

Article

Data-Driven Modeling of Lateral and Cracking Loads in Confined Masonry Walls Using Machine Learning

Hamza Mahamad Bile ^{1,2,*}  and Kadir Güler ¹ ¹ Department of Civil Engineering, Istanbul Technical University, 34469 Istanbul, Türkiye; kguler@itu.edu.tr² The Africa Center of Excellence for Logistics and Transport (CEALT), University of Djibouti, Djibouti 77000, Djibouti

* Correspondence: bileha20@itu.edu.tr

Abstract: Confined masonry (CM) is becoming a widely adopted construction building method even in earthquake-prone regions due to its economic viability, construction simplicity, and material availability. However, existing empirical models for predicting lateral and cracking loads often fall short due to varied material properties, detailing of confining elements and construction practices. In this study, machine learning (ML) algorithms, such as Extreme Gradient Boosting (XGB), Random Forest (RF), and Extremely Randomized Tree (ERT), were employed to predict the seismic performance of CM walls, focusing on maximum lateral load capacity and cracking load based on an experimental dataset from 84 published studies, with 59 samples for training and 25 for testing. Different material, load, geometrical, and reinforcement detailing, related to the lateral load capacity of CM, were considered. This study also compares the performance of the existing empirical equations against the proposed ML models. The ML models demonstrated strong predictive capabilities, outperforming empirical equations in both maximum lateral load and cracking load predictions, with XGBoost yielding the highest accuracy, reflected by R^2 values of 0.903 for lateral load and 0.876 for cracking load predictions, and lowest the RMSE (28.742 for lateral and 23.982 for cracking load). Additionally, a comparative analysis shows that while some empirical equations produce reasonably accurate predictions, most exhibit significant deviations from experimental results. This study finally employs Partial Dependence Plot (PDP) analysis to explain the importance and contribution of the factors that influence the lateral strength, and concludes that ML models, especially XGBoost, are highly effective in capturing the complex behavior of CM walls under vertical and lateral loads, making them valuable tools for enhancing the accuracy of seismic performance evaluations.

Keywords: confined masonry walls; machine learning; extreme gradient boosting; random forest; lateral load capacity; cracking load; extremely randomized trees; empirical models



Citation: Bile, H.M.; Güler, K. Data-Driven Modeling of Lateral and Cracking Loads in Confined Masonry Walls Using Machine Learning. *Buildings* **2024**, *14*, 4016. <https://doi.org/10.3390/buildings14124016>

Academic Editor: Muhammad Junaid Munir

Received: 30 October 2024

Revised: 29 November 2024

Accepted: 3 December 2024

Published: 18 December 2024



Copyright: © 2024 by the authors. Licensee MDPI, Basel, Switzerland. This article is an open access article distributed under the terms and conditions of the Creative Commons Attribution (CC BY) license (<https://creativecommons.org/licenses/by/4.0/>).

1. Introduction

Masonry is one of the most traditional and commonly used construction materials and remains a prevalent choice for the cost-effective construction of low- to mid-rise buildings. Its popularity is attributed to the abundant availability of materials, construction simplicity, aesthetic appeal, and superior heat and sound insulation properties. However, the use of unreinforced masonry (URM) structures in medium- to high-seismic regions has been a subject of concern due to their poor earthquake performance, often leading to significant economic and life losses. To address these deficiencies, reinforcement techniques have been introduced, such as reinforced masonry (RM), in which steel bars are embedded within the vertical hollows of masonry units and horizontal mortar joints, and CM, where unreinforced masonry walls are enclosed by small-sized, in situ-cast reinforced concrete elements [1]. CM construction emerged in the early 20th century as a practical and economical alternative to both reinforced concrete (RC) frame structures and URM. Its first documented application was during the reconstruction following the Messina earthquake (M7.2, Italy) in 1908 [2].

The CM system ensures that masonry panels and reinforced concrete elements work as a unified structure under both lateral and vertical loads. This construction method is distinct from RC frame buildings, (shown in Figure 1) as the masonry walls in CM buildings are erected before the confining concrete elements, facilitating cost savings and enhanced structural performance. Additionally, masonry walls in CM systems serve as the primary load-bearing elements, unlike RC frames, where the structural frame is the main load-bearing system [2,3].

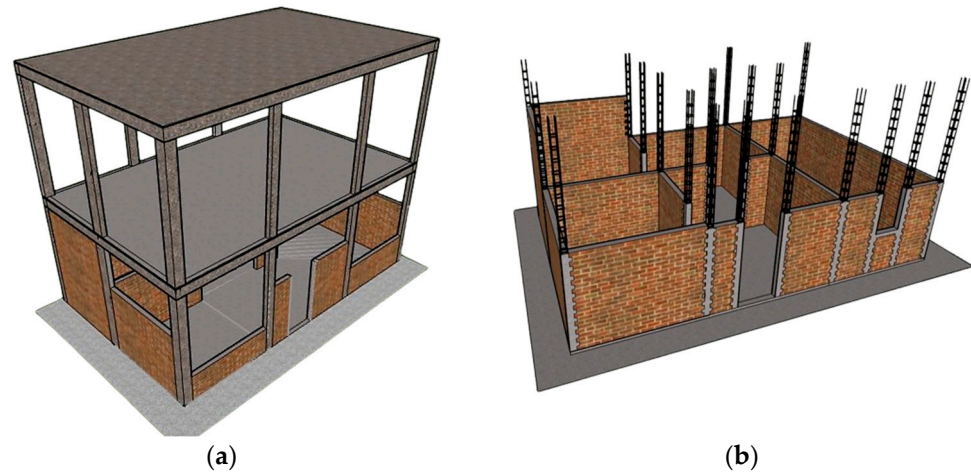


Figure 1. Comparison of reverse construction sequence in CM and RC frame buildings with masonry infill walls: (a) RC frames; large RC elements first, masonry infill walls later. (b) CM; masonry walls first, small RC ties later.

The confining members are critical components in CM buildings, playing a pivotal role, as they contribute the structural integrity and stability of masonry panels under both in-plane and out-of-plane seismic forces. They significantly increase the strength, ductility, and resistance of these masonry panels to horizontal seismic forces, ultimately improving their overall earthquake performance [4–6].

Over the last century, CM construction has been widely adopted in seismically active regions across Latin America, Asia, Eastern Europe, and Africa, demonstrating exceptional earthquake performance [2–4,7–9]. For instance, well-constructed CM buildings have consistently outperformed URM and poorly constructed RC frame buildings during major seismic events, such as the 1985 Mexico earthquake (MW 8.0), the 2007 Peru earthquake (MW 8.0) [2], the 2010 Chile earthquake (MW 8.8) [10], the 2001 El Salvador earthquake (MW 7.7) [11], and the 2004 Indonesian earthquake (MW 9.3) [12]. Despite these successes, challenges remain in accurately predicting the seismic behavior of CM walls, particularly their lateral load capacity, due to variations in materials, construction practices, and confining element details across regions.

The shear load–displacement behavior of CM walls has been extensively studied both experimentally and analytically and described using an idealized tri-linear load–displacement curve (shown in Figure 2). This curve identifies critical performance points: cracking load (V_{cra} – point A), maximum load capacity (V_{max} – point B, and ultimate load (V_{ult} – point C, which is closely linked to the collapse drifts, a key measure of seismic resilience. Numerous empirical equations have been proposed to estimate [7,12–26] these critical points, but their predictive accuracy varies significantly due to regional differences in construction practices, material properties, and detailing of confining elements. While our study focuses on load-based performance prediction, incorporating deformation measures could provide a comprehensive evaluation of CM structures. Consequently, a comparative evaluation regarding the effectiveness of the existing empirical equations in estimating the maximum strength and the cracking load of CM walls subjected to gravity and lateral loadings is needed [17,18].

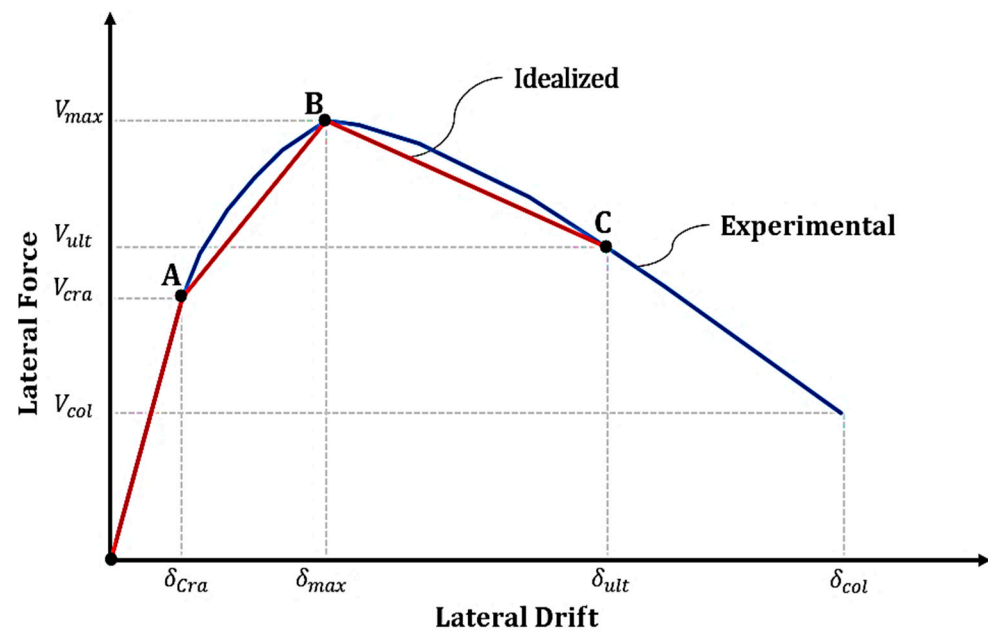


Figure 2. Idealized tri-linear load–deformation curve.

Recent advancements in numerical modeling and soft computing techniques have provided alternative approaches to address the limitations of empirical models. Finite element (FE) modeling, ranging from detailed 3D models to simplified 2D line element models, has been widely used to study the seismic behavior of CM walls. Lang et al. [27] and Bonisha et al. [28] provided a comprehensive review of various such numerical models. However, these methods often require significant computational resources. To overcome these challenges, ML models have emerged as promising tools for capturing the complex behavior of CM structures. The integration of ML in seismic studies not only reduces computational complexity but also enhances prediction reliability, as seen in optimization-based Stacked ML models for RCSWs (reinforced concrete shear walls), which efficiently estimate key seismic parameters and facilitate rapid risk assessments, as shown by Kazemi et al. [29]. Most studies in masonry-related research have employed ML techniques; among these techniques, Artificial Neural Networks (ANNs) and Adaptive Neuro-Fuzzy Inference Systems (ANFISs) are prominent models designed to address various engineering challenges. For instance, Seung-Chang Lee [30] and Sah et al. [31] developed an ANN-based model that significantly improves concrete strength prediction accuracy compared to traditional maturity methods and ML models. N. Sathiparan [32] and P. Jeyanthan [32], as well as P.G. Asteris et al. [33], employed ANNs alongside other models including Linear Regression (LR), Decision Tree (DT), Ridge Regression (RR), Random Forest Regression (RFR), and XGBoost to predict the compressive strength of masonry prisms using experimental dataset. Sathiparan's study highlighted that ANNs outperformed other ML models in predicting compressive strength. Additionally, Q. Zhou et al. [34,35] and Lan Guanqi et al. [36] integrated an ANFIS with ANNs to predict the compressive and shear strength of masonry prisms, with findings indicating that the ANFIS outperformed ANNs and provided superior predictions compared to empirical models. Feng et al. [37] proposed the Adaptive Boosting algorithm to predict concrete compressive strength. The method combines multiple weak learners, enhancing overall model accuracy.

Similarly, Hongbo L. et al. [38] employed a Back Propagation Multi-Layer Perceptron (BPMLP) to assess the flexure and shear strength of masonry shear walls, while V. Aguilar et al. [39] and A. Cascardi et al. [40] investigated the shear resistance of reinforced masonry walls based on an extensive experimental dataset of different typologies. Mishra et al. [41] evaluated the compressive strength of unreinforced brick masonry by employing ANNs, Support Vector Regression (SVR), and ANFISs, trained on data from the Nehru

Museum (India). J. Garzón-Roca et al. [42] used ANNs to estimate the axial load limit of masonry walls, and Sreedhara B. Marulasiddappa et al. [43] employed three machine learning techniques, Gradient Tree Boosting (GTB), Elman Neural Networks (ENNs), and Multivariate Adaptive Regression Splines (MARSs) to predict the load-bearing capacity of masonry walls using the compressive strength and modulus of elasticity of mortar and masonry units as inputs. Their findings highlighted MARS as the most accurate and reliable method across different scenarios. Some studies assessed the masonry structures through vision-based ML models. Dais et al. [44] applied deep learning for automated crack detection in masonry walls, achieving 95.3% accuracy representing a pioneering effort in pixel-level crack segmentation. Likewise, Adaileh et al. [45] introduced a conditional generative adversarial network (cGAN) to predict the mechanical response of masonry structures using image-based strain maps, bypassing traditional finite element simulations and providing a revolutionary metamodel for masonry analysis. These developments complement earlier research, where machine learning techniques like ANN, SVM, and RF were used to assess masonry strength and seismic vulnerability. Notably, Harirchian et al. [46] demonstrated the potential of ML models for deriving fragility curves for masonry walls, further highlighting the growing application of vision-based ML models in masonry assessments.

A very few research studies have explored the use of ML models to CM walls or buildings. Juan Carlos et al. [47] utilized ANNs for the structural design of a CM building and found that the ANNs achieved a margin of error within 10% compared to traditional design methods. In similar way, Ojeda et al. [48] employed tree-based models to evaluate and classify the seismic vulnerability of self-built CM houses in Peru. The study found XGB to be the most accurate among the tested models, demonstrating its effectiveness in capturing intricate structural behaviors and aiding in reliable vulnerability assessments. Rui M. et al. [13] employed Multiple Regression (MR), Regression Trees (RTs), K-Nearest Neighbors (KNNs), an ANN, and Support Vector Machines (SVMs) to develop an analytical model capable of accurately capturing the lateral force–displacement behavior of CM walls.

This study employs advanced tree-based ML algorithms, including Random Forest (RF), Extremely Randomized Tree (ERT), and Extreme Gradient Boosting (XGBoost), to predict both the maximum lateral capacity (V_{max}) and cracking load (V_{cra}) of CM walls. This research represents the first application of these tree-based ML models to evaluate the lateral load behavior of CM walls; the models were developed using large experimental datasets collected from the literature, encompassing the material, geometry, and reinforcement details characteristics. This research compares the results of the proposed models with those of traditional empirical equations found in design codes and published research. A Partial Dependence Plot (PDP) analysis was conducted to evaluate the influence of key input features on the predicted outputs, offering valuable insights into the complex interactions between variables. Additionally, the models' predictive performance and efficiency were assessed using robust evaluation metrics, including root mean square error (RMSE), coefficient of determination (R^2), Willmott's refined index of agreement (WI), mean absolute percentage error (MAPE), adjusted R^2 , and Nash–Sutcliffe efficiency (NSE). The findings address the potential of ML tools to provide rapid and accurate preliminary designs, particularly for resource-constrained practitioners. By advancing computational methods for lateral load capacity prediction, this work also contributes to the limited body of research on ML applications in CM walls and underscores the capability of tree-based models to enhance seismic performance evaluations and the design of CM systems.

2. Methodology

2.1. Experimental Database

2.1.1. Experimental Data Collection

In this study, the experiment databases of CM walls were collected from the existing literature [5,13,16,19,25,48–64]. The specimens were selected based on the following criteria: (1) applied static vertical load and monotonic or cyclic lateral in-plane loads to the wall;

(2) no horizontal reinforcement in the wall panel, no grouting, and additional dowel anchors between the wall panel and tie-columns; (3) no aspect ratio (AR) and slenderness ratio (SR) greater than 2.5 and 30, respectively; (4) area of tie columns (A_c) not less than 0.01 m^2 and their number not greater than 4, except the specimen from [26,65], where despite the relatively small size of the tie-columns, the anticipated seismic behavior mechanism has been accurately replicated; (5) no openings in the wall panels. The typical selected CM wall is shown in (Figure 3), in which both the horizontal and vertical forces are applied in the plane of the wall.

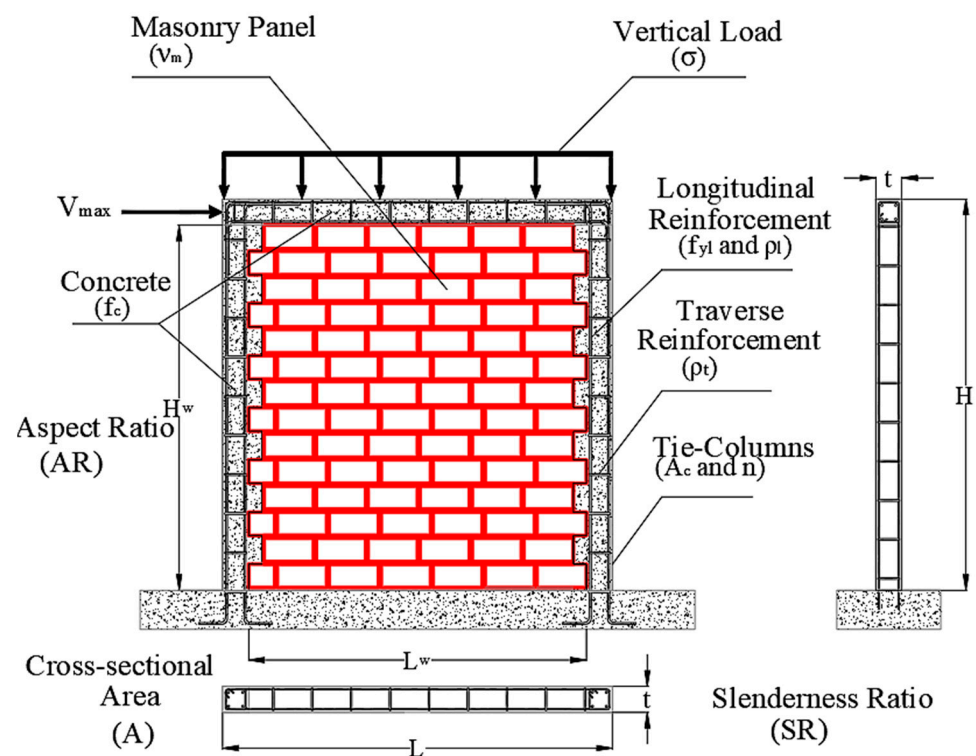


Figure 3. Typical CM wall with input parameters.

As stated earlier, the primary failure modes associated with CM buildings are shear and flexure, and in-plane damage to these structures typically arises at the first-story level while the out-of-plane failure effects are predominantly observed in the upper stories. The primary concern in the failure mechanisms of CM walls is in-plane failure, as it occurs along the principal lateral load transfer path. This failure mode depends on several factors, such as the material parameters (compressive strength of mortar, concrete, and masonry; masonry shear resistance; yield capacity of main reinforcement), load parameters (load intensity and load application point), wall geometrical factors (aspect ratio, slenderness ratio, wall area, and wall reinforcement), and detailing parameters (cross-section, spacing and number of tie-columns, and reinforcement details). The shear-induced cracks that develop from the middle of the panel through the tie-column depend on the tensile strength of the masonry. The cracking arrangement depends on the strength of the units, mortar, and mortar–unit joints, and they can be either in a stepped form traversing the joints between the mortar and units (when the units are stronger than the mortar) or pass through the units (when the mortar is stiffer than the units).

The main in-plane failures in CM walls are flexural cracks, compressive, diagonal tension, and sliding shear failures. Typically, lateral loading creates a compressive diagonal strut in the wall perpendicular to tensile stresses (Figure 4a) [20,26,56,64,66]. However, in some instances, particularly in slender CM walls, tensile stresses may cause tensile, horizontal flexural cracks in the lower sections of the wall (Figure 4b) [53,59,64,67,68]. The compressive failure occurs (Figure 4c), especially when the vertical loads are high, or the

compressive strength of masonry units is low. On the contrary, bed-joint sliding shear failures (Figure 4d) are associated with low vertical load, weak horizontal mortar joints, and low concrete shear strength [17,56,69,70].

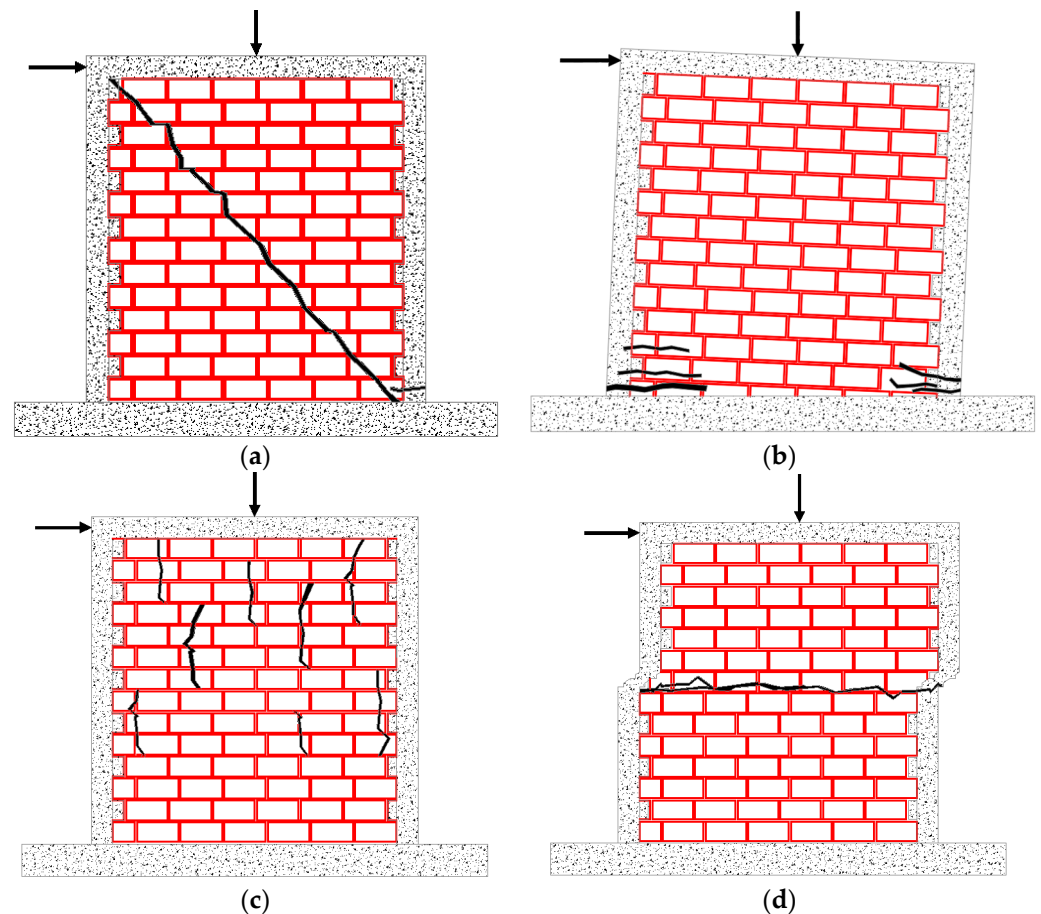


Figure 4. Different in-plane failure mechanisms: (a) compressive diagonal strut; (b) tensile, horizontal flexural mode; (c) compressive failure; (d) bed-joint sliding shear failures.

Based on the established criteria, twenty-eight reputable published experimental studies were used to construct a total of 84 datasets for developing prediction models for the lateral in-plane strength of CM walls. The typical parameters selected for CM walls are illustrated in Figure 3. From the collected database, two primary types of masonry units were identified: concrete blocks and clay bricks. The maximum and minimum compressive strengths of concrete, mortar, and masonry are 43.8 MPa, 45.4 MPa, and 40.3 MPa, respectively. The maximum aspect ratio (AR) and slenderness ratio (SR) of the walls are 2.385 and 25.3, respectively. Most of the walls have two tie-columns, except for those in the experiments conducted by V. Singhal and D. Rai [65] and the ME7 wall by J. Perez Gavilan et al. [17], which have three and four tie-columns, respectively. The maximum and minimum yield strengths of tie-column longitudinal reinforcement are 623 MPa and 266 MPa, respectively. Twelve parameters were collected from each specimen, with the maximum lateral strength (V_{max}) and cracking load (V_{cra}) considered as the output variables.

Figure 5 shows the distribution of the 12 input variables, along with the corresponding fitted distribution curves. Additionally, the terms min., max., mean, median, best fit, and standard deviation (Std. dev.) in the figure represent the minimum value, maximum value, mean, median, and standard deviation of the input variables. The function of the best fit is selected by using the Akaike Information Criterion (AIC) to choose the distribution that best explains the data and the variables exhibited three types of distribution such as normal, log-normal, and gamma distributions.

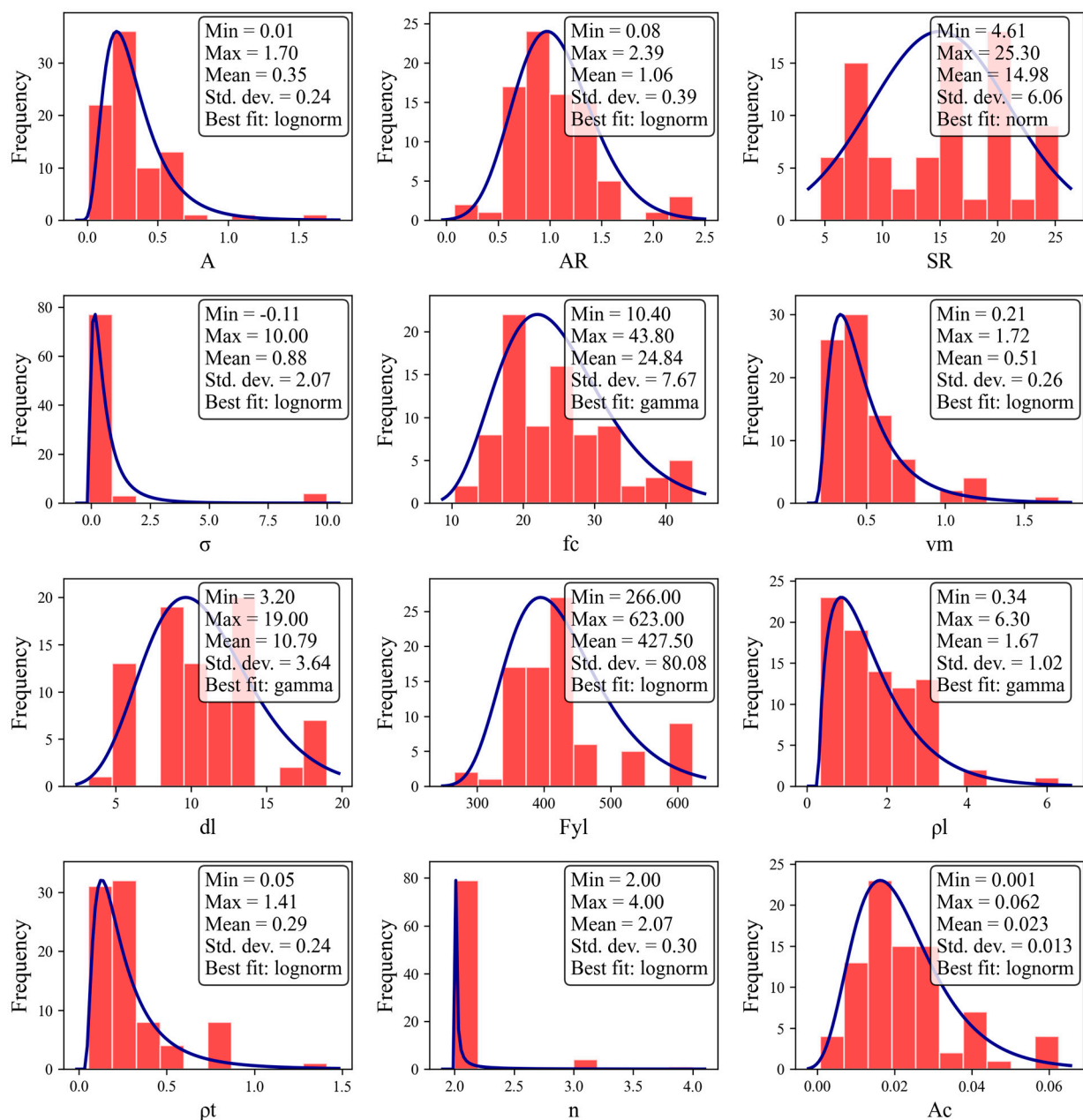


Figure 5. Distribution of input variables in the database.

2.1.2. Data Preprocessing

Data preprocessing is crucial for enhancing ML model performance by increasing accuracy, accelerating training, and mitigating overfitting. It addresses missing data through imputation, ensures feature consistency via normalization and scaling, and manages outliers with techniques like truncation. Additionally, categorical variables (unit type) are converted into numerical values using encoding methods to make them suitable for algorithms. In this work, two major preprocessing steps were implemented. First, data encoding was applied to the categorical attribute of lithology (LT) to convert it into numerical form. Data normalization was also addressed as input variables often differ significantly in terms of units, magnitude, and scale, which can negatively impact model performance. The 12 variables in this study varied widely in scale, requiring normalization. Two widely used techniques for normalization are MinMaxScaler and Standard-Scaler. MinMaxScaler adjusts the range of variables between 0 and 1, whereas Standard-Scaler centers the variables around a mean of 0 and a standard deviation of 1 [71]. In this study, Standard-Scaler

was chosen due to its successful application, ensuring all variables were standardized with a mean of 0 and a standard deviation of 1, as shown in Equation (1). This process is essential because features with significantly larger variances, such as the yield strength of longitudinal reinforcement (ranging from 266.0 to 623.0 MPa), could dominate smaller features like the cross-sectional area of tie-columns (ranging from 0.001 to 0.063 m²), skewing the model's predictions. The output variables in this study were the predicted cracking and maximum lateral loads. In total, 84 collected samples were randomly divided; 70% was used for training, and the remaining 30% of the dataset was used for testing and validation.

$$y = \frac{x_i - \bar{x}}{\sigma} \quad (1)$$

where x_i and y are the i data before and after normalization, respectively; Ω is the standard deviation; and $\bar{x}$ is the mean of the data. The descriptions and statistical characteristics of the input variables are presented in Table 1. It should be noted in Table 1 that COV and St. Dev denote the coefficient of variation and the standard deviation, respectively.

Table 1. Statistical characteristics of input parameters of collected experiments.

Variables	Units	Min	Max	Mean	St. Dev	COV (%)	Type
A	m ²	0.01	1.70	0.35	0.24	55.8	Input
AR	-	0.08	2.39	1.06	0.39	45.3	Input
SR	-	4.61	25.30	14.98	6.06	38.5	Input
σ	MPa	−0.11	10.00	0.88	2.07	68.3	Input
f_c	MPa	10.40	43.80	24.84	7.67	30.7	Input
v_m	MPa	0.21	1.72	0.51	0.26	51.5	Input
d_l	mm	3.20	19.00	10.79	3.64	33.5	Input
f_{yl}	MPa	266.00	623.00	427.50	80.08	18.6	Input
ρ_l	%	0.34	6.30	1.67	1.02	62.0	Input
ρ_t	%	0.05	1.41	0.29	0.24	81.2	Input
n	-	2.00	4.00	2.07	0.30	21.2	Input
A_c	m ²	0.001	0.062	0.023	0.013	56.5	Input
V_{max}	kN	2.07	834.97	195.30	146.99	75.3	Output
V_{cra}	kN	0.89	627.80	142.04	109.82	77.3	Output

The lateral load capacity of CM walls at the different limit states depends on different variables, which are generally material-related parameters (f_c , f_m , f_{yl} , and v_m), geometry-related parameters (A , A_c , AR , A_o , n , l_i/l_p , and n_i), reinforcement detailing parameters (d_l , ρ_l , ρ_t , and n_r), and loading parameters (σ) [14,72–76]. The influence of these parameters was mainly observed by analyzing the experimental results. Many previous studies have analyzed the influence of each parameter on the overall lateral capacity of CM walls. In all studies, the factor that contributed most to lateral strength (cracking as well as maximum strength) was the masonry panel in terms of either masonry shear strength (v_m) or compressive strength (f_m), whereas the influence of overburden pressure (σ) was considered the next parameter with the greatest impact on strength [14,72,74–78]. Additionally, wall geometry- and reinforcement detailing-related parameters (A , SR , AR , A_c , f_{yl} , d_l , ρ_l , and ρ_t), confinement-related parameters (l_i/l_p , n , and n_i), and masonry unit type were considered in some studies. In some studies [15,22], the aspect ratio and masonry unit type were found to not have much influence on the strength of CM walls, while others found that traverse and longitudinal reinforcements in the tie-columns do not have much influence on strength [24,79,80].

In this study, a comprehensive set of 12 key input variables is considered to characterize the lateral strength of CM walls, while excluding less influential parameters. The input variables include five variables related to wall geometry: wall area (A), aspect ratio (AR), slenderness ratio (SR), column cross-sectional area (A_c), and the number of tie-columns (n). Material properties are represented by the concrete compressive strength (f_c), yield

strength of longitudinal bars (f_{yl}), and masonry shear strength (v_m). To account for the influence of reinforcement detailing and axial load, the overburden pressure (σ), diameter of longitudinal reinforcement (d_l), and reinforcement ratios for longitudinal and transverse reinforcements (ρ_l , ρ_t) are included. The correlation matrix for the selected input variables is presented in Figure 6, where each element, known as the correlation coefficient, indicates the strength of the relationship between two input variables. Notably, A_c is strongly correlated with SR (correlation coefficient of 0.51), as both variables are tied to the geometry of the wall cross-section; as the slenderness ratio increases, the column cross-sectional area typically decreases, given that the wall thickness and tie-column width remain mostly the same.

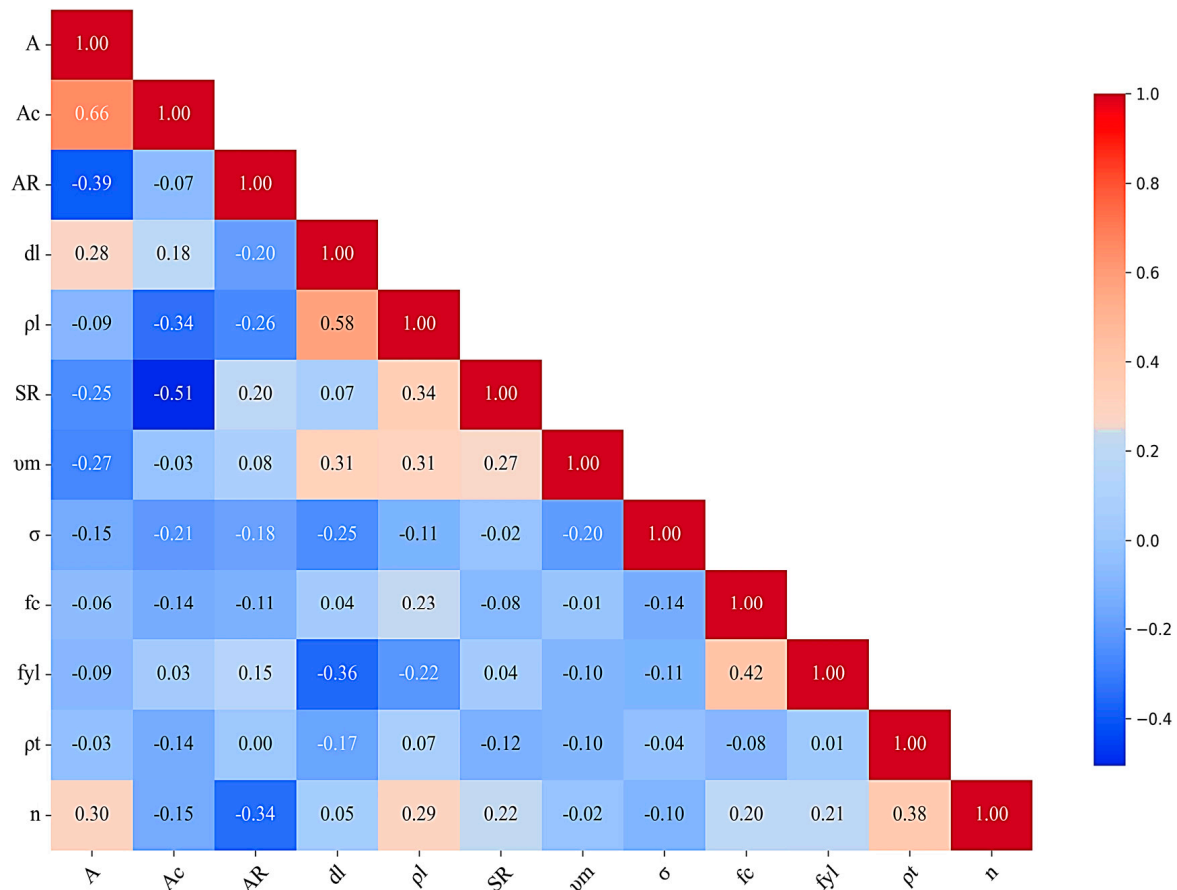


Figure 6. Correlation matrix for input variables.

Parameters not considered in this study include the number of intermediate columns (n_i), the confinement effect measured by the ratio of the total centerline length of internal confining elements to the centerline length (l_i/l_p), the total longitudinal reinforcement area (A_l), transverse reinforcement area (A_t), and the total number of longitudinal bars in each column (n_r). The first two parameters (n_i and l_i/l_p) are accounted for indirectly, as they are not widely included in previous studies, while A_l , A_t , and n_r are implicitly addressed through the calculation of reinforcement ratios (ρ_l , ρ_t) and are not treated as direct input variables. The output variables considered in this study are the cracking and maximum lateral loads of CM walls, as these represent the most critical performance points among the three (cracking, maximum, and ultimate/collapse).

The interpretability of ML models was examined using Partial Dependence Plots (PDPs) as proposed by Friedman [81]. PDPs help to estimate changes in mean prediction values based on variations in individual input features, isolating their effects while keeping other features constant. Figures 7 and 8 illustrate the PDPs for the two datasets (cracking

and maximum lateral load) using the XGBoost model. These plots provide a structured visualization of the relationships between each feature and the prediction targets. In these figures, each plot represents the change in the XGBoost-based model prediction when compared with the change in the input variable. It can be seen that all the features have fluctuated alongside of vertical axis and show the complicated relationship between the targets of prediction. Therefore, the input features have a direct influence on the results and cannot be neglected during analysis. It is essential to emphasize that, given constant effects of other features, they were excluded from the comparison and were not taken into account when assessing ML models.

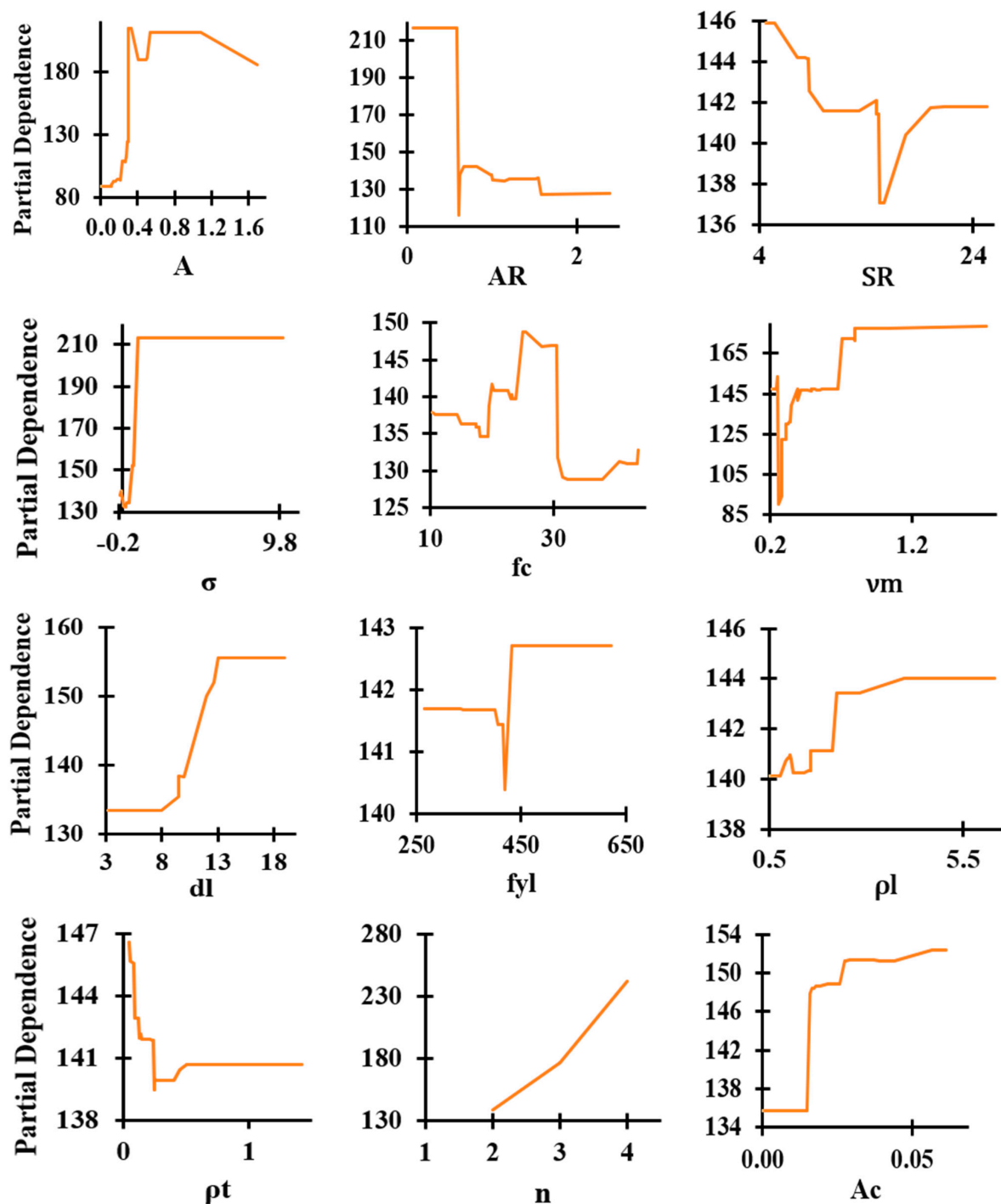


Figure 7. PDP presentation of input features of cracking load dataset.

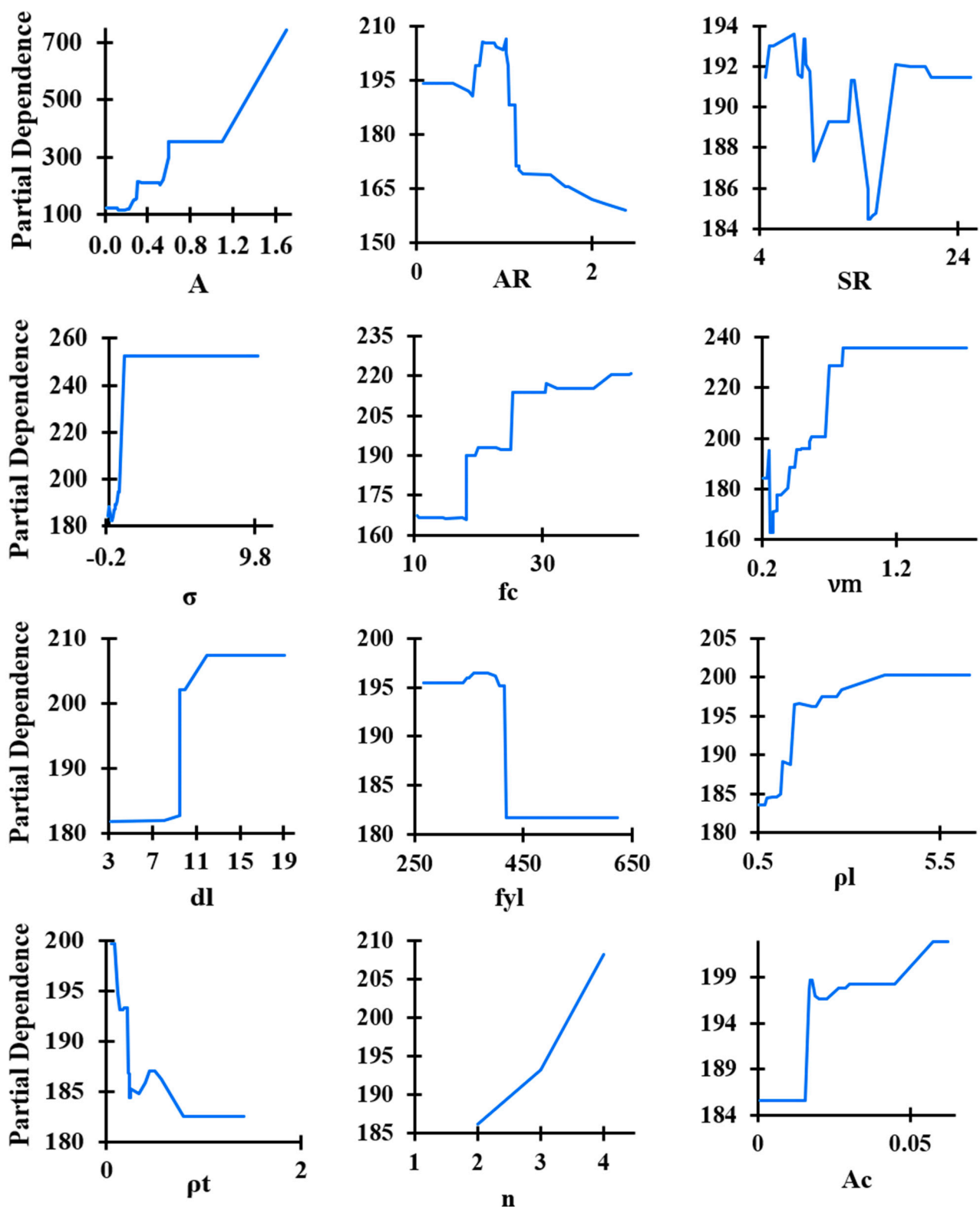


Figure 8. PDP presentation of input features of maximum lateral load dataset.

For both datasets, the PDPs reveal diverse and complex influences of the 12 input variables on the model predictions. Features like the number of tie-columns (n), concrete compressive strength (f_c), cross-sectional area of tie-columns (A_c), wall area (A), and masonry shear strength (v_m) display gradual or exponential relationships, while overburden pressure (σ) shows sharp initial impacts, stabilizing as its values increase, and aspect ratio

(AR) exhibits impact with fewer values [17,57,70,82], highlighting these features' significant contributions to both cracking and maximum load capacities, which aligns with findings from several studies identifying masonry shear strength as the most influential variable for the shear strength of CM walls. However, the slenderness ratio (SR) and reinforcement ratios (ρ_l) and (ρ_t) exhibit more intricate patterns, with fluctuating or non-linear effects. Rui et al. [13], B. Bonisha et al. [18], and Z. Riahi et al. [15] also noted that the longitudinal reinforcement ratio (ρ_l) has low relevance in the sensitivity analysis of CM wall shear strength, suggesting a non-linear influence, a hypothesis supported by earlier studies and some international standards [23,24,79,80].

The PDPs highlight the complex dependencies of each input feature on the prediction targets, with fluctuations across the vertical axes underscoring the non-linear nature of these relationships. These results reinforce the critical roles of masonry shear strength, wall geometry, and other key variables in determining the cracking and maximum loads of CM walls.

2.2. Existing Empirical Prediction Models

Due to the monolithic interaction between the masonry panel and the surrounding confining elements, the out-of-plane strength of CM structures is superior compared to URM and infilled RC frame structures. Consequently, the in-plane load–displacement behavior of CM walls has received significant attention in seismic research. Under seismic forces, shear failure is the predominant failure mode in CM walls due to their inherent material characteristics and the typical geometry of structural walls [1]. In previous studies, empirical models have been created to predict the cracking and maximum lateral load responses of CM walls, using either experimental research or through regression analysis of data collected from earlier experiments [7,12–25]. In this study, twenty-three empirical equations to predict the cracking (V_{cr}) and maximum lateral load (V_{max}) of CM walls, recommended in the studies or design codes, were reviewed and are shown in Tables 2 and 3.

Table 2. Empirical models for maximum lateral load estimation.

References	Models	Eq's.
Rui Marques and P. B. Lourenco (RP2, RP3) [7]	$(0.5f_{AR}v_m + 0.4\sigma) A$, where $f_{AR} = 1.15 - 0.15H/L$	(2)
	$\{(0.45v_m + 0.3\sigma) + 0.4\sqrt{f_c}(1 + n_i) n_c A_c / A\} A$	(3)
M. Tomaževic and I. Klemenc (TK) [26]	$[1 + \sqrt{c_i^2(1 + \frac{\sigma}{v_m})} + 1] / (c_i f_{AR}) v_m A_w + (0.8059 n_r d_l^2 \sqrt{f_{yl} f_c})$ where; $c_i = \frac{5f_{AR}}{2AR}$, $f_{AR} = 1$ for $AR \leq 1$, AR for $1 < AR \leq 1.5$, and 1.5 for $1.5 \leq AR$	(4)
Marinilli and E.Castilla (MC) [14]	$(0.47v_m + 0.29\sigma) (A - n_c A_c) + 4200 n_c$, (in kg cm)	(5)
Rui Marques et al. (RP1) [13]	$\{(0.49v_m + 0.53\sigma) - 0.14(H/L) - (A_w/A) + 1\} A$	(6)
Z. Riahi et al. (ZR) [15]	$[0.21v_m + 0.36\sigma + 0.0141\sqrt{\rho_l f_{yl} f_c}] A$	(7)
L. Flores and S.M. Alcocer (FA) [16]	$\text{Min} \{(0.5v_m + 0.3\sigma) A; 1.5 v_m A\} + 0.3(1.26 d_l^2 \sqrt{f_{yl} f_c})$	(8)
A. Bourzam et al. (BA2 and BA3) [19]	$[1 + \sqrt{c_i^2(1 + (\sigma/v_m) + 1)}] / C_i f_{AR} v_m A_w + (0.537 n_c n_r d_l^2 \sqrt{f_{yl} f_c})$	(9)
	$[A_w / \{f_{AR} (1 + v_m / f_m)\}] (\sqrt{v_m^2 + \sigma v_m (1 - v_m / f_m - \sigma^2 v_m / f_m)} + (0.537 n_c n_r d_l^2 \sqrt{f_{yl} f_c})$	(10)
A. Bourzam et al. (BA1) [20]	$\{\sqrt{1 + (\sigma/v_m)} / f_{AR}\} v_m A_w + (0.537 n_c n_r d_l^2 \sqrt{f_{yl} f_c})$	(11)
Bonisha Borah et al. (BB) [18]	$(AR^{-0.7}) [f_m^{0.4} (n_c A_c / A)^{0.9}] (1 + \sigma) A$	(12)
V. Singhal and D.Rai (SR) [22]	$(0. L_i / L_p + 2.15) \{\text{Min} (0.2 + 0.4\sigma; 0.25\sqrt{f_m})\} A_w$	(13)
M. Moroni et al. (MM) [23]	$\text{Min} \{(0.45v_m + 0.3\sigma) A; 1.5v_m A\}$	(14)
Inpres-2018 (AC) [24]	$(0.6v_m + 0.3\sigma) A$	(15)
Colombia code (CC) [25]	$\text{Min} \{(0.0833\sqrt{f_m} + 0.3333\sigma); 0.1667\sqrt{f_m}\} A$	(16)

Table 3. Empirical models for cracking load estimation.

References	Models	Eq's.
L. Flores and S.M. Alcocer (FA) [15]	Min $\{(0.5v_m + 0.3\sigma) A; 1.5v_m A\}$ or, $V_{cra} = 0.8V_{max}$	(17)
M. Tomaževic and I. Klemenc (TK) [26]	$0.7V_{max}$ to $0.8V_{max}$	(18)
Marinilli and E.Castilla (MC) [14]	$0.7V_{max}$ to $0.8V_{max}$, (in kg cm)	(19)
A. Bourzam et al. (BA) [19]	$0.6V_{max}$ to $0.8V_{max}$	(20)
Z. Riahi et al. (ZR) [15]	Min $\{(0.424v_m + 0.374\sigma) A; v_m A\}$ or $V_{cra} = 0.7V_{max}$	(21)
R. Marques et al. (RP) [7]	$0.8V_{max}$	(22)
B. Borah et al. (BB) [18]	$0.7V_{max}$	(23)
J. J. Perez Gavilan et al. (PG) [17]	Min $\{(0.5v_m + 0.3\sigma) f_{AR}A; 1.5v_m f_{AR}A\}$, where $f_{AR} = 1.55$, for $H/L \leq 0.2$; ($1.69-0.69H/L$), for $0.2 < H/L < 1.0$; and 1.0 , for $H/L \geq 1.0$	(24)

Across all formulas developed for the prediction of the lateral capacity, the primary contributions to lateral strength were attributed to the masonry panels, using either the masonry shear strength (v_m) or the compressive strength (f_m); vertical loads (σ); wall geometry-related factors (A and AR). Other equations include the impact of tie-column longitudinal reinforcement (as reinforcement ratio ρ_l , diameter d_l , and yield strength f_{yl}) and concrete tie-column area (A_c), though some studies indicated that longitudinal reinforcement has a negligible impact on the shear strength of CM walls [13,15,18].

The CM walls behave as a single, elastic unit until the first visible crack appears, corresponding to the cracking load. At this point, a diagonal crack typically forms in the center of the masonry wall due to diagonal tension. Once the diagonal cracking is fully developed, the panel acts as two triangular sections confined by the tie-columns [83]. Several studies that created empirical models to estimate the lateral strength capacity of CM walls also developed models to predict the cracking load, often based on friction theory. These empirical models for the first visible cracking were defined mostly as a function of lateral strength, given by $V_{cra} = \alpha V_{max}$, where α represents the strength reduction factor with a range of 0.6–0.8. In this study, an average of 0.75 is considered in Equations (18) and (19) and 0.7 for Equation (20). The precision of these models is evaluated and compared with the outcome of ML models in Section 3.

2.3. Tree-Based Machine Learning Models

In this research, three tree-based ML models (RF, ERT, and XGBoost) were utilized to predict the cracking and maximum lateral load of CM walls. Tree-based approaches are widely favored in ML due to their ability to handle complex relationships through recursive splitting, which helps estimate numerical values or class labels. To improve the accuracy of predictions and mitigate issues like overfitting and computational inefficiency, ensemble methods that combine multiple models were applied. These models offer the advantage of interpretability, providing insights into how input variables influence predictions [84,85]. Moreover, this study emphasizes the importance of multi-stage ensemble modeling, which integrates multiple algorithms, yielding improved prediction accuracy compared to traditional ensemble methods and demonstrating its effectiveness in modeling the behavior of CM walls.

The tree-based models were chosen due to their demonstrated effectiveness in handling structured data. These models are ensemble-based, improving performance by reducing variance and bias compared to standalone decision trees [37]. RF and ERT provide robust mechanisms for addressing overfitting, while XGBoost excels in efficiently capturing non-linear patterns due to its gradient-based optimization [86,87]. Such characteristics are particularly suitable for CM walls, which under lateral and vertical loads involve complex interactions between masonry panel and RC elements and diverse global constructions and reinforcement detailing practices. The models were further selected for their scalability and relatively low computational requirements [88,89], enabling seamless training on the experimental dataset of CM walls. Furthermore, several studies validate the effectiveness of ensemble methods in predicting complex structural behaviors. For

instance, Ojeda et al. [48] used these models plus DT to assess and categorize the seismic vulnerability of self-built CM houses in Peru. Their study highlighted that XGB was the most accurate model among those tested, demonstrating the efficacy of these methods in handling complex structural interactions and providing reliable predictions. Feng et al. [90] and Mangalathu et al. [91] found XGB and RF outperformed individual models like ANNs and decision trees (DTs) in predicting shear strength for RC walls. Comparative analyses (e.g., Bentéjac et al. [92]) highlight XGB's balance between speed and accuracy, while others (e.g., Sreedhara et al. Sathiparan [43,93]) report strong correlations between boosting algorithm predictions and experimental results in masonry studies. Although models like ANN, DT, and ANFIS have been applied to masonry problems [35,36,42,94,95], tree-based methods are particularly adept at capturing the complex behaviors of masonry walls. This section presents the relevant information on the classical tree-based models used in this study, and the working principles of these methods are illustrated in Figure 9.

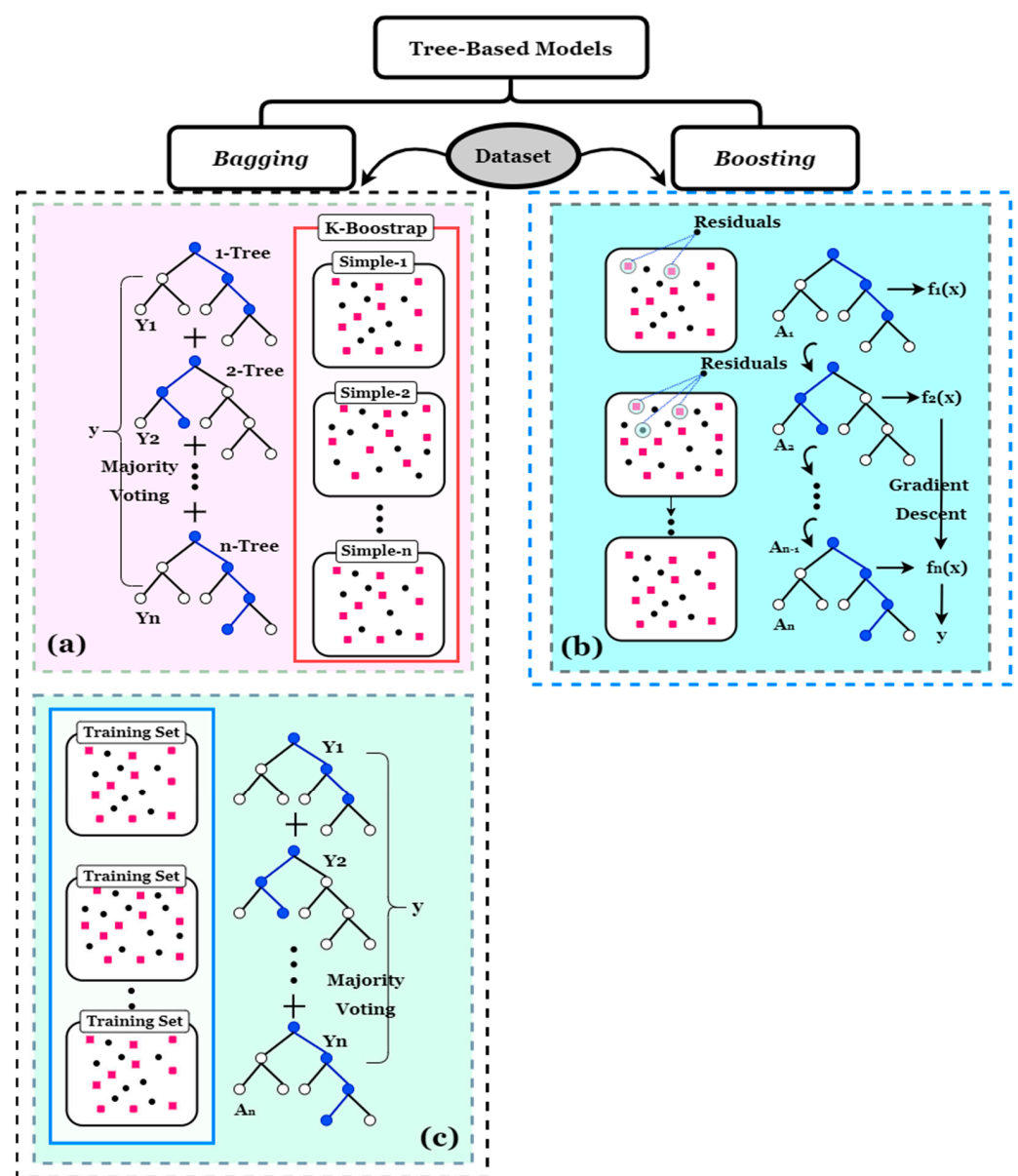


Figure 9. Working principles of tree-based methods. (a) Random Forest; (b) XGBoost; (c) Extra Trees. Note: Y_i refers to the prediction of each tree, A_i refers to the regularization parameter computed through each tree, $F_i(x)$ refers to the prediction of each gradient boosted tree.

2.3.1. Extreme Gradient Boosting (XGBoost)

XGBoost, developed by Chen and Guestrin [96], is a highly efficient machine learning algorithm that utilizes the principles of gradient boosting to improve the accuracy and precision of predictive models. XGBoost's main advantage over other boosting algorithms, such as Adaptive Boosting and Gradient Boosting, lies in its computational efficiency, particularly in handling large datasets, thanks to its parallel processing and distributed computing capabilities. The algorithm builds sequential decision trees, iteratively adding new trees to enhance the predictive power of the model. A key feature of XGBoost is its objective function, which consists of two components: a loss function to optimize accuracy and a regularization term to control model complexity, reducing the risk of overfitting. The loss and regularization functions are expressed in Equations (25) and (26), respectively:

$$L^t = \sum_{i=1}^n l(y_i, \hat{y}_i^{t-1} + f_t(x_i)) + \Omega(f_t) \quad (25)$$

$$\Omega(f_t) = \alpha T_t + \frac{1}{2} \lambda \sum_{j=1}^T \|\omega_j\|^2 \quad (26)$$

Here, L^t represents the loss function value at the t -th iteration. Moreover, y_i and $\hat{y}_i$ denote the actual and predicted class labels for sample i , respectively. f_t refers to the decision tree function, and n indicates the total number of instances in the training dataset.

XGBoost further improves model performance by incorporating second-order Taylor expansion to approximate the loss function, enhancing its ability to capture complex patterns in data. Additionally, cross-validation is used during the training process to minimize overfitting, making XGBoost well suited for regression, ranking, and classification tasks. Its superior handling of complex, non-linear problems sets it apart from other tree-based methods like Random Forest, which, while robust, can be computationally expensive in such scenarios [97].

2.3.2. Random Forest (RF)

RF algorithm, first introduced by Breiman [98], is a non-parametric ensemble learning method widely used for classification and regression tasks. It operates by constructing multiple decision trees using bootstrapped samples of the data and aggregating their predictions through “bagging” to enhance predictive performance [99]. RF excels in handling large datasets with numerous input variables and is particularly robust against overfitting, making it an ideal choice for complex problems involving imbalanced datasets, missing values, and non-linear relationships [100,101]. One of the key advantages of RF is its ability to maintain high classification accuracy by using the Gini index to measure class homogeneity at each node, ensuring optimal branching decisions. Moreover, RF is superior to traditional Classification and Regression Trees (CARTs), as it exhibits lower variance and greater resistance to overfitting [98]. This makes RF especially effective in predictive modeling, even in the presence of imbalanced class distributions, as demonstrated by its success in outperforming other machine learning algorithms under such conditions [102,103]. Additionally, the RF algorithm allows for the tuning of important hyperparameters such as the number of trees, tree depth, and minimum number of samples for splitting to improve model accuracy and further reduce overfitting [104]. Despite its advantages, RF has a noted limitation of being sensitive to categorical attributes, where different levels of the feature can disproportionately impact the results. Nonetheless, its overall reliability and performance make it a widely adopted method across diverse fields for tackling complex predictive tasks [105–107].

2.3.3. Extremely Randomized Trees (ERTs)

The ERT algorithm, introduced by Geurts et al. [108], is a machine learning technique developed as an extension of the Random Forest (RF) algorithm. The ERT algorithm shares similarities with RF in that both methods involve constructing numerous decision trees, but ERT introduces greater randomness, which makes it less prone to overfitting.

Specifically, at each node, a random subset of K features is selected to determine the split, and instead of choosing the best cut-point based on the local sample, ERT randomly selects a discretization threshold for each feature. This randomness results in larger tree structures that are built using the entire training sample, improving generalization ability and enhancing the algorithm's resistance. The ERT algorithm's main parameter, K , controls the number of features considered at each node, and when K is set to one, the tree structure is independent of the output labels. Unlike RF, ERT does not employ bagging to train each tree but instead relies on the complete learning sample to minimize model deviation. The algorithm constructs a forest of decision trees, and the final prediction is made by majority voting. This approach offers several advantages, including accurate results, faster computation times, and the ability to handle large datasets with high-dimensional input variables. Furthermore, ERT can evaluate the importance of variables during its execution, making it highly efficient for both regression and classification tasks. Its unique combination of randomness and computational efficiency allows for ERT to outperform other ensemble methods in terms of accuracy and generalization while avoiding overfitting [109].

In this study, an ERT model is employed to predict the cracking and maximum lateral load capacities of CM walls due to its ability to handle high-dimensional input variables without overfitting. Its use of random discretization thresholds at each node allows for efficient learning from the complete dataset, making it highly suitable for complex structural analysis. Furthermore, ERT provides accurate results with reduced computational complexity, faster processing times, and strong generalization, making it particularly effective for predicting structural capacities in masonry walls.

2.4. Performance Evaluation Indicators

Various performance indicators are used to evaluate the model performance. In this study, Nash–Sutcliffe efficiency (NSE), Willmott's index of agreement (WI), determination coefficient (R^2), RMSE, and MAE values were used to evaluate the prediction efficiency of the tree-based ML models, as in most masonry wall-related studies [32,35,43,110].

- Nash–Sutcliffe efficiency (NSE) is a commonly used performance indicator in the literature and varies between $(-\infty)$ and 1. If the efficiency value is 1, then it means that the model has a perfect match with experimental results. In other words, all the variance can be explained by the model, when this value approaches to 1 and the values above 0.7 indicate that the predictions have acceptable accuracy.

$$NSE = 1 - \frac{\sum_{i=1}^n (y_i - \hat{y}_i)^2}{\sum_{i=1}^n (y_i - \bar{y}_0)^2} \quad (27)$$

- Willmott's refined index of agreement (WI) varies between (-1) and 1. If the WI value approaches to 1, then it means that the model has a high accuracy same as the NSE. If the WI value is -1 , model interpretation should be performed carefully. For detailed information, see Willmott et al. [111].

$$WI = 1 - \frac{A}{c \times B} \quad \text{when } A \leq c \times B \quad (28)$$

$$WI = \frac{c \times B}{A} - 1 \quad \text{when } A > c \times B \quad (29)$$

$$\text{With } A = \sum_{i=1}^n |D_{pi} - D_{oi}|, \quad B = \sum_{i=1}^n |D_{oi} - o_i| \text{ and } c = 2$$

- The coefficient of determination (R^2) measures the strength of the relationship between the predicted and actual values, ranging from -1 to 1. Positive values indicate a direct relationship, negative values indicate an inverse one, and a value of zero shows no relationship. R^2 is used to assess model accuracy, with values closer to 1 reflecting higher accuracy.

$$R^2 = 1 - \frac{\sum (y_i - \hat{y}_i)^2}{(y_i - \bar{y}_i)^2} \quad (30)$$

- The root mean square error (RMSE) offers a distinct advantage over other statistical metrics, such as the mean absolute error (MAE), because it does not require the calculation of absolute values. This is particularly important because determining the sensitivity or gradient of MAE with respect to model parameters can be challenging [112]. As a result, RMSE is employed in this study and is defined by the following function [113]:

$$\text{RMSE} = \sqrt{\text{MSE}}, \text{ with } \text{MAE} = \frac{1}{n} \sum_{i=1}^n (y_i - \hat{y}_i)^2 \quad (31)$$

- Mean absolute percentage error (MAPE) is used to measure how accurate the predictions of ML are in percentage. Lower MAPE values show more accuracy of the given model.

$$\text{MAPE} = \frac{1}{n} \sum_{i=1}^n \left| \frac{y_i - \hat{y}_i}{y_i} \right| \times 100 \quad (32)$$

- The adjusted R^2 is a modified version of the coefficient of determination that accounts for the number of predictors in a model. Unlike R^2 , which always increases with the addition of more predictors, the adjusted R^2 adjusts for the model's complexity, penalizing the inclusion of predictors that do not significantly improve the model's fit. It indicates a model that explains the variability in the data effectively while avoiding overfitting.

$$\text{Adjusted } R^2 = 1 - \left(\frac{(1 - R^2)(n - 1)}{n - k - 1} \right) \quad (33)$$

3. Results and Discussion

In this study, tree-based ML models, including RF, ERT, and XGB, were used to predict the maximum lateral capacity and cracking load of CM walls. These models were trained on an extensive experimental dataset collected from the literature, offering a robust approach to understand and predict the performance of CM walls under lateral loads. The data consisted of 84 studies from reputable published experimental journals and were divided into two sets: 59 for training and 25 for testing. Twelve attributes (A , AR , SR , σ , f_c , v_m , d_l , f_{yl} , ρ_l , ρ_t , n_c , and A_c) of the dataset are used as input variables while V_m and V_{cr} were the outputs. This section gives performance comparison of the methods, and the results of maximum lateral load capacity of the models are presented first, then the cracking load.

3.1. ML Predictions for Maximum Load

The performance of the models in terms of maximum lateral load is summarized in Table 4. The RF model exhibited reasonable predictive capability, achieving an R^2 of 0.871 and 0.850 in the training and testing phases, respectively. Despite the slight decrease during testing, the RF model demonstrated moderate predictive accuracy, as evidenced by its RMSE and MAE values during testing. The adjusted R^2 (0.843) and WI (0.953) further confirm its utility, although as a less optimal choice compared to the other models. The ERT model showed slightly improved generalization compared to the RF model with an R^2 of 0.938 and 0.819 during training and testing, respectively. The model's RMSE and MAE in testing were slightly higher than RF, but its adjusted R^2 (0.811) and MAPE (49.806) indicate better alignment with experimental data.

Table 4. Summary of the performances of ML methods for maximum lateral load data.

Model	Testing			Training		
	ERT	RF	XGB	ERT	RF	XGB
RMSE	38.808	35.352	28.742	30.934	44.707	31.317
MAE	32.885	29.944	22.541	25.683	34.990	23.826
R ²	0.819	0.850	0.903	0.938	0.871	0.944
NSE	0.819	0.850	0.903	0.938	0.871	0.944
WI	0.942	0.953	0.973	0.982	0.962	0.984
MAPE	49.806	43.730	24.590	96.531	105.915	21.192
Adjusted R ²	0.811	0.843	0.898	0.936	0.868	0.943

The scatter plots in Figure 10 show the relationship between the predicted and actual values of maximum lateral loads, providing visual evidence of the models' effectiveness in both training and testing phases. Among the models tested, the XGB model outperformed both RF and ERT, particularly in the testing set. XGB achieved an impressive R² value of 0.903 in the testing phase, and 0.944 during training, demonstrating its ability to capture the non-linearities and complexities of the dataset. Additionally, the model exhibited the lowest RMSE and MAE values, along with a MAPE of 24.590 in testing, reflecting its superior predictive accuracy and minimal deviation from actual values. The high adjusted R² (0.898) and WI (0.973) further emphasize XGB's robustness in handling the non-linearities inherent in the dataset.

In summary, while all three models—RF, ERT, and XGB—perform well, the XGB model demonstrates superior accuracy and generalization. Its lower error rates and higher R² values in both training and testing phases highlight its robustness in capturing the lateral capacity of CM walls under lateral and vertical loads.

3.2. ML Predictions for Cracking Load

Based on the aforementioned analyses regarding models for predicting the cracking strength capacity of CM walls, the performance of the proposed model was evaluated. The scatter plots in Figure 11 and contents of Table 5 illustrate the relationship between predicted and actual values for the cracking load capacity. The RF model provided reasonable results, achieving an R² of 0.908 in the training phase and 0.754 in the testing phase. Its testing performance, with RMSE and MAE, indicates moderate predictive accuracy, even though with a higher margin of error than the other models. The adjusted R² (0.744) and MAPE (61.924) further highlight the RF model's limited ability to minimize errors in cracking load predictions. The ERT model demonstrated improved accuracy and generalization over RF. It achieved an R² of 0.948 in training and 0.798 in testing. The RMSE and MAE values during testing, along with an adjusted R² of 0.790 and a MAPE of 36.008, indicate that ERT consistently captures the underlying patterns of the data. The close alignment of WI (0.987 in training, 0.949 in testing) and NSE (0.948 in training, 0.798 in testing) between the phases further highlights ERT's reliability.

The XGB model emerged as the most effective predictor for cracking load capacity, achieving the highest R² of 0.985 and 0.876 during training and testing, respectively. With the lowest RMSE, MAE, and MAPE values in the testing phase, the XGB model demonstrated superior accuracy and minimal deviation from actual values. Its adjusted R² (0.871) and WI (0.968) further reinforce its robustness and applicability in predicting cracking loads of CM walls.

Overall, the XGB model consistently outperformed the other models, achieving the lowest RMSE (28.742) and the highest R² (0.903) for maximum lateral load capacity prediction during testing, while RF and ERT exhibited lower predictive accuracy with R² values of 0.850 and 0.819, respectively. Similarly, for cracking load predictions, XGB demonstrated superior performance with an R² of 0.876 and the lowest RMSE (23.982), followed by ERT (R² = 0.798) and RF (R² = 0.754). These findings were further supported by the scatter plots, which showed that XGB's predicted values were closely aligned with the actual values,

indicating its greater reliability in both tasks. The XGB model also consistently achieved the best performance metrics, including the lowest MAE and MAPE values, demonstrating its robustness and effectiveness for both maximum lateral load and cracking load predictions.

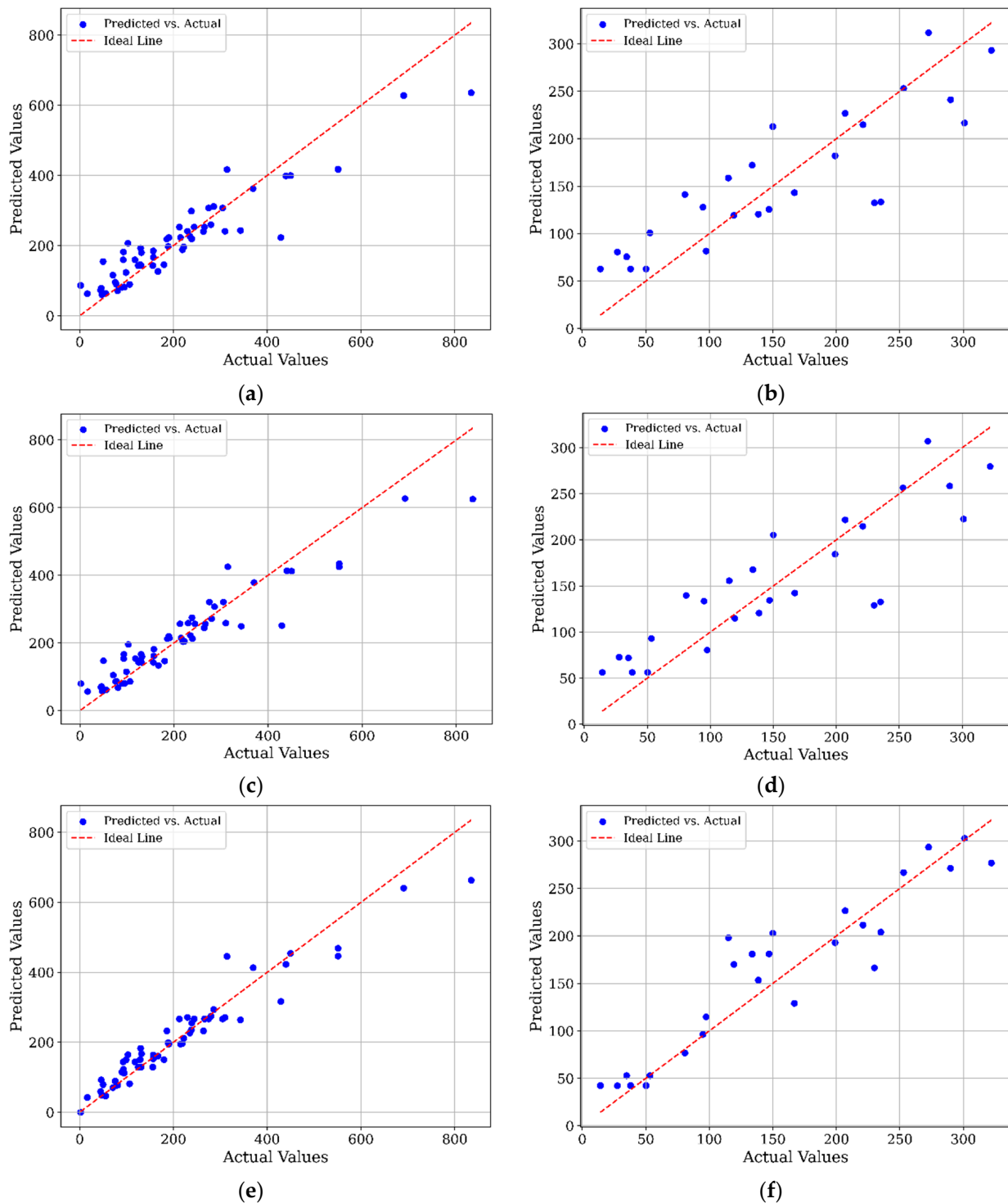


Figure 10. Scatter plots generated for maximum load predictions: (a) RF for training set, (b) RF for testing set, (c) ERT for training set, (d) ERT for testing set, (e) XGB for training set, and (f) XGB for testing set.

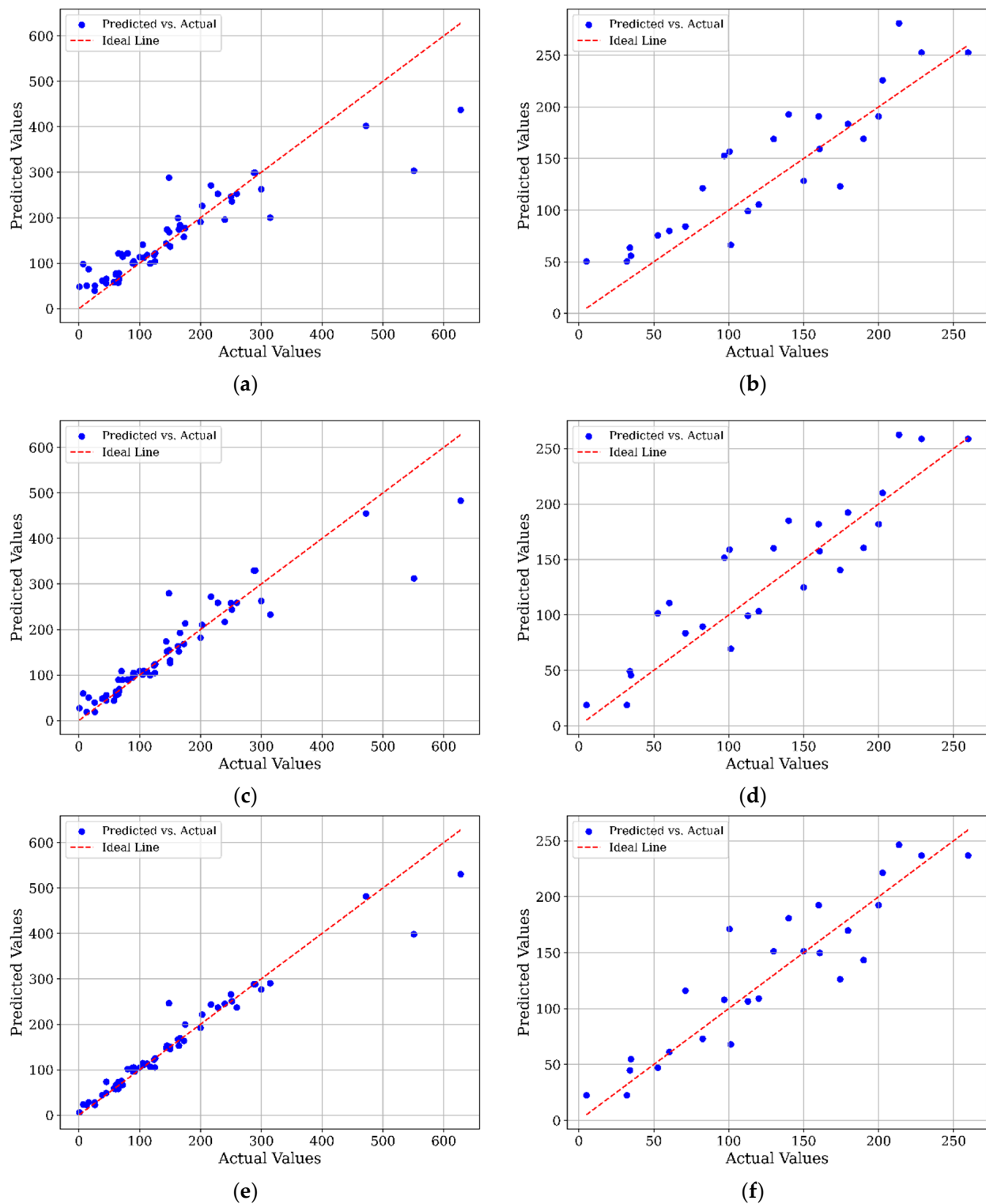


Figure 11. Scatter plots generated for cracking load predictions: (a) RF for training set, (b) RF for testing set, (c) ERT for training set, (d) ERT for testing set, (e) XGB for training set, and (f) XGB for testing set.

Table 5. Summary of the performances of ML methods for cracking load data.

Model	Testing			Training		
	ERT	RF	XGB	ERT	RF	XGB
RMSE	30.140	33.235	23.982	20.775	27.375	11.646
MAE	25.139	28.296	19.253	15.536	21.098	8.722
R ²	0.798	0.754	0.876	0.948	0.908	0.985
NSE	0.798	0.754	0.876	0.948	0.908	0.985
WI	0.949	0.936	0.968	0.987	0.973	0.996
MAPE	36.008	61.924	31.019	85.205	132.761	24.027
Adjusted R ²	0.790	0.744	0.871	0.947	0.907	0.984

3.3. Assessing the Predictive Accuracy of Proposed ML Models Against Empirical Equations

3.3.1. Comparative Analysis on the Maximum Lateral Load Capacity

The scatter plots presented in Figure 12 are based on 84 experimental data collected on CM walls subjected to both vertical and in-plane lateral loads. In Figure 12, the prediction of shear strength capacity of CM walls with empirical equations and ML models is established and the performance of the proposed model is evaluated.

From the plots, it is evident that ML models proposed in this study generally outperform the empirical equations in predicting the load capacities. The ML models display a tighter clustering of points around the red line ($y = x$), indicating that their predictions are aligned with the actual experimental values. Specifically, the XGB and ERT models show good accuracy, with 62.3% and 59.5% of their predictions falling within the $\pm 20\%$ range (a20-index), a significant marker of reliability in this study. The RF model also performs well, though slightly below ERT and XGB, with 56% of its predictions within this range.

When comparing the empirical equations, some equations such as BB, RP1, and BA1 and BA3 stand out for their relatively high accuracy, especially those regression analysis-based models, as Borah, B. et al. [18] and Marques, R. and Lourenço, P. B. [7] have stated. However, many other equations, including MC, CC, FA, ZR, RS, and MM, show more scatter, with fewer predictions falling within the $\pm 20\%$ bounds, indicating larger deviations from the experimental results. These discrepancies suggest that while empirical equations have been widely used, they may not consistently capture the complexities of CM wall behavior, especially when the effect of the wall geometry in terms of aspect ratio, reinforcement-related parameters, and number of tie-columns are not considered. Likewise, oversimplified models tend to have weaker correlation with the actual experimental results.

In comparison to the ML models, the empirical equations demonstrate variable performance. While a few equations are competitive with the models, most exhibit larger errors, with fewer data points falling within the $\pm 20\%$ limits. The strong performance of these models may be attributed to their ability to handle non-linear interactions among multiple parameters, which empirical equations, being more constrained in form, might fail to capture effectively, suggesting that these models could be a valuable tool for engineers seeking more precise load predictions.

To obtain further insight, Table 6 provides an overview of the overestimated and underestimated cases in predicting the maximum lateral load capacity of CM walls. The data presents a clear comparison between the accuracy of empirical methods and machine learning-based approaches, with insights into the strengths and weaknesses of each method. This table reveals significant discrepancies in the overestimation or underestimation of lateral loads predicted by all the empirical equations. The mean values of the predicted-to-experimental response ratios for all models are also shown in Table 6, and they demonstrate high accuracy when using the BB, AC, RP1, and RP2 equations. Additionally, the standard deviations for these equations are notably low.

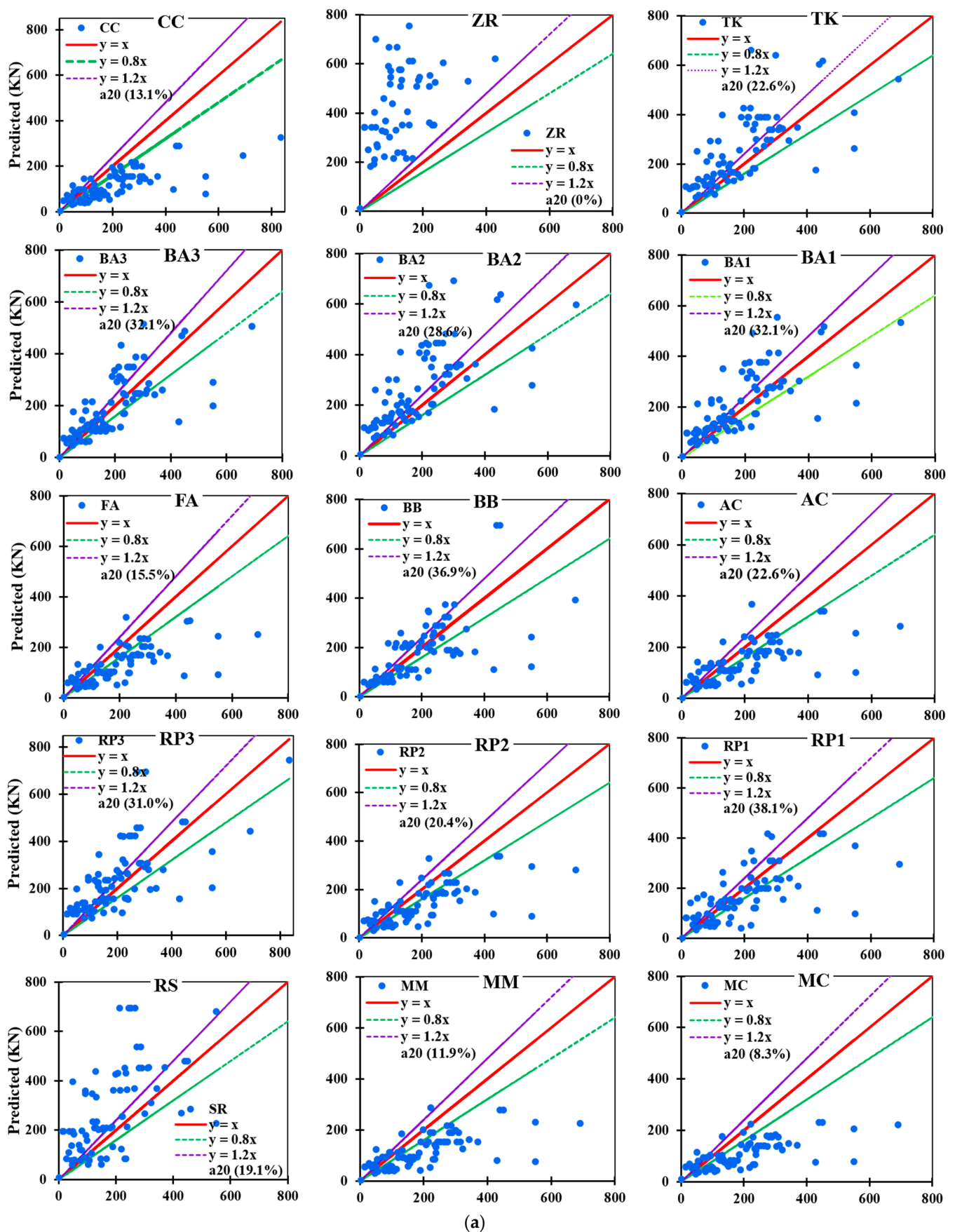


Figure 12. Cont.

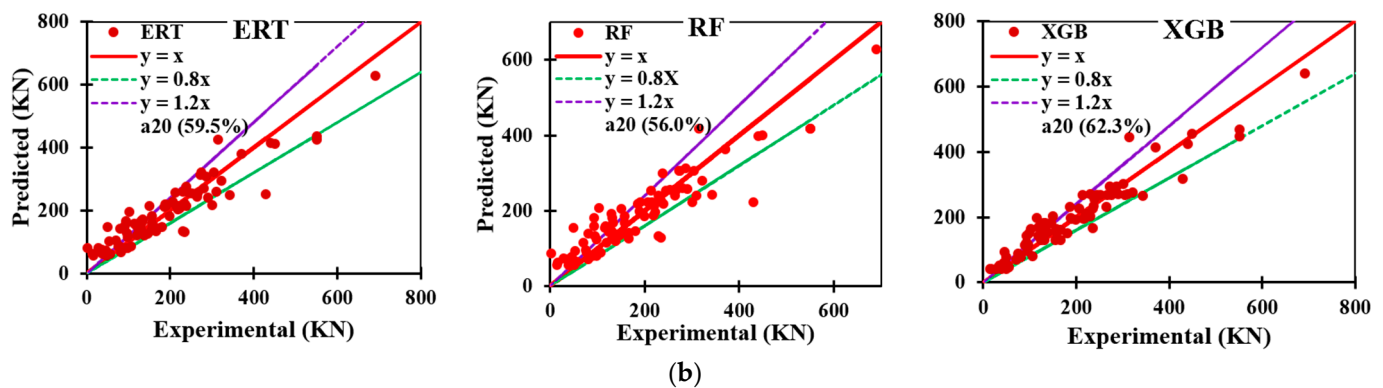


Figure 12. Comparison of empirical and proposed ML models on maximum load predictions: (a) empirical equation results; (b) ML predictions. The alphabetical identifiers (IDs) correspond to the following: AC = Argentinean Code [24]; BA1 = Bourzam et al. [20]; BA2,3 = Bourzam et al. [19]; BB = Bonisha et al. [18]; CC = Colombia Code [25]; FA = Flores and Alcocer [16]; MC = Marinilli and Castilla [14]; MM = Moroni et al. [23]; RP1 = Rui Marques and P. B. Lourenco [13]; RP2,3 = Rui Marques and P. B. Lourenco [7]; SR = V. Singhal and D. Rai [22]; TK = M. Tomaževic and I. Klemenc [26]; ZR = Z. Riahi et al. [15]; PG = J. J. Perez Gavilan et al. [17]; RF = Random Forest; ERT = Extremely Randomized Tree; XGB = Extreme Gradient Boosting.

Table 6. Summary of underestimated and overestimated instances.

Equation/Model	Overestimated	Underestimated	Average ($V_{m,c}/V_{m,a}$)	St. Dev
FA	17	67	0.88	0.65
TK	65	19	1.67	1.14
MC	21	63	1.28	4.32
BA1	54	30	1.43	0.98
BA2	68	16	1.76	1.17
BA3	48	36	1.26	0.77
ZR	84	0	4.61	3.53
RM1	30	54	1.11	0.94
RM2	18	66	0.94	0.74
RM3	59	25	1.54	1.01
SR	65	19	2.09	2.06
AC	19	65	0.95	0.71
MM	16	68	0.79	0.61
CC	13	71	0.77	0.55
BB	41	43	1.09	0.61
ERT	48	36	1.65	4.09
RF	48	36	1.69	4.44
XGB	46	38	1.11	0.38

The comparison shows that while traditional empirical methods can be useful, they are often less reliable, either overestimating or underestimating the lateral load capacity of CM walls. In contrast, ML models, particularly XGB, demonstrate superior predictive performance, providing more accurate and consistent results. The findings suggest that ML models have significant potential to outperform traditional empirical equations in predicting the structural behavior of CM walls under lateral loading, making them a promising alternative in structural engineering applications.

3.3.2. Comparative Analysis on Cracking Load

The experimental data of 84 CM walls collected from the literature was used to evaluate the accuracy of proposed and existing empirical models (presented in Tables 2 and 3). Empirical equations provide a range for the cracking load, the midpoint of the interval for consistent comparison, and the results are normalized (predicted/experimental results) in

this study. The comparison shown in Figure 13 reveals notable differences in accuracy and consistency. Empirical equations such as FA, MC, and TK display significant variability and inconsistency, with many predictions falling outside the acceptable range of 1.0 ± 0.3 , leading to potential overestimation or underestimation. The high standard deviations across these models highlight their overall poor performance. Other models, like ZR and RP, show mixed results with several underestimations, while the MC equation has the highest scatter under the 0.3 limit, making it the least reliable. This model, introduced by Marinilli and Castilla [14], predicts cracking load within a range of $0.7V_m$ to $0.8V_m$. However, its use of a constant value of 8200 N in the second of the models predicting V_m could be the cause of the significant errors in estimating both lateral strength and cracking load, as noted in some other studies [18].

In contrast, the ML models, ERT, RF, and especially XGB, exhibit significantly better accuracy. The scatter plots for these models show most data points concentrated around the ideal ratio of 1.0, with minimal deviations (0.75 for XGB). The XGB model stands out as the best performer, with the highest concentration of points around 1.0 and the lowest standard deviation, highlighting again its robust predictive capability. The superior performance of the machine learning models, especially XGB, can be attributed to their ability to capture non-linear relationships between multiple influencing variables, which the empirical models, constrained by their simplified assumptions, fail to consider.

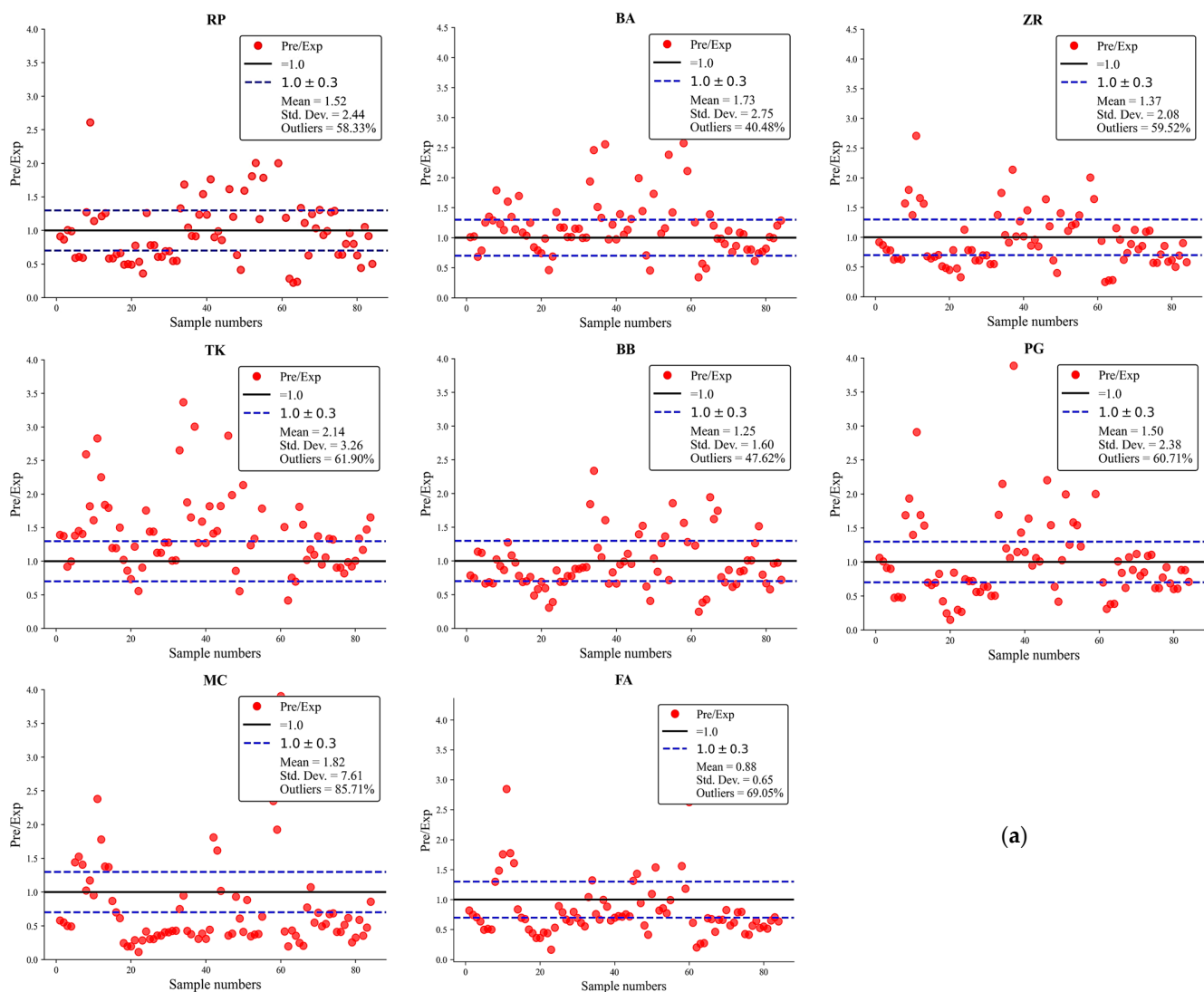


Figure 13. Cont.

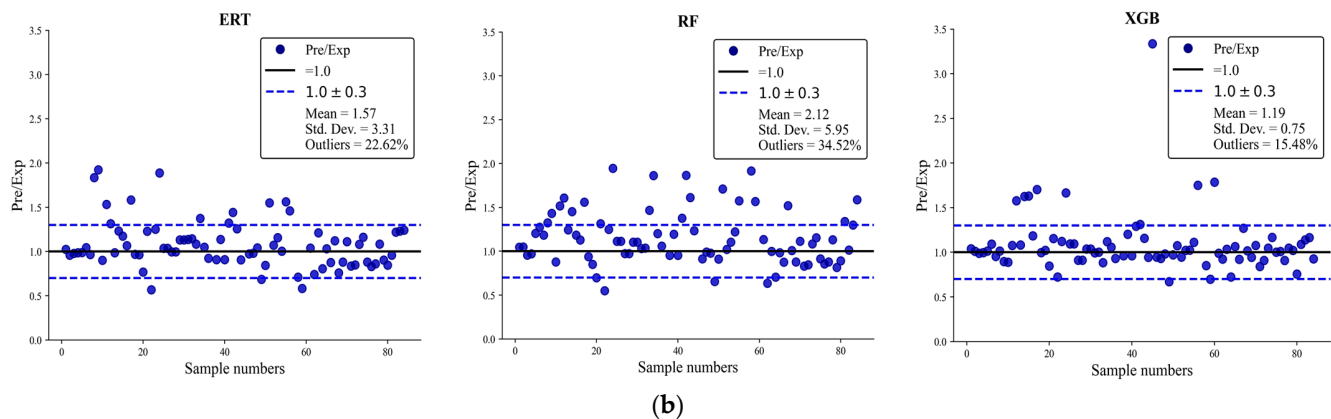


Figure 13. Comparison of empirical and proposed ML models on cracking load predictions: (a) empirical equation results; (b) ML predictions.

These results clearly indicate that traditional empirical models are less capable of accurately predicting cracking loads due to their simplified assumptions, whereas ML models provide a robust and reliable alternative. Given their superior performance, the adoption of machine learning models, particularly XGB, is recommended for structural design and assessment, ensuring safer and more cost-effective predictions that can be continually refined as more data become available.

4. Conclusions

The seismic analysis of CM walls necessitates an accurate estimation of their lateral strength capacity. Predicting the in-plane response of CM walls is often challenging when using empirical models from previous research. These models incorporate region-specific parameter assumptions and significant variability in key input parameters, limiting their generalizability due to their calibration for specific CM wall configurations. This study developed three efficient tree-based ML models, RF, ERT, and XGB, to predict the maximum lateral load capacity and cracking load of CM walls. Using a comprehensive dataset of 84 specimens collected from published experimental studies, covering a wide range of influential factors associated with different limit states, 12 input variables, including the number of tie-columns, cross-sectional area of tie-columns, wall area, masonry shear strength, wall aspect ratio (AR), wall slenderness ratio (SR), longitudinal and traverse reinforcement ratios, yield strength and diameter of longitudinal reinforcement, overburden pressure, and concrete compressive strength, were considered. Partial Dependence Plot (PDP) analysis was used to investigate the influence of input variables. The results of the proposed models were compared with those of twenty-four existing empirical formulas in design codes and published studies. The following conclusions were drawn:

- The developed tree-based models in this study predict lateral loads at cracking and maximum strength of CM walls more accurately than existing equations. The accuracy of the model is verified by the statistical properties of the predicted-to-measured ratio including the standard deviation, mean value, R^2 value, RMSE, MAE, NSE, WI, MAPE, adjusted R^2 , and a20 index
- Generally, the proposed tree-based models, particularly the XGBoost model, consistently demonstrated the highest predictive accuracy among the tested models, achieving R^2 values of 0.903 for maximum lateral load prediction and 0.876 for cracking load prediction during the testing phase. Its performance was superior to that of the RF and ERT models, both of which also outperformed traditional empirical equations but with slightly lower accuracy. The ML models' ability to handle complex, non-linear relationships among multiple parameters, such as material properties, geometric factors, and reinforcement details, enabled them to capture the behavior of CM walls more accurately than simplified empirical formulas.

- The comparison with empirical models revealed significant discrepancies, with most empirical equations either overestimating or underestimating the load capacities of CM walls. Although a few equations, such as those by Borah et al. (BB) [18] and Marques and Lourenço (RP1) [13], performed reasonably well, many others, such as those by Marinilli and Castilla (MC) [14], exhibited a high degree of scatter and poor prediction accuracy. This inconsistency underscores the limitations of empirical models, which are often tailored to specific regions or wall configurations and are difficult to generalize across different CM wall designs.
- The results indicate that ML models, particularly XGBoost, are well suited for practical engineering applications, offering more reliable and efficient tools for predicting the lateral strength and cracking load of CM walls. The higher accuracy of ML models makes them a valuable resource for engineers, particularly in regions with diverse construction practices and material properties, where empirical models may fall short. These findings also suggest that ML models can enhance the preliminary design and assessment of CM structures, improving both safety and cost-effectiveness.

In conclusion, this research demonstrates that ML, especially XGBoost, provides a robust and accurate alternative to traditional empirical models for predicting the seismic performance of confined masonry walls. By leveraging large experimental datasets and advanced modeling techniques, ML models offer a significant improvement in predictive accuracy, contributing to safer and more efficient structural design of CM buildings in earthquake-prone regions. The adoption of such models could revolutionize the way engineers approach the design and assessment of CM walls, providing a more reliable framework for evaluating seismic resilience. Future evaluations are suggested to assess the effects of other contributing factors, such as wall openings, panel reinforcement, wall density, and interface between wall panel and tie-columns, as they affect the lateral load–displacement behavior of CM walls.

Potential for Further Development: This study highlights the potential for further refinement of ML models to expand their applicability. Future research could integrate additional parameters, such as construction practices or regional variations in materials, to further enhance the models’ predictive capabilities. Moreover, as more experimental data become available, the accuracy and generalizability of these ML models are expected to improve, offering even more precise tools for predicting the seismic performance of CM walls and buildings.

Author Contributions: Conceptualization, H.M.B. and K.G.; formal analysis, writing—original draft preparation, methodology, H.M.B.; validation, writing—review and editing, supervision, K.G. All authors have read and agreed to the published version of the manuscript.

Funding: This research received no external funding.

Data Availability Statement: The data presented in this study are available on request from the corresponding authors.

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

References

1. Tomazevic, M. *Earthquake-Resistant Design of Masonry Buildings*; World Scientific: Singapore, 1999; Volume 1, ISBN 1860940668.
2. Brzev, S. *Earthquake-Resistant Confined Masonry Construction*; NICEE: Uttar Pradesh, India, 2007; ISBN 8190419099.
3. Meli, R.; Crisafulli, F.; Junwu, D.; Farsi, M.; Hart, T.; Mebarki, A.; Moghadam, A.S.; Quiun, D.; Tomazevic, M.; Yamin, L. *Seismic Design Guide for Low-Rise Confined Masonry Buildings*; WHE—World Housing Encyclopedia; Earthquake Engineering Research Institute (EERI): Oakland, California, 2011.
4. Borah, B.; Singhal, V.; Kaushik, H.B. Sustainable Housing Using Confined Masonry Buildings. *SN Appl. Sci.* **2019**, *1*, 983. [\[CrossRef\]](#)
5. Okail, H.; Abdelrahman, A.; Abdelkhalik, A.; Metwaly, M. Experimental and Analytical Investigation of the Lateral Load Response of Confined Masonry Walls. *HBRC J.* **2016**, *12*, 33–46. [\[CrossRef\]](#)
6. Chourasia, A. *Design Guidelines for Confined Masonry Buildings*; CSIR-Central Building Research Institute: Roorkee, India, 2017.

7. Marques, R.; Lourenço, P.B. Structural Behaviour and Design Rules of Confined Masonry Walls: Review and Proposals. *Constr. Build. Mater.* **2019**, *217*, 137–155. [\[CrossRef\]](#)
8. Encyclopedia, W.H. Confined Brick Masonry Building with Concrete Tie Columns and Beams. *Building* **2002**, *100060*, 1–10.
9. The International Bank for Reconstruction and Development. *Guide Pour La Construction Parasismique Des Maisons Individuelles*; The International Bank for Reconstruction and Development: Washington, DC, USA, 2015.
10. Brzev, S.; Astroza, M.; Ofelia, M.; Yadlin, M. Performance of Confined Masonry Buildings in the Chile Earthquake. *Earthq. Spectra* **2010**, *28*, S385–S406. [\[CrossRef\]](#)
11. Earthquake Engineering Research Institute (EERI). *Preliminary Observations on the El Salvador Earthquakes of January 13 and February 13, 2001*; EERI Special Earthquake Report, Newsletter; Earthquake Engineering Research Institute: Oakland, CA, USA, 2001; Available online: <https://learningfromearthquakes.org/earthquakes/el-salvador-2001-series/#eeri> (accessed on 16 August 2024).
12. Boen, T. *Sumatra Earthquake 26 December 2004*; Earthquake Engineering Research Institute: Oakland, CA, USA, 2005; pp. 1–27.
13. Marques, R.; Lourenço, P.B. A Model for Pushover Analysis of Confined Masonry Structures: Implementation and Validation. *Bull. Earthq. Eng.* **2013**, *11*, 2133–2150. [\[CrossRef\]](#)
14. Marinlli, A.; Castilla, E. Experimental Evaluation of Confined Masonry Walls with Several Confining-Columns. In Proceedings of the 13th World Conference on Earthquake Engineering, Vancouver, BC, Canada, 1–6 August 2004.
15. Riahi, Z.; Elwood, K.J.; Alcocer, S.M. Backbone Model for Confined Masonry Walls for Performance-Based Seismic Design. *J. Struct. Eng.* **2009**, *135*, 644–654. [\[CrossRef\]](#)
16. Flores, L.E.; Alcocer, S.M. Calculated Response of Confined Masonry Structures. In Proceedings of the 11th World Conference on Earthquake Engineering, Acapulco, Mexico, 23–28 June 1996.
17. Perez Gavilan, J.J.; Flores, L.E.; Alcocer, S.M. An Experimental Study of Confined Masonry Walls with Varying Aspect Ratios. *Earthq. Spectra* **2015**, *31*, 945–968. [\[CrossRef\]](#)
18. Borah, B.; Kaushik, H.B.; Singhal, V. Lateral Load-Deformation Models for Seismic Analysis and Performance-Based Design of Confined Masonry Walls. *J. Build. Eng.* **2022**, *48*, 103978. [\[CrossRef\]](#)
19. Bourzam, A.; Goto, T.; Miyajima, M. Shear Capacity Prediction of Confined Masonry Walls Subjected to Cyclic Lateral Loading. *Doboku Gakkai Ronbunshuu A* **2008**, *64*, 692–704. [\[CrossRef\]](#)
20. Bourzam, A.; Ikemoto, T.; Miyajima, M. Lateral Resistance of Confined Brick Wall Under Cyclic Quasi-Static Lateral Loading. In Proceedings of the 14th World Conference on Earthquake Engineering, Beijing, China, 12–17 October 2008.
21. Rai, D.C.; Singhal, V.; Paikara, S.; Mukherjee, D. Sub-Paneling of Masonry Walls Using Precast Reinforced Concrete Elements for Earthquake Resistance. *Earthq. Spectra* **2014**, *30*, 913–937. [\[CrossRef\]](#)
22. Singhal, V.; Rai, D.C. In-Plane and out-of-Plane Behavior of Confined Masonry Walls for Various Tothing and Openings Details and Prediction of Their Strength and Stiffness. *Earthq. Eng. Struct. Dyn.* **2016**, *45*, 2551–2569. [\[CrossRef\]](#)
23. Moroni, M.; Astroza, M.; Mesias, P. Displacement Capacity and Required Story Drift in Confined Masonry Buildings. In Proceedings of the 11th World Conference on Earthquake Engineering, Acapulco, Mexico, 23–28 June 1996; pp. 1–7.
24. INPRES-CIRSOC 103 Normas Argentinas Para Construcciones Sismorresistentes. Parte III—Construcciones de Mampostería (Argentinean Code for Seismic-Resistant Construction. Part III—Masonry Construction); Instituto Nacional de Prevención Sísmica (INPRES) and Centro de Investigación de los Reglamentos Nacionales de Seguridad para las Obras Civiles (CIRSOC): Argentina. 2018. (In Spanish). Available online: <http://contenidos.inpres.gob.ar/acelerografos/inpres-cirsoc> (accessed on 29 September 2024).
25. Asociación Colombiana de Ingeniería Sísmica (AIS). *NSR-98: Normas Colombianas de Diseño y Construcción Sismo Resistente. Título D: Mampostería Estructural (Colombian Design and Construction Standards. Earthquake Resistant. Title D: Structural Masonry)*; AIS: Colombia, DC, USA, 2010. (In Spanish)
26. Tomažević, M.; Klemenc, I. Seismic Behaviour of Confined Masonry Walls. *Earthq. Eng. Struct. Dyn.* **1997**, *26*, 1059–1071. [\[CrossRef\]](#)
27. Lang, A.F.; Crisafulli, F.J.; Torrisi, G.S. Overview and Assessment of Analysis Techniques for Confined Masonry Buildings. In Proceedings of the 10th National Conference on Earthquake Engineering, Anchorage, Alaska, 21–25 July 2014. [\[CrossRef\]](#)
28. Borah, B.; Kaushik, H.B.; Singhal, V. Evaluation of Modeling Strategies for Gravity and Lateral Load Analysis of Confined Masonry Structures. *Bull. Earthq. Eng.* **2023**, *21*, 1273–1301. [\[CrossRef\]](#)
29. Kazemi, F.; Asgarkhani, N.; Jankowski, R. Optimization-Based Stacked Machine-Learning Method for Seismic Probability and Risk Assessment of Reinforced Concrete Shear Walls. *Expert Syst. Appl.* **2024**, *255*, 124897. [\[CrossRef\]](#)
30. Lee, S.C. Prediction of Concrete Strength Using Artificial Neural Networks. *Eng. Struct.* **2003**, *25*, 849–857. [\[CrossRef\]](#)
31. Sah, A.K.; Hong, Y.M. Performance Comparison of Machine Learning Models for Concrete Compressive Strength Prediction. *Materials* **2024**, *17*, 2075. [\[CrossRef\]](#)
32. Sathiparan, N.; Jeyananthan, P. Prediction of Masonry Prism Strength Using Machine Learning Technique: Effect of Dimension and Strength Parameters. *Mater. Today Commun.* **2023**, *35*, 106282. [\[CrossRef\]](#)
33. Asteris, P.G.; Argyropoulos, I.; Cavaleri, L.; Rodrigues, H.; Varum, H.; Thomas, J.; Lourenço, P.B. Masonry Compressive Strength Prediction Using Artificial Neural Networks. In *Communications in Computer and Information Science*; Springer Verlag: Berlin/Heidelberg, Germany, 2019; Volume 962, pp. 200–224.

34. Zhou, Q.; Wang, F.; Zhu, F. Estimation of Compressive Strength of Hollow Concrete Masonry Prisms Using Artificial Neural Networks and Adaptive Neuro-Fuzzy Inference Systems. *Constr. Build. Mater.* **2016**, *125*, 417–426. [\[CrossRef\]](#)
35. Zhou, Q.; Zhu, F.; Yang, X.; Wang, F.; Chi, B.; Zhang, Z. Shear Capacity Estimation of Fully Grouted Reinforced Concrete Masonry Walls Using Neural Network and Adaptive Neuro-Fuzzy Inference System Models. *Constr. Build. Mater.* **2017**, *153*, 937–947. [\[CrossRef\]](#)
36. Lan, G.; Wang, Y.; Zeng, G.; Zhang, J. Compressive Strength of Earth Block Masonry: Estimation Based on Neural Networks and Adaptive Network-Based Fuzzy Inference System. *Compos. Struct.* **2020**, *235*, 111731. [\[CrossRef\]](#)
37. Feng, D.C.; Liu, Z.T.; Wang, X.D.; Chen, Y.; Chang, J.Q.; Wei, D.F.; Jiang, Z.M. Machine Learning-Based Compressive Strength Prediction for Concrete: An Adaptive Boosting Approach. *Constr. Build. Mater.* **2020**, *230*, 117000. [\[CrossRef\]](#)
38. Li, H.; Li, J.; Farhangi, V. Determination of Piers Shear Capacity Using Numerical Analysis and Machine Learning for Generalization to Masonry Large Scale Walls. *Structures* **2023**, *49*, 443–466. [\[CrossRef\]](#)
39. Aguilar, V.; Sandoval, C.; Adam, J.M.; Garzón-Roca, J.; Valdebenito, G. Prediction of the Shear Strength of Reinforced Masonry Walls Using a Large Experimental Database and Artificial Neural Networks. *Struct. Infrastruct. Eng.* **2016**, *12*, 1661–1674. [\[CrossRef\]](#)
40. Cascardi, A.; Micelli, F.; Aiello, M.A. Analytical Model Based on Artificial Neural Network for Masonry Shear Walls Strengthened with FRM Systems. *Compos. Part B Eng.* **2016**, *95*, 252–263. [\[CrossRef\]](#)
41. Mishra, M.; Bhatia, A.S.; Maity, D. Predicting the Compressive Strength of Unreinforced Brick Masonry Using Machine Learning Techniques Validated on a Case Study of a Museum through Nondestructive Testing. *J. Civ. Struct. Health Monit.* **2020**, *10*, 389–403. [\[CrossRef\]](#)
42. Garzón-Roca, J.; Adam, J.M.; Sandoval, C.; Roca, P. Estimation of the Axial Behaviour of Masonry Walls Based on Artificial Neural Networks. *Comput. Struct.* **2013**, *125*, 145–152. [\[CrossRef\]](#)
43. Marulasiddappa, S.B.; Naganna, S.R.; KM, P.; Tantri, A.; Kuntoji, G.; Sammen, S.S. Strength Assessment of Structural Masonry Walls: Analysis Based on Machine Learning Approaches. *HBRC J.* **2024**, *20*, 505–524. [\[CrossRef\]](#)
44. Dais, D.; Bal, I.E.; Smyrou, E.; Sarhosis, V. Automatic Crack Classification and Segmentation on Masonry Surfaces Using Convolutional Neural Networks and Transfer Learning. *Autom. Constr.* **2021**, *125*, 103606. [\[CrossRef\]](#)
45. Adaileh, A.; Ghiassi, B.; Briganti, R. A Novel Machine Learning-Based Approach for Nonlinear Analysis and in-Situ Assessment of Masonry. *Constr. Build. Mater.* **2023**, *408*, 133291. [\[CrossRef\]](#)
46. Harirchian, E.; Aghakouchaki Hosseini, S.E.; Novelli, V.; Lahmer, T.; Rasulzade, S. Utilizing Advanced Machine Learning Approaches to Assess the Seismic Fragility of Non-Engineered Masonry Structures. *Results Eng.* **2024**, *21*, 101750. [\[CrossRef\]](#)
47. Sichá Pillaca, J.C.; Molina Ramirez, A.; Vasquez, V.A. Structural Design of Confined Masonry Buildings Using Artificial Neural Networks. In Proceedings of the 2020 Congreso Internacional de Innovación y Tendencias en Ingeniería, Bogotá, Colombia, 30 September–2 October 2020. CONIITI 2020—Conference Proceedings.
48. Ojeda, J.M.P.; Huatangari, L.Q.; Arce, J.R.; Fernández, N.A.; Santisteban, M.A.G.; Serrano, M.A.M. Assembly Algorithms for Seismic Vulnerability Estimation in Confined Masonry Dwellings. *Int. J. Saf. Secur. Eng.* **2024**, *14*, 967–984. [\[CrossRef\]](#)
49. Gouveia, J.P.; Lourenço, P.B. Masonry Shear Walls Subjected to Cyclic Loading: Influence of Confinement and Horizontal Reinforcement. In Proceedings of the Tenth North American Masonry Conference, St. Louis, MO, USA, 3–6 June 2007.
50. Ibrar, M.; Naseer, A.; Ashraf, M.; Badshah, E.; Ullah, S. Evaluation of Confined Masonry Walls with Varying Sizes of Confining Elements and Reinforcement Ratios against Cyclic Loading. *J. Build. Eng.* **2022**, *50*, 104094. [\[CrossRef\]](#)
51. Kumazawa, F.; Ohkubo, M. Nonlinear Characteristics of Confined Masonry Wall with Lateral Reinforcement in Mortar Joints. In Proceedings of the 12th World Conference on Earthquake Engineering, Auckland, NZ, USA, 30 January–4 February 2000; p. 0743.
52. Liu, G.A.; Wang, X.; Yang, Z.; Wang, L.Y.; Zhou, Y.W.; Chen, G. Bin Experimental Study on Seismic Performance of Confined Masonry Walls with Window Openings Strengthened by Using Hybrid-Fiber Modified Reactive Powder Concrete. *Front. Mater.* **2022**, *9*, 832579. [\[CrossRef\]](#)
53. Matošević, Đ.; Sigmund, V.; Guljaš, I. Cyclic Testing of Single Bay Confined Masonry Walls with Various Connection Details. *Bull. Earthq. Eng.* **2015**, *13*, 565–586. [\[CrossRef\]](#)
54. Pérez-Gavilán, J.J. The Effect of Shear-Moment Interaction on the Shear Strength of Confined Masonry Walls. *Constr. Build. Mater.* **2020**, *263*, 120087. [\[CrossRef\]](#)
55. Sarrafi, B.; Eshghi, S. Experimental Study on Lateral Strength of Confined Masonry Walls. In Proceedings of the 15th World Conference on Earthquake Engineering (15WCEE), Lisbon, Portugal, 24–28 September 2012.
56. Wijaya, W.; Kusumastuti, D.; Suarjana, M.; Rildova; Pribadi, K. Experimental Study on Wall-Frame Connection of Confined Masonry Wall. In Proceedings of the Procedia Engineering, Athens, Greece, 4–7 September 2011; Volume 14, pp. 2094–2102.
57. Yáñez, F.; Astroza, M.; Holmberg, A.; Ogaz, O. Behavior of Confined Masonry Shear Walls with Large Openings. In Proceedings of the 13th World Conference on Earthquake Engineering, Tokyo, Japan, 1–6 August 2004; p. 3438.
58. Yang, L.; Yang, X.; Zhou, Y.; Ren, Q.; Liang, B. Quasi-Static Cyclic Tests and Numerical Study of Seismic Performance of Confined Masonry Walls Reinforced with Horizontal Steel Bars. *Structures* **2023**, *57*, 105191. [\[CrossRef\]](#)
59. Zabala, F.; Bustos, J.L.; Masanet, A.; Santalucía, J. Experimental Behavior of Masonry Structural Walls Used in Argentina. In Proceedings of the 13th World Conference on Earthquake Engineering, Vancouver, BC, Canada, 1–6 August 2004.

60. Aguilar, G.; Meli, R.; Díaz, R.; Vázquez del Mercado, R. Influence of Horizontal Reinforcement on the Behavior of Confined Masonry Walls. In Proceedings of the Eleventh World Conference on Earthquake Engineering, Acapulco, Mexico, 23–28 June 1996; Volume 11 WCEE. paper No.1380.
61. Amouzadeh Tabrizi, M.; Soltani, M. In-Plane Response of Unreinforced Masonry Walls Confined by Reinforced Concrete Tie-Columns and Tie-Beams. *Adv. Struct. Eng.* **2017**, *20*, 1632–1643. [\[CrossRef\]](#)
62. Borah, B.; Singhal, V.; Kaushik, H.B. Assessment of Seismic Design Provisions for Confined Masonry Using Experimental and Numerical Approaches. *Eng. Struct.* **2021**, *245*, 112864. [\[CrossRef\]](#)
63. Cruz, O.A.I.; Pérez-Gavilán, E.J.J.; Flores, C.L. Experimental Study of In-Plane Shear Strength of Confined Concrete Masonry Walls with Joint Reinforcement. *Eng. Struct.* **2019**, *182*, 213–226. [\[CrossRef\]](#)
64. Kato, H.; Goto, T.; Mizuno, H.; Iiba, M. Cyclic Loading Tests of Confined Masonry Wall Elements for Structural Design Development of Apartment in Third World. In Proceedings of the 10th World Conference on Earthquake Engineering, Madrid, Spain, 19–24 July 1992; Volume 10, pp. 3539–3544.
65. Singhal, V.; Rai, D.C. Role of Tothing on In-Plane and Out-of-Plane Behavior of Confined Masonry Walls. *J. Struct. Eng.* **2014**, *140*, 04014053. [\[CrossRef\]](#)
66. Yoshimura, K.; Kikuchi, K.; Kuroki, M.; Liu, L. Experimental Study on Effect of Height of Lateral Forces, Applied Vertical Axial Loads and Wall Reinforcements on Seismic Behavior of Confined Concrete Masonry Walls. *J. Struct. Constr. Eng. (Trans. AIJ)* **1999**, *64*, 141–148. [\[CrossRef\]](#) [\[PubMed\]](#)
67. Yoshimura, K.; Kikuchi, K.; Okamoto, T.; Sanchez, T. Effect of Vertical and Horizontal Wall Reinforcement on Seismic Behavior of CM Walls. In Proceedings of the 11th WCEE, Acapulco, Mexico, 23–28 June 1996.
68. Liba, M.; Mizuno, H.; Goto, T.; Kato, H. Shaking Table Test on Seismic Performance of Confined Masonry Wall. In Proceedings of the Eleventh World Conference on Earthquake Engineering, Acapulco, Mexico, 23–28 June 1996.
69. Kuroki, M.; Kikuchi, K.; Nonaka, H.; Shimosako, M. Experimental Study on Reinforcing Methods Using Extra RC Elements for Confined Masonry Walls with Openings. In Proceedings of the 15th World Conference on Earthquake Engineering, Lisbon, Portugal, 24–28 September 2012; Volume 10.
70. Yoshimura, K.; Kikuchi, K.; Kuroki, M.; Liu, L.; Ma, L. Effect of Wall Reinforcements, Applied Lateral Forces and Vertical Axial Loads on Seismic Behavior of Confined Concrete Masonry Walls. In Proceedings of the 12th World Conference on Earthquake Engineering, Auckland, New Zealand, 30 January–4 February 2000; p. 0984.
71. Luo, M.; Xie, J.; Yan, Y.; Ke, Z.; Yu, P.; Wang, Z.; Zhang, J. Comparing Machine Learning Algorithms in Predicting Thermal Sensation Using ASHRAE Comfort Database II. *Energy Build.* **2020**, *210*, 109776. [\[CrossRef\]](#)
72. Borah, B.; Singhal, V.; Kaushik, H.B. *Assessment of Important Parameters for Seismic Analysis and Design of Confined Masonry Buildings: A Review*; Springer Science and Business Media: Deutschland, Germany, 2021; Volume 81, pp. 261–275.
73. Jasiński, R.; Gąsiorowski, T. Comparative Studies of the Confined Effect of Shear Masonry Walls Made of Autoclaved Aerated Concrete Masonry Units. *Materials* **2023**, *16*, 5885. [\[CrossRef\]](#)
74. Varela-Rivera, J.; Fernandez-Baqueiro, L.; Moreno-Herrera, J. Shear and Flexure-Shear Strengths of Autoclaved Aerated Concrete Confined Masonry Walls. *ACI Struct. J.* **2023**, *120*, 207–215. [\[CrossRef\]](#)
75. Agnihotri, P.; Singhal, V.; Rai, D.C. Effect of In-Plane Damage on out-of-Plane Strength of Unreinforced Masonry Walls. *Eng. Struct.* **2013**, *57*, 1–11. [\[CrossRef\]](#)
76. Pérez Gavilán Escalante, J.J.; Brzev, S.; Espinosa Cazarin, E.F.; Ganzerli, S.; Quiun, D.; Reiter, M.T. Experimental Research Studies on Seismic Behaviour of Confined Masonry Structures: Current Status and Future Needs. *Buildings* **2023**, *13*, 1776. [\[CrossRef\]](#)
77. Jasiński, R. Comparisons of Confined and Different Types of Reinforcement on the Behavior of Masonry Shear Walls. *Ce/Papers* **2018**, *2*, 353–365. [\[CrossRef\]](#)
78. Borah, B.; Kaushik, H.B.; Singhal, V. Analysis and Design of Confined Masonry Structures: Review and Future Research Directions. *Buildings* **2023**, *13*, 1282. [\[CrossRef\]](#)
79. Ministerio de Ambiente, Vivienda y Desarrollo Territorial—República de Colombia. *Reglamento Colombiano de Construcción Sismo Resistente NSR-10: Título A—Requisitos Generales de Diseño y Construcción Sismo Resistente (Colombian Seismic-Resistant Construction Regulations)*; Bogotá, Colombia, 2010. (In Spanish). Available online: <https://confinedmasonry.org/codes-and-standards> (accessed on 10 July 2024).
80. Bartolome, A.S.; Quiun, D. Proposal of a Standard for Seismic Design of Confined Masonry Buildings. In *Bulletin of Earthquake Resistant Structure Research Center (ERS)*; No. 37; University of Tokyo: Tokyo, Japan, 2004; Available online: <http://www.ers.iis.u-tokyo.ac.jp/ers-no37.html> (accessed on 10 July 2024).
81. Friedman, J.H. Greedy Function Approximation: A Gradient Boosting Machine. *Ann. Stat.* **2001**, *29*, 1189–1232. [\[CrossRef\]](#)
82. Varela-Rivera, J.; Fernandez-Baqueiro, L.; Gamboa-Villegas, J.; Prieto-Coyoc, A.; Moreno-Herrera, J. Flexural Behavior of Confined Masonry Walls Subjected to In-Plane Lateral Loads. *Earthq. Spectra* **2019**, *55*, 405–422. [\[CrossRef\]](#)
83. Bartolome, A.S. *Construcciones de Albañilería: Comportamiento Sísmico y Diseño Estructural*; Fondo Editorial; Pontificia Universidad Católica del Perú: Lima, Peru, 1994. [\[CrossRef\]](#)
84. Chou, J.S.; Pham, A.D. Enhanced Artificial Intelligence for Ensemble Approach to Predicting High Performance Concrete Compressive Strength. *Constr. Build. Mater.* **2013**, *49*, 554–563. [\[CrossRef\]](#)
85. Zhang, J.; Li, D.; Wang, Y. Toward Intelligent Construction: Prediction of Mechanical Properties of Manufactured-Sand Concrete Using Tree-Based Models. *J. Clean. Prod.* **2020**, *258*, 120665. [\[CrossRef\]](#)

86. Bakouregui, A.S.; Mohamed, H.M.; Yahia, A.; Benmokrane, B. Explainable Extreme Gradient Boosting Tree-Based Prediction of Load-Carrying Capacity of FRP-RC Columns. *Eng. Struct.* **2021**, *245*, 112836. [\[CrossRef\]](#)
87. Ho, L.S.; Tran, V.Q. Evaluation and Estimation of Compressive Strength of Concrete Masonry Prism Using Gradient Boosting Algorithm. *PLoS ONE* **2024**, *19*, e0297364. [\[CrossRef\]](#) [\[PubMed\]](#)
88. Nisbet, R.; Yale, K.; Gray, M. *Handbook of Statistical Analysis and Data Mining Applications*; Academic Press: Cambridge, MA, USA, 2018; ISBN 9780124166325.
89. Mousavi, M.; TohidiFar, A.; Alvanchi, A. BIM and Machine Learning in Seismic Damage Prediction for Non-Structural Exterior Infill Walls. *Autom. Constr.* **2022**, *139*, 104288. [\[CrossRef\]](#)
90. Feng, D.-C.; Wang, W.-J.; Mangalathu, S.; Taciroglu, E. Interpretable XGBoost-SHAP Machine-Learning Model for Shear Strength Prediction of Squat RC Walls. *J. Struct. Eng.* **2021**, *147*, 04021173. [\[CrossRef\]](#)
91. Mangalathu, S.; Karthikeyan, K.; Feng, D.C.; Jeon, J.S. Machine-Learning Interpretability Techniques for Seismic Performance Assessment of Infrastructure Systems. *Eng. Struct.* **2022**, *250*, 112883. [\[CrossRef\]](#)
92. Bentéjac, C.; Csörgő, A.; Martínez-Muñoz, G. *A Comparative Analysis of Gradient Boosting Algorithms*; Springer: Dordrecht, The Netherlands, 2021; Volume 54, ISBN 0123456789.
93. Sathiparan, N. Predicting Compressive Strength of Grouted Masonry Using Machine Learning Models with Feature Importance Analysis. *Mater. Today Commun.* **2024**, *41*, 110487. [\[CrossRef\]](#)
94. Zhou, G.; Pan, D.; Xu, X.; Rafiq, Y.M. Innovative ANN Technique for Predicting Failure/Cracking Load of Masonry Wall Panel under Lateral Load. *J. Comput. Civ. Eng.* **2010**, *24*, 377–387. [\[CrossRef\]](#)
95. Thango, S.G.; Drosopoulos, G.A.; Motsa, S.M.; Stavroulakis, G.E. Prediction of the Response of Masonry Walls under Blast Loading Using Artificial Neural Networks. *Infrastructures* **2024**, *9*, 5. [\[CrossRef\]](#)
96. Chen, T.; Carlos, G. XGBoost: A Scalable Tree Boosting System. In Proceedings of the 22nd acm sigkdd International Conference on Knowledge Discovery and Data Mining, San Francisco, CA, USA, 13–17 August 2016; pp. 785–794.
97. Özger, M.; Serencam, U.; Ekmekcioğlu, Ö.; Başakın, E.E. Determining the Water Level Fluctuations of Lake Van through the Integrated Machine Learning Methods. *Int. J. Glob. Warm.* **2022**, *27*, 123–142. [\[CrossRef\]](#)
98. Breiman, L. Random Forests. *Mach. Learn.* **2001**, *45*, 5–32. [\[CrossRef\]](#)
99. Probst, P.; Wright, M.N.; Boulesteix, A.L. Hyperparameters and Tuning Strategies for Random Forest. *Wiley Interdiscip. Rev. Data Min. Knowl. Discov.* **2019**, *9*, 1–15. [\[CrossRef\]](#)
100. Wang, Z.; Wang, Y.; Zeng, R.; Srinivasan, R.S.; Ahrentzen, S. Random Forest Based Hourly Building Energy Prediction. *Energy Build.* **2018**, *171*, 11–25. [\[CrossRef\]](#)
101. Hengl, T.; Nussbaum, M.; Wright, M.N.; Heuvelink, G.B.M.; Gräler, B. Random Forest as a Generic Framework for Predictive Modeling of Spatial and Spatio-Temporal Variables. *PeerJ* **2018**, *2018*, e5518. [\[CrossRef\]](#)
102. Pal, M. Random Forest Classifier for Remote Sensing Classification. *Int. J. Remote Sens.* **2005**, *26*, 217–222. [\[CrossRef\]](#)
103. Choi, J.; Gu, B.; Chin, S.; Lee, J.S. Machine Learning Predictive Model Based on National Data for Fatal Accidents of Construction Workers. *Autom. Constr.* **2020**, *110*, 102974. [\[CrossRef\]](#)
104. Başakın, E.E.; Ekmekcioğlu, Ö.; Çitakoğlu, H.; Özger, M. A New Insight to the Wind Speed Forecasting: Robust Multi-Stage Ensemble Soft Computing Approach Based on Pre-Processing Uncertainty Assessment. *Neural Comput. Appl.* **2022**, *34*, 783–812. [\[CrossRef\]](#)
105. Ekmekcioğlu, Ö.; Koc, K.; Özger, M.; Işık, Z. Exploring the Additional Value of Class Imbalance Distributions on Interpretable Flash Flood Susceptibility Prediction in the Black Warrior River Basin, Alabama, United States. *J. Hydrol.* **2022**, *610*, 127877. [\[CrossRef\]](#)
106. Ekmekcioğlu, Ö.; Başakın, E.E.; Özger, M. Tree-Based Nonlinear Ensemble Technique to Predict Energy Dissipation in Stepped Spillways. *Eur. J. Environ. Civ. Eng.* **2022**, *26*, 3547–3565. [\[CrossRef\]](#)
107. Barkhordari, M.S.; Jawdhari, A. Machine Learning Based Prediction Model for Plastic Hinge Length Calculation of Reinforced Concrete Structural Walls. *Adv. Struct. Eng.* **2023**, *26*, 1714–1734. [\[CrossRef\]](#)
108. Geurts, P.; Ernst, D.; Wehenkel, L. Extremely Randomized Trees. *Mach. Learn.* **2006**, *63*, 3–42. [\[CrossRef\]](#)
109. Li, F.; Gong, H.; Chen, B.; Zhou, C.; Guo, L. Analysis of the Contribution Rate of the Influencing Factors to Land Subsidence in the Eastern Beijing Plain, China Based on Extremely Randomized Trees (ERT) Method. *Remote Sens.* **2020**, *12*, 2963. [\[CrossRef\]](#)
110. Khaleghi, M.; Salimi, J.; Farhangi, V.; Moradi, M.J.; Karakouzian, M. Application of Artificial Neural Network to Predict Load Bearing Capacity and Stiffness of Perforated Masonry Walls. *CivilEng* **2021**, *2*, 48–67. [\[CrossRef\]](#)
111. Cort, J.W.; Robeson, S.M.; Matsuura, K. A Refined Index of Model Performance. *Int. J. Climatol.* **2012**, *32*, 2088–2094. [\[CrossRef\]](#)
112. Chai, T.; Draxler, R.R. Root Mean Square Error (RMSE) or Mean Absolute Error (MAE)? -Arguments against Avoiding RMSE in the Literature. *Geosci. Model Dev.* **2014**, *7*, 1247–1250. [\[CrossRef\]](#)
113. Hyndman, R.J.; Koehler, A.B. Another Look at Measures of Forecast Accuracy. *Int. J. Forecast.* **2006**, *22*, 679–688. [\[CrossRef\]](#)

Disclaimer/Publisher’s Note: The statements, opinions and data contained in all publications are solely those of the individual author(s) and contributor(s) and not of MDPI and/or the editor(s). MDPI and/or the editor(s) disclaim responsibility for any injury to people or property resulting from any ideas, methods, instructions or products referred to in the content.