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Total Dissipated Energy Prediction for Flexure-Dominated Reinforced Concrete Columns via Extreme Gradient Boosting

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Eğilme Etkisi Altındaki Betonarme Kolonlar için Toplam Tüketilen Enerji Seviyesinin Aşırı Gradyan Artırma Yaklaşımı ile Tahmini

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Abstract

This study aims to provide an efficient framework for predicting the total dissipated energy level of flexure-dominated reinforced concrete columns via a commonly used machine learning method, extreme gradient boosting. A database including 177 reinforced concrete columns is compiled using open-access databases. The proposed framework predicts the target total dissipated energy depending on seven fundamental features: concrete compressive strength, longitudinal rebar yield strength, shear span-to-depth ratio, longitudinal rebar ratio, transverse rebar volumetric ratio, peak drift ratio, and equivalent damping ratio. Results of a correlation-based quantitative analysis reveal that peak drift ratio, yield strength of longitudinal rebars, and concrete compressive strength are the most effective parameters on a target parameter among the other features. K-Fold cross-validation is implemented for the classification process. Validation results show that three fundamental performance indicators such as the means of correlation of determination, normalized root mean square error, and mean absolute percentage error are evaluated as 0.75, 0.38, and 0.33, respectively. Moreover, the accuracy level of the algorithm is tested by comparing with the results obtained based on support vector machine, multilayer perceptron, and random forest techniques. Among these, the implemented extreme gradient boosting is the most successful model for predicting the energy levels that represent the highest correlation of determination. The sensitivity of predicted targets to algorithm-based hyperparameters is also investigated for the implemented algorithm. The results of this study are expected to contribute to energy-based design applications in the scope of predicting the dissipated energy capacity of flexure-dominated reinforced concrete column members.

***Keywords:** Energy-based design; Total dissipated energy; XGBoost; Reinforced concrete columns.*

Öz

Bu çalışma, betonarme kolonlarda tüketilen toplam enerji seviyesinin uygulamalarda yaygın olarak kullanılan aşırı gradian artırma yaklaşımı ile tahminine yönelik etkin bir algoritma önerilmesini amaçlamaktadır. Bu kapsamda, açık erişimli veri tabanları kullanılarak 177 adet betonarme kolona ait özellikleri içeren bir veri tabanı derlenmiştir. Öne sürülen çerçeve, hedef toplam tüketilen enerji seviyesini 7 temel özelliğe bağlı olarak tahmine olanak sağlamaktadır: beton basınç dayanımı, boyuna donatı akma dayanımı, kesme açıklığı-derinlik oranı, boyuna donatı oranı, enine donatı hacimsel oranı, maksimum ötelenme oranı ve eşdeğer sönüm oranı. Gerçekleştirilen korelasyon esaslı sayısal analizler sonucunda, seçilen özellikler arasında toplam tüketilen enerji üzerinde en etkin olan parametrelerin maksimum ötelenme oranı, boyuna donatı akma dayanımı ve beton dayanımı olduğu belirlenmiştir. Verilerin sınıflandırılması sürecinde K-katlı çapraz geçerlilik yaklaşımı uygulanmıştır. Geçerlilik sonuçları, üç temel performans göstergesine (belirleme katsayısı, normalize edilmiş kök ortalama kare hatası ve ortalama mutlak yüzde hatası) ait ortalama değerlerin sırasıyla 0.75, 0.38 ve 0.33 olarak belirlendiğini göstermiştir. İlave olarak, çalışmada kullanılan model ile tahmin edilen sonuçların hassasiyeti, destek vektör makinesi, çoklu katman algılayıcı ve rastgele orman modelleri esaslı sonuçlar ile test edilmiştir. Sonuç olarak enerji seviyesinin tahmininde en başarılı modelin aşırı gradian artırma yaklaşımı olduğu, belirleme katsayısına dikkate alınarak belirlenmiştir. Çalışma kapsamında, tahmin edilen enerji seviyelerinin kullanılan algoritma bazlı parametrelere bağlı hassasiyet seviyeleri de araştırılmıştır. Çalışma sonuçlarının, özellikle son yıllarda artan enerji esaslı tasarım uygulamalarına, eğilme etkisi altındaki betonarme kolon elemanlarda tüketilen toplam enerji seviyesinin tahmini kapsamında katkı sağlayacağı düşünülmektedir.

***Anahtar Kelimeler:** Enerji-esaslı tasarım; Toplam tüketilen enerji seviyesi; Aşırı gradyan artırma yaklaşımı; Betonarme kolonlar.*

1. Introduction

The energy dissipation capacity of a reinforced concrete member is usually considered to indicate the cyclic behavior with two more critical parameters: strength and deformability (Park and Eom 2006). The accurate prediction of dissipated energy capacity and the identification of factors that affect the capacity play critical roles in both conventional and recently popular

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energy-based seismic design approaches (Yalçın et al. 2021). Consequently, several studies based on the investigation of the energy dissipation capacity of reinforced concrete members have been performed in the past. Park and Eom (2006) developed a simplified method to predict the dissipated energy level for flexure-dominated RC members via nonlinear finite element analysis.

The accuracy of the proposed method was verified by comparing the results with existing experiments. Results indicated that the method showed good performance in predicting the dissipated energy level based on various design variables. Poljanšek et al. (2009) proposed a non-parametric empirical approach to predict the energy dissipation and the deterioration of deformation capacity using the axial load index, index related to confinement, shear span index, concrete compressive strength, and longitudinal reinforcement index. Moreover, the effects of these parameters on the predicted capacity levels were also discussed in detail. Acun and Sucuoğlu (2012) developed an analytical model to predict the cyclic dissipated energy capacity of reinforced concrete (RC) columns under constant and variable inelastic displacement cycles.

Additionally, the effect of failure modes, material characteristics, and ductility level on the dissipated energy was also investigated in the scope of a related study. Liu et al. (2018) proposed a two-parameter analytical model for rectangular members under flexure to represent the variation of the dissipated energy with the cumulative hysteretic energy in each displacement cycle. The impact of corrosion levels of rebar to the energy dissipation of reinforced concrete columns was reported by Yang et al. (2016) via experimental way. Comparisons based on different levels of maximum amounts of corrosion showed that the dissipated energy level decreases with increasing amount of corrosion in rebars. The effects of axial load level to the energy dissipation capacities of reinforced concrete type short columns were investigated by Vu et al. (2022).

The study stated that the dissipated energy level is highly affected by the intensity and the fluctuation of applied axial load level. Muderrisoglu et al. (2023) proposed a quantitative framework that reveals a relationship between the structural member and loading features and the total energy dissipated by reinforced concrete columns. It was observed that maximum drift ratio, the amount of transverse rebar, and yield strength of rebars are the most effective ones among selected features in terms of correlation-based analysis. Yıldızel et al. (2023) investigated the effects of additional materials (i.e., recycled waste steel wires from tyres) on the stiffness, ductility, and energy dissipation characteristics of RC beams, experimentally.

Based on the experimental results, an equation was proposed to predict the capacity of investigated hybrid beams. Depending on the advances in using machine learning (ML) techniques in structural engineering (Thai 2022, Tapeh and Naser 2023), practices based on predicting the cyclic behavior characteristics of reinforced concrete members via ML-based frameworks have also been performed. Abdalla and Hawileh (2021) considered the Artificial Neural Networks technique to predict the dissipated energy level in steel rebars in a reinforced concrete member. It was concluded that the accuracy of the model in predicting the dissipated energy is considerably higher under low-cycle fatigue loads.

An ML-based model was developed by Topaloglu et al. (2022) to predict the energy dissipation capacity of shear walls. Specifically, the Gaussian Process Regression technique was implemented to develop a function depending on fundamental wall design parameters. Deger et al. (2023) proposed empirical equations to predict the energy dissipation capacity of RC shear walls using meta-modeling methodologies. The proposed framework resulted in a high coefficient of determination value (i.e., R^2=0.93) representing the level of accuracy in prediction. Yaghoubi et al. (2023) developed a Gaussian process regression-based algorithm that predicts the equivalent damping ratio of RC shear walls at displacements captured at 1.0% lateral drift ratio. For this purpose, a test database including 161 rectangular shear wall features was compiled using the existing test results available in the literature. It was concluded that the selected ML technique is accurate in the prediction of a selected target. Hamidia et al. (2024) proposed machine learning-based frameworks to predict seismic energy dissipation levels of RC beam-column connections. Specifically, 934 images of RC joint were utilized to predict the target parameter.

Results indicated that the prediction accuracy obtained using Cat Boost technique shows higher levels compared to those predictions evaluated via other techniques. A review of existing literature shows that a research gap based on a prediction of energy dissipation capacity of RC column type members practically that would be a good base for future studies and practices in energy design-based structural design and/or performance assessment applications is available. Therefore, a machine learning implemented analytical framework is proposed for predicting the total energy dissipation capacity of RC columns. Following a compilation of a comprehensive dataset, the effects of essential structural member characteristics on the total dissipated energy level were investigated quantitatively. A commonly-used extreme gradient boosting -XGBoost- (Chen and Guestrin 2016) algorithm was selected as a machine learning technique among the investigated techniques. Finally, the sensitivity of predicted results to the ML technique-based hyperparameters was discussed in detail.

2. Proposed Machine Learning-Assisted Framework for Predicting the Total Dissipated Energy Level

Details of the proposed machine learning-assisted framework that contributes to the energy-based design concept in terms of predicting the total dissipated energy capacity of flexure-dominated RC columns are presented in this section. For structural members subjected to cyclic loading, the total dissipated energy capacity is evaluated using an area under the force-displacement hysteresis captured during the loading (Figure 1). In practice, this is achieved by constructing analytical models to simulate the response of a member, performing experiments, or considering both processes. In this study, the capability of a machine learning technique is taken into account for a prediction-based analytical framework to evaluate the total dissipated energy level. Specifically, the XGBoost technique is selected to teach the computer how to predict the target of interest using the available dataset.

2.1. Extreme gradient boosting technique

Extreme gradient boosting, XGBoost (Chen and Guestrin 2016) is a scalable tree-boosting technique proposed to increase the speed and the efficiency of the existing gradient boosting (Friedman 2001) method. Three fundamental tools are implemented in the improved technique such as (1) compressed column format (i.e., to store data for reducing the time consumed during the process depending on the cost of sorting), (2) randomization technique to increase the speed of training process and decreasing the level of overfitting, and (3) parallel and distributed computing for split finding procedure (Thai 2022). In an extreme gradient boosting model, the objective function needs to be minimized at iteration t is expressed as follows:

$$\tilde{\mathcal{L}}^{(t)} = \sum_{i=1}^{k}[g_i f_t(x_i) + \frac{1}{2} h_i f_t^2(x_i)] + \Omega(f_t) \tag{1}$$

where f_t represents the added function to iteration to improve the speed of a model for optimization and $\Omega(f_t)$ is considered to penalize the model-based complexity. Moreover, g_i and h_i indicate the first and the second order gradient statistics on the loss function (i.e., $l(\hat{r}_i, r_i)$) depending on the difference between the predicted, $\hat{r}_i$ and the target, r_i parameters:

$$g_i = \partial_{\hat{r}^{(t-1)}} l(r_i, \hat{r}^{(t-1)}) \tag{2}$$

$$h_i = \partial^2{}_{\hat{r}^{(t-1)}} l(r_i, \hat{r}^{(t-1)}) \tag{3}$$

Here, Equation 1 is rewritten to consider the contribution of each leaf j (i.e., in a tree structure) during the iteration process as follows:

$$\tilde{\mathcal{L}}'^{(t)} = \sum_{j=1}^{T}[(\sum_{i\in I_j} g_i) w_j + \frac{1}{2}(\sum_{i\in I_j} h_i + \lambda) w_j^2] + \gamma\mathrm{T} \tag{4}$$

where T is the total number of leaves in a tree, and I_j is the instance set of leaf during the iteration process. Accordingly, the optimal weight of leaf j, $w_{j,opt}$ and the corresponding optimal value for a fixed tree structure, q are evaluated via solving the quadratic function given in Equation 4 on w_j as follows (i.e., Equations 5 and 6, respectively):

$$w_{j,opt} = -\frac{\sum_{i\in I_j} g_i}{\sum_{i\in I_j} h_i + \lambda} \tag{5}$$

$$\tilde{\mathcal{L}}'^{(t)}(q) = -\frac{1}{2}\sum_{j=1}^{T}\frac{(\sum_{i\in I_j} g_i)^2}{\sum_{i\in I_j} h_i + \lambda} + \gamma\mathrm{T} \tag{6}$$

Then, the split candidates in a tree learning process are evaluated using the loss reduction after the split as follows:

$$\mathcal{L}_{split} = \frac{1}{2}\left[\frac{(\sum_{i\in I_L} g_i)^2}{\sum_{i\in I_L} h_i + \lambda} + \frac{(\sum_{i\in I_R} g_i)^2}{\sum_{i\in I_R} h_i + \lambda} - \frac{(\sum_{i\in I} g_i)^2}{\sum_{i\in I} h_i + \lambda}\right] - \gamma \tag{7}$$

Here, I_L and I_R indicate the left and right node's instance sets considered after the split, respectively. Finally, the best split is found by maximizing the difference between the objective functions considered before and after the split node (i.e., using the Exact Greedy algorithm to minimize Equation 4). In this study, a Python-based (van Rossum and Drake 1995) framework supported by the advanced machine learning tools (Pedregosa et al. 2011) is considered to predict the target parameter. Additionally, assessing the performance of implemented technique in machine learning-based studies is also crucial to provide more accurate results. For this purpose, the K-Fold cross-validation procedure is considered during the analysis.

2.2. K-Fold cross-validation

The K-Fold cross-validation is a widely used technique in statistical analysis to assess the level of accuracy of a selected model and to predict the classifiers' errors (Anguita et al. 2012).

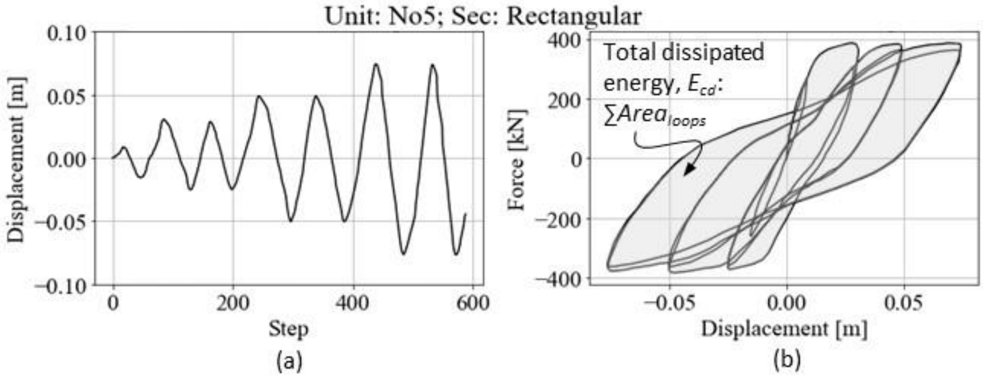

Figure 1. Experiment-based evaluation of total dissipated energy for a specimen tested by Tanaka (1990): (a) loading protocol, (b) force-displacement hysteresis

Here, the parameter, *K* basically refers to the number of folds that a selected dataset would be split into. Following the random split process, a cross-validation-based training is applied by considering the training (e.g., *K*-1 folds) and a test set. Accordingly, a machine learning technique of interest (e.g., as XGBoost in this study) is implemented to predict the target parameter using the folds including training and test data. Finally, means of performance indicators are evaluated to assess the accuracy of the trained model. Specifically, commonly used statistical performance indicators such as (1) the normalized root mean square error -*NRMSE*-, (2) mean absolute percentage error -*MAPE*-, and (3) coefficient of determination -R^2- are selected to assess the trained data in this study. These indicators are evaluated as follows:

$$NRMSE = \frac{\sqrt{\frac{1}{n}\sum_{i=1}^{n}(y_i - y_i')^2}}{\frac{\sum_{i=1}^{n} y_i}{n}} \tag{8}$$

$$MAPE = \frac{1}{n}\sum_{n}^{i=1}\left|\frac{y_i - y_i'}{y_i}\right| \tag{9}$$

$$R^2 = 1 - \frac{\sum_{i=1}^{n}(y_i - y_i')^2}{\sum_{i=1}^{n}(y_i - \bar{y})^2} \tag{10}$$

where *n* refers to the number of samples, *y* is the actual and *y′* is the predicted value. In this study, the coefficient of determination, R^2 (Equation 10) is selected as a performance indicator. A general overview of a proposed framework is represented in Figure 2.

3. Dataset Properties

The database considered in this study was compiled by taking into account two fundamental open-access studies (Ghannoum et al. 2015a, 2015b). Specifically, the selected dataset includes RC column information focused on rectangular and circular sections subjected to flexural actions. The study was based on 177 column specimens (i.e., 113 rectangular and 64 circular RC columns). In the scope of machine learning-based research, quantifiable features available in a database are considered as input data to predict the target parameter.

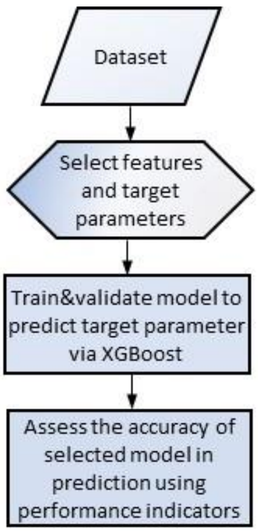

Figure 2. A general overview of a proposed framework

Accordingly, a wide range of feature sets including the compressive strength of concrete, f_c, longitudinal rebar yield strength, f_{yl}, shear span-to-depth ratio, *a*/*d*, longitudinal rebar ratio, ρ_l, transverse rebar volumetric ratio, ρ_t, peak drift ratio, Δ_{max}, and equivalent damping ratio, ξ_{eqv} (Kwan and Billington 2003) is considered during the analysis. Relative frequencies of selected features and target parameter (i.e., total dissipated energy, E_{cd}) are given in Figure 3. The total dissipated energy capacities of specimens in a selected dataset vary between 51.5kNm and 635.7kNm. Fundamental factors including sectional, material, loading, and mechanical properties have a significant effect on the total dissipated energy level of column members (Poljanšek et al. 2009, Muderrisoglu et al. 2023). Following the identification of features and the target parameter, correlations between these quantities are investigated via Pearson's correlation coefficient (Pearson 1920) as follows:

$$\rho_{FT} = \frac{\sigma_{FT}}{\sigma_F \sigma_T} \qquad (11)$$

where σ_{FT} indicates the covariance between the feature and the target, σ_F is the standard deviation of feature and σ_T is the standard deviation of target data. The correlation coefficient, ρ_{FT} takes values between -1 and +1 where these boundary levels correspond to complete negative and positive cases, respectively. Correlation levels between selected features and the total dissipated energy level are given as a matrix in Figure 4.

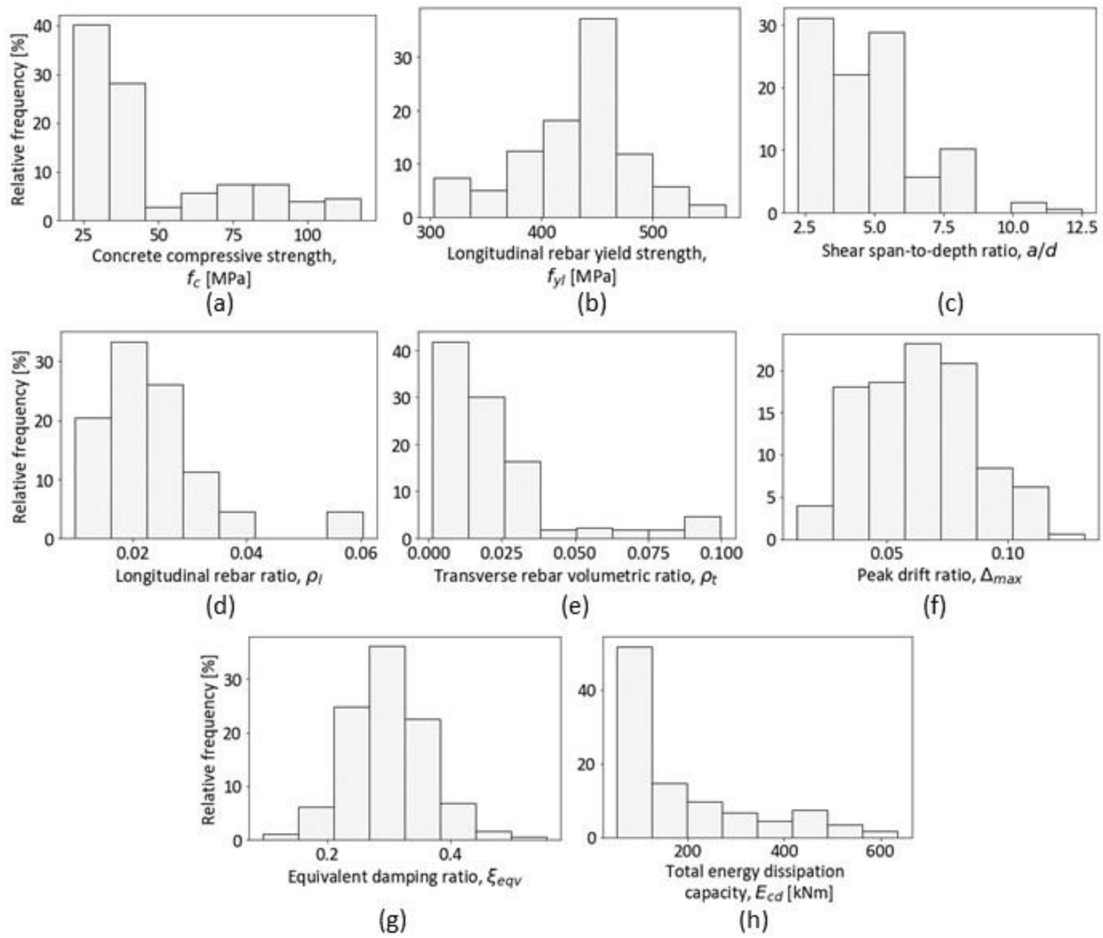

Figure 3. Relative frequency distributions of selected features and the target parameter: (a) f_c, (b) f_{yl}, (c) a/d, (d) ρ_l, (e) ρ_t, (f) Δ_{max}, (g) ξ_{eqv}, (h) E_{cd}

Preliminary results indicate that the total dissipated energy level captured in flexure-dominated RC column specimens under cyclic loading is mostly influenced by peak drift ratio (i.e., $\rho_{\Delta max,Ecd}$=0.43). This result shows a good agreement with observations available in the study by Muderrisoglu et al. (2023). Moreover, an opposite trend (i.e., negative correlation) is observed for a relationship between the concrete compressive strength and the total dissipated energy level. Actually, the correlation level for this case is considerably low (i.e. $\rho_{fc,Ecd}$=-0.2). Comprehensive research (Poljanšek et al. 2009) based on considering the normal (e.g., between 20 MPa and 40 MPa) and high-strength concrete features in detail reported that the energy capacity of a specimen with normal concrete is higher than that capacity of a high strength concrete specimen due to the inverse relationship between the ductility and the strength of material.

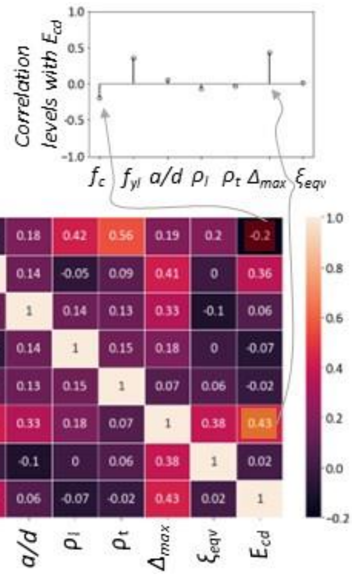

Figure 4. A heatmap representing the correlation levels between selected features and target parameter

4. Proposed Predictive Model Results

In this section, results obtained via the proposed framework are given. For this purpose, means of performance indicators calculated using the K-Fold cross-validation analysis are presented. Additionally, sensitivity analyses are performed to investigate the effect of fundamental hyperparameters considered in the XGBoost technique on the predicted results.

4.1. Accuracy of predictions

Following the compilation of a dataset and selecting the features and a target parameter, training of a proposed model including the XGBoost technique is implemented by evaluating the optimum ML technique-based hyperparameters using the random search technique. Specifically, the hyperparameters are searched as: an objective for a loss function, [*reg:logistic,binary:logistic]* supported for XGBoost, number of estimators, n_{est} in a range of [50,1000], max tree depth, max_d of [1,20], boosting learning rate, r_l of [0.001,1.0]. Finally, the optimum parameters are determined to evaluate for the best mean performance indicator. Moreover, other model-based parameters such as degree of polynomial for fitting used to generate the train and test sets is selected as 2, and the booster type is considered as *gbtree* during the process. In this study, a K-Fold cross-validation technique is utilized instead of a standard train-test split methodology to evaluate the performance of implemented ML-based model in a more robust way. Specifically, the number of folds, n_{fold} is considered as 6 to partition the existing dataset into multiple parts such as n_{fold}-1 (i.e., 5 folds) for training and the remaining for testing data. Specifically in each part, 83% of total data (i.e., 148 members) are considered for training while 29 samples (i.e., 17%) are taken into account to train the relevant model. Here, it should be noted that an L2 regularization method is utilized to prevent overfitting when training the model. Performance indicators evaluated in each fold are provided in Table 1. As expected, different values of performance indicators are obtained for folds including randomly generated training and test data depending on the level of variabilities in predicted and actual energy levels in each fold. Results show that the maximum and the minimum values of selected performance indicator (i.e., coefficient of determination, R^2) are evaluated as 0.82 and 0.58 for a selected set of hyperparameters, respectively (Figure 5). Accordingly, the accuracy level of the proposed model is tested by taking into account the mean of performance indicator, R^2 calculated for generated folds (Figure 6). As the mean of performance indicators is calculated as 0.75 and considering the high variabilities in features of a selected dataset, the proposed model is assumed to be considerably accurate in predicting the total dissipated

Table 1. Performance indicators evaluated in each fold in K-Fold cross validation process

Fold #/ Performance indicator	R^2	NRMSE	MAPE
1	0.58	0.46	0.28
2	0.74	0.35	0.35
3	0.82	0.33	0.29
4	0.82	0.34	0.36
5	0.75	0.47	0.46
6	0.77	0.33	0.26

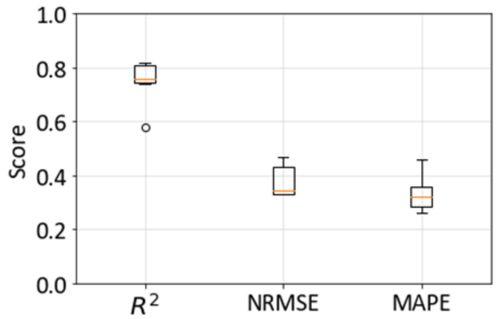

Figure 5. Variabilities in performance indicators evaluated via K-Fold cross-validation process

energy level of flexure-dominated RC columns subjected to cyclic loadings (Chicco et al. 2021, Moore et al. 2013).

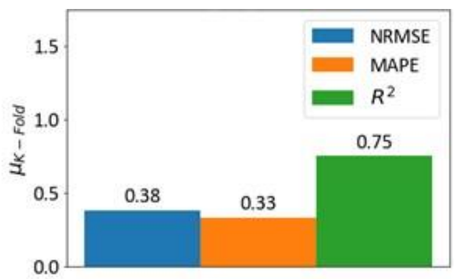

Figure 6. Means of performance indicators evaluated via K-Fold cross-validation process

In addition to the implemented ML technique-wise performance evaluation (Figure 6), the accuracy level of the implemented algorithm in predicting the energy levels is also tested by comparing with the results obtained based on commonly used machine learning models in structural engineering such as support vector machine (SVM), multilayer perceptron (MLP), and random forest (RF) (Table 2). Here, the means of selected performance indicators evaluated using the optimum hyperparameters (i.e., using a random search algorithm) are presented. Preliminary results show that the implemented extreme gradient boosting is concluded as the most successful model among the selected techniques to predict the energy levels as representing the highest correlation of determination (i.e., R^2=0.75).

Table 2. Comparison of the performance of different algorithms

ID	Hyperparameter	R^2	NRMSE	MAPE
XGB	n_{est}=150; objective=reg:logistic max_d=1; r_l=0.6	0.75	0.38	0.33
SVM	kernel=rbf; *C*=10; epsilon=0.05; gamma=0.3	0.43	0.57	0.52
MLP	solver=adam; alpha=0.0001; hidden layer sizes=400,400 max. iterations=500;	0.63	0.46	0.46
RF	n_{est}=10	0.66	0.49	0.44

The capability of the validated model is investigated by evaluating the correlation level between the predicted, $\mu_{Ecd,p}$ and actual, $\mu_{Ecd,a}$ total dissipated energy capacities corresponding to the mean coefficient of determination case of 0.75. In Figure 7, a strong correlation between the predicted and actual total dissipated energy capacities (i.e., $\rho_{a,p}$=0.94) that indicates a high-level prediction case, is observed.

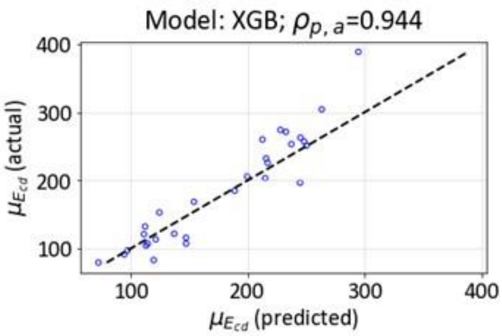

Figure 7. Correlation between actual and predicted total dissipated energy levels

The preliminary results indicate that the proposed model shows high accuracy in predicting the total dissipated energy level for selected hyperparameters.

4.2. Sensitivity of the performance indicator to the fundamental hyperparameters

Effects of fundamental parameters on the selected performance indicator, R^2 (i.e., hence on the prediction results) are investigated in this section.

Number of estimators&Maximum depth

The means of performance indicator obtained for a set of a number of estimators and maximum depth values are presented in Figure 8. Here, a constant boosting learning rate of 0.6 is considered. Results show that, following the increment of coefficient of determination values up to a peak level of a number of estimators (i.e., 150 for a set of interest), a decrement tendency is observed for low values of maximum depth hyperparameter. Moreover, it is also concluded that the indicator becomes constant for high levels of maximum depth (i.e., max_d≥10).

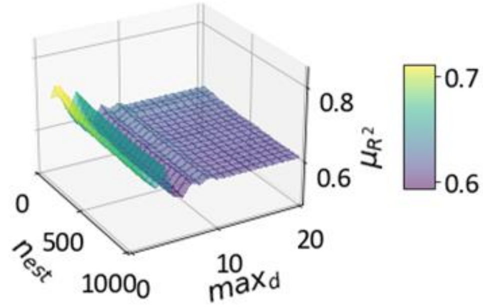

Figure 8. Effects of number of estimators and maximum depth on the performance indicator (r_l=0.6)

Maximum depth&boosting learning rate

The sensitivity of performance indicators to the variabilities in maximum depth and boosting learning rate is investigated in this sub-section (i.e., for a constant number of estimators as 150). In Figure 9, a sudden increment in R^2 values is observed up to a learning rate of 0.2 for a selected interval of maximum depth parameter.

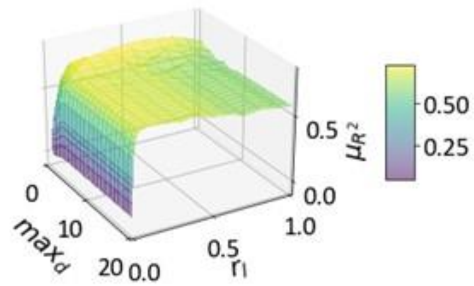

Figure 9. Effects of maximum depth and boosting learning rate on the performance indicator (n_{est}=150)

Number of estimators&Boosting learning rate

The effect of a number of estimators and boosting learning rate on the evaluated R^2 values is illustrated in Figure 10. Here, a constant maximum depth parameter of 1 is considered during the analysis. It is observed that higher R^2 values are evaluated for low values of the number of estimators. Moreover, the indicator is significantly affected for decreasing levels of boosting learning rate parameter.

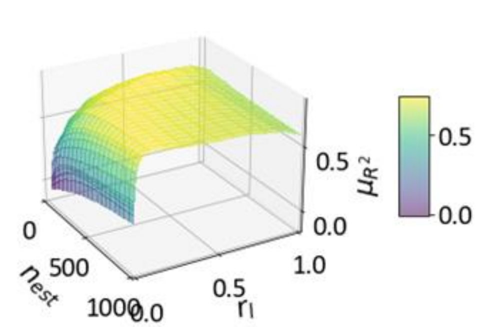

Figure 10. Effects of number of estimators and boosting learning rate on the performance indicator max_d=1)

5. Conclusions

A machine learning technique implemented analytical framework based on predicting the total energy dissipated by flexure-dominated reinforced concrete columns is presented. The proposed framework takes into account the XGBoost technique to train the selected data. Data characteristics are detailed using statistical approaches. The accuracy level of a proposed model in predicting the energy capacity level is illustrated using the coefficient of determination as a performance indicator. The effects of critical ML technique-based hyperparameters on the selected performance indicator are investigated by performing sensitivity analyses. Following results can be derived based on the outcomes of detailed analysis:

- The dependency of the total dissipated energy capacity on the selected parameters is quantified via correlation coefficients. The highest positive (i.e., $\rho_{\Delta max,Ecd}$=0.43) and negative correlations ($\rho_{fc,Ecd}$=-0.2) are evaluated for peak drift ratio and concrete compressive strength features, respectively.
- The proposed model yielded considerably accurate results in predicting the total dissipated energy capacity by taking into account the coefficient of determination, R^2 as a performance indicator with a mean of 0.75.
- The accuracy level of the implemented algorithm in predicting the energy levels is also tested by comparing with the results obtained based on support vector machine (SVM), multilayer perceptron (MLP), and random forest (RF) algorithms. Preliminary results show that the implemented extreme gradient boosting is concluded as the most successful model among the selected techniques to predict the energy levels as representing the highest correlation of determination.
- A strong correlation level of $\rho_{a,p}$=0.94 is obtained via the proposed model based on a comparison between the actual and predicted total dissipated energy capacities.
- Sensitivity analysis performed to investigate the effects of ML technique-based hyperparameters showed the importance of tuning the parameters in an optimal way. Preliminary results indicated that among the considered hyperparameters, the number of estimators has a significant effect on the level of performance indicator selected in the scope of this study, coefficient of determination.

Evaluating the total energy dissipated by RC columns during cyclic loadings is a crucial issue in the energy-based design approach that is widely applied in practice. Hence, the outcomes of this study are believed to make an important contribution to future studies based on this topic. Moreover, the proposed ML assisted framework can be also implemented to other structural and earthquake engineering applications.

Declaration of Ethical Standards
The author declares that he complies with all ethical standards.

Declaration of Competing Interest
The author has no conflict of interest to declare regarding the content of this article.

Data Availability
All data generated or analyzed during this study are included in this published article.

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