domains, due to its ability to handle large-scale datasets and efficiently tackle complex problems. The superior performance and scalability of the algorithm make it a valuable asset in engineering domains where data volume and computational resources are paramount concerns, empowering engineers to make informed decisions and deliver efficient and accurate solutions.

4. Results and Discussion

In this study, a comprehensive analysis employing four distinct ML models was conducted to perform regression analyses. The primary objective of the investigation was to accurately predict the shear strength (*Vmax*) of the RC columns. The dataset was split into training and test sets using the train_test_split function from the scikit-learn library, with a test size of 25% and a random state of 0. Specifically, 75% of the data was used for training the models, while the remaining 25% was reserved for testing. This approach ensures that the models are trained on a sufficiently large portion of the data while also allowing for robust evaluation on unseen data. The regression models used in the study were RF, DT, XGBoost, and LightGBM. The parameters of these ML models, including maximum depth, learning rate, and other hyperparameters, were detailed in Table 2. It is important to note that Python programming language (Van Rossum & Drake Jr, 1995), along with its libraries such as scikit-learn and XGBoost, was utilized for implementing and training these ML models.

Table 2. Specifications of Machine Learning Models

Model	Parameters
RF	n_estimators=19, random_state=0, max_depth=None, min_samples_split=2
DT	max_depth=10, min_samples_split=2, random_state=42
XGBoost	n_estimators=100, max_depth=10, random_state=42, learning_rate=0.2, subsample=1.0, colsample_bytree=0.8
LightGBM	n_estimators=100, random_state=0, max_depth=10, min_child_samples=10

The performance of each model was evaluated based on several key metrics, including Coefficient of Determination (R^2), Root Mean Squared Error (RMSE), Mean Absolute Error (MAE), and Mean Absolute Percentage Error (MAPE). The obtained results are summarized in Table 3.

Table 3. Performance Evaluation of Regression Models

Algorithm	Data	R^2	RMSE	MAE	MAPE (%)
RF	Test	0.939	48.278	28.972	13.862
DT	Test	0.939	48.327	30.863	16.530
XGBoost	Test	0.937	49.048	27.119	12.215
LightGBM	Test	0.936	49.560	29.155	15.302
RF	Train	0.985	20.830	12.555	7.045

DT	Train	0.998	8.411	3.586	2.055
XGBoost	Train	0.999	0.218	0.120	0.095
LightGBM	Train	0.994	13.372	8.493	4.729

The results indicate strong predictive capabilities of the employed ML models, with R^2 values ranging from 0.936 to 0.939. These coefficients of determination suggest that the models can explain approximately 93.6% to 93.9% of the variability in the shear strength of RC columns. Moreover, the relatively low values of RMSE, MAE, and MAPE demonstrate the accuracy of the predictions and the robustness of the models across different algorithms. The RF and DT models yield comparable results in terms of R^2, while the RF model outperforms slightly in terms of RMSE, MAE, and MAPE. This underscores the effectiveness of ensemble methods in capturing complex relationships within the dataset. Furthermore, both XGBoost and LightGBM exhibit promising results, demonstrating their potential for accurate shear strength estimation. It is worth noting that the observed MAPE values, ranging from 12.215% to 16.530%, indicate the percentage error in the predictions. This insight is valuable for assessing the practical utility of the models in engineering applications, as it provides an understanding of the potential variability in the estimated shear strength.

In Figure 2, scatter plots illustrating the predictions of the four employed ML regression models are presented. These plots depict the relationship between the predicted shear strength values and the actual shear strength values for each data point in the test dataset. This visual representation enables a comprehensive assessment of the predictive performance of the model and provides information on its accuracy in the range of shear strength values. The scatter plots highlight the alignment of the predicted values with the ideal diagonal line, which represents perfect predictions. Notably, all four models exhibit a consistent pattern of predictions closely clustered around this diagonal line, indicating strong predictive capabilities. Despite slight variations, the scatter plots reveal that the predictions closely follow the actual values, affirming the models' ability to capture the underlying trends and relationships within the dataset. This observation is consistent with the quantitative results presented in Table 1, where metrics such as R^2, RMSE, MAE, and MAPE indicated favorable predictive performance. Moreover, the dispersion of points around the diagonal line suggests that the models perform consistently across the entire range of shear strength values. This consistency is crucial in engineering applications where accurate predictions are essential across a broad spectrum of scenarios. The scatter plots further emphasize the proficiency of the RF and DT models, as their predictions align more closely with the ideal diagonal line compared to the other models. This alignment signifies the robustness of the models to handle the various patterns present in the dataset. The XGBoost and LightGBM models also demonstrate respectable alignment, reinforcing their viability for shear strength estimation.

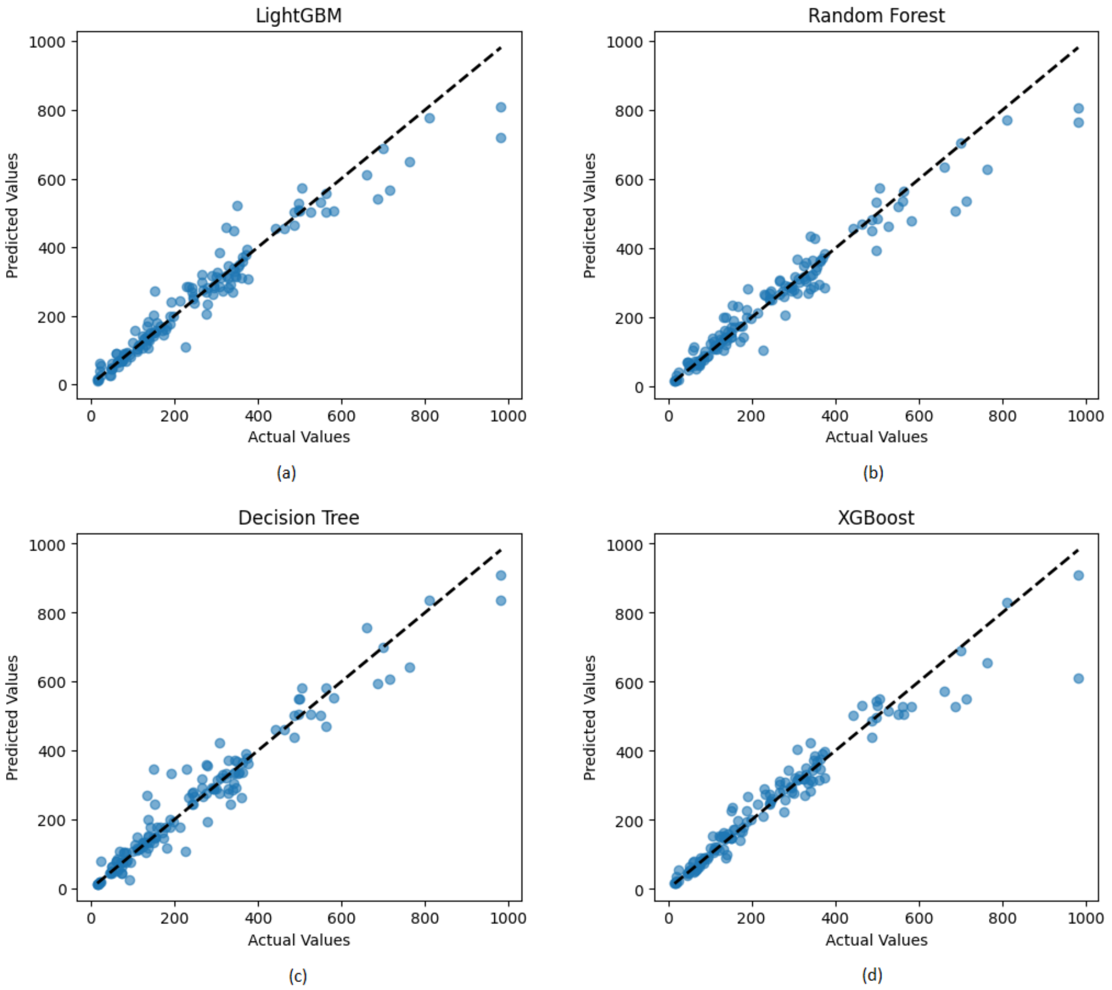

Figure 2. Scatter Plots for Regression Models

Figure 3 displays the error distribution plots corresponding to the predictions generated by the four distinct ML regression models. These plots illustrate the distribution of errors between the predicted shear strength values and the actual shear strength values across the test dataset. This visualization provides insight into the ability of the models to consistently estimate shear strength and the magnitude of errors associated with their predictions. The error distribution plots depict a symmetric distribution of errors centered around zero for all four models. This symmetry signifies that the models tend to produce predictions with balanced overestimations and underestimations, indicating the absence of systemic biases. While the majority of errors are clustered around zero, there are occasional instances of larger errors. However, these occurrences are limited and do not deviate significantly from the central trend. This observation aligns with the quantitative metrics reported earlier, such as the MAE and RMSE, which demonstrated relatively low magnitudes. Furthermore, the error distribution plots provide evidence of the consistency of the models in terms of error magnitudes across the entire range of shear strength values. This uniformity in the error distribution is an essential characteristic in applications where reliable predictions are crucial in various scenarios. The RF and DT models exhibit narrower error distributions, indicating their precision in generating predictions close to the actual shear strength values. This precision is consistent with the visual and numerical findings presented in the scatter plots (Figure 2) and the performance metrics in Table 1. The XGBoost and LightGBM models also demonstrate commendable error distribution patterns, indicating their potential utility for shear strength estimation tasks.

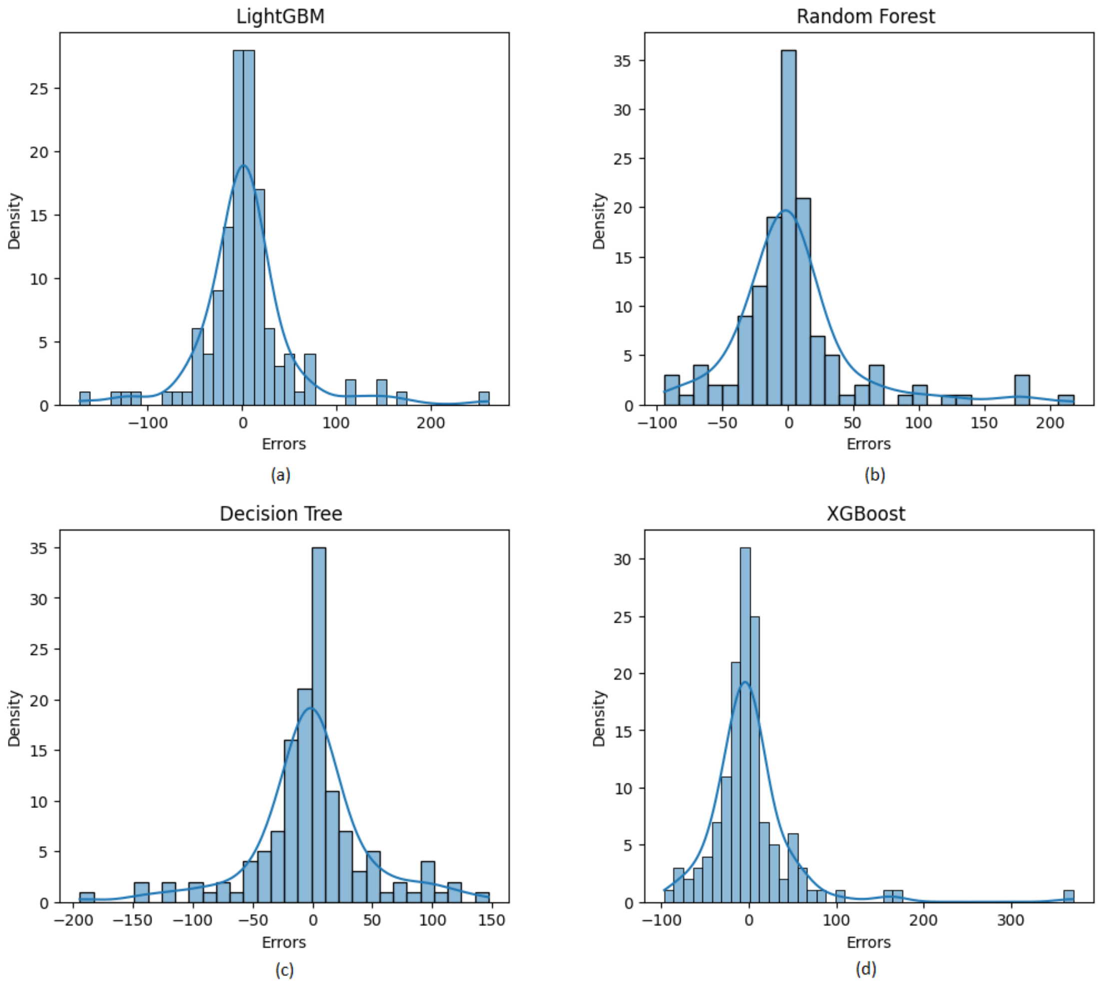

Figure 3. Error Distribution Plots for Regression Models

5. Conclusions

This research underscores the formidable potential of ML models in estimating shear strength, contributing substantially to advances in structural engineering methodologies. Research findings highlight the significant predictive capacity inherent in the ML models, demonstrating exceptional coefficients of determination ranging from 93.6% to 93.9% in relation to the variations observed in the shear strength of the RC columns. The comparative analysis highlights the effectiveness of the ensemble methods, with the RF model showing slight superiority in predictive performance over the DT model. Moreover, the expansion of the investigation to incorporate XGBoost and LightGBM models accentuates their promising role in precise estimation tasks related to shear strength. Scatter plots visually validate the models' proficiency in predicting shear strength values across a range of scenarios, while error distribution plots emphasize the models' balanced overestimations and underestimations, reinforcing their reliability. In essence, this study underscores the potential of ML models to significantly enhance shear strength estimation accuracy, thus contributing to the advancement of structural engineering practices. While this study provides valuable insights into the estimation of shear strength using ML models, several avenues for future research could be explored to further advance this field. One potential direction could involve investigating the applicability of advanced ML techniques, such as deep learning algorithms, in predicting shear strength with even greater accuracy. Additionally, incorporating more diverse datasets encompassing a wider range of structural configurations and material properties could enhance the generalizability of the developed models. However, it is imperative to acknowledge the limitations inherent in the present study. The reliance on experimental data entails inherent constraints regarding the extrapolation of findings to real-world applications within the field of structural engineering. Furthermore, the accuracy of the predictive models is contingent upon the quality and representativeness of the dataset, which may not fully encapsulate the intricate nuances of structural behavior across diverse operational conditions. Additionally, the narrow focus on shear strength estimation may inadvertently disregard other pivotal factors influencing structural performance, including but not limited to material aging, variations in construction methodologies, and environmental influences.

Conflict of Interest

The authors declare that they have no conflicts of interest regarding the publication of this manuscript.

Informed Consent

The research and publication processes adhered to ethical standards and guidelines. No legal or special permissions were required for conducting or publishing this research.

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