XLVI CILAMCE
VITÓRIA - ES - BRAZIL - 2025
XLVI IBERO-LATIN AMERICAN CONGRESS ON COMPUTATIONAL METHODS IN ENGENEERING

A machine learning-based method for analyzing the axial load capacity of rectangular reinforced concrete columns

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Abstract. The axial load capacity of columns is a critical variable for structural systems, as the failure of a single element can lead to the collapse of the entire structure. Therefore, an accurate prediction of this variable is essential to ensure the safety of the system. In this context, machine learning methods have gained prominence in modeling the behavior of reinforced concrete structures. Accordingly, this study aimed to investigate the axial load capacity of rectangular reinforced concrete columns using Artificial Neural Networks (ANNs) and Tree/Forest-based algorithms. Ten input parameters related to the geometric and mechanical properties of this type of structural element were selected in order to capture their behavior under different loading conditions. Prior to training, data preprocessing was carried out to identify the importance of each input variable with respect to the output of interest. Model training was performed using supervised learning, with the Python programming language and the Scikit-Learn library. To assess model performance, error metrics such as the Mean Absolute Percentage Error (MAPE), Root Mean Square Error (RMSE), and the coefficient of determination (R^2) were used. The results indicated that both models (ANNs and tree/forest algorithms) achieved satisfactory performance in predicting the ultimate load capacity of the columns. However, the tree/forest-based model stood out, which can be attributed to its robustness against potential outliers and its efficiency during the training process.

Keywords: Reinforced concrete, columns, neural networks, random forests, axial load

1 Introduction

The geometric and material properties are essential factors for analyzing the structural performance of an element. In addition to these aspects, according to Shirmohammadi and Esmaeily [1], in the case of columns, axial loading plays a significant role, as its intensity and position directly influence stress distribution, failure mode, durability, and the safety of the element throughout its service life. Determining the maximum load a column can withstand is a decisive factor in structural design. In this context, machine learning-based methods emerge as a promising alternative, offering significant reductions in analysis time and cost. According to Thai [2], this approach is especially relevant considering that conventional analyses often require complex and time-consuming calibrations, whose practical application can become unfeasible in certain situations.

In this context, this study aimed to investigate the axial load capacity of rectangular reinforced concrete columns using two distinct methods: Artificial Neural Networks (ANNs) and tree/forest-based algorithms. These methods present specific characteristics that justify their application. ANNs, as highlighted by Yao et al. [3], are an artificial intelligence technique inspired by the functioning of the human brain, recognized for their strong performance in identifying complex patterns and handling high-dimensional data. On the other hand, tree- and forest-based algorithms, according to Jun [4], stand out for their high predictive power combined with a lower need for complex hyperparameter tuning. The error metrics obtained for each model were analyzed to compare the performance of the methods considering the dataset used in this study.

2 Methodology

The database used in this study consisted of 306 experimental records from the ACI 369 Rectangular Column Database[1]. These data originated from studies that investigated various characteristics of reinforced concrete columns, including geometric properties, axial load, transverse load, and the influence of the arrangement of longitudinal reinforcement in multiple layers, among other aspects. A common point among all the studies analyzed is the consideration of the axial load applied to the columns, which motivated the use of this database in the present investigation. Table 1 presents the parameters initially selected as inputs for the predictive models, along with their statistical data. It is noteworthy that the output variable (axial load) is expressed in kN, with a lower limit of 15.3 kN and an upper limit of 32.7 kN.

Table 1. Initial model parameters

Variable	Meaning	Unit	Std	Mean	Min	Max
$Section(h)$	Column height	mm	111.51	310	80	700
$Section(b)$	Column base	mm	109.22	290	80	600
pL	Reinforcement ratio	%	0.010	0.024	0.007	0.07
f_c	Concrete compressive strength	MPa	28.21	46.34	13.09	117.89
f_y	Steel yield strength	MPa	58.80	428.95	317.70	586.49
l_c	Column length	mm	508.76	1243	200	2946
Bars face 1	Number of bars (first layer)	–	0.95	3.36	2	6
Bars face 2	Number of bars (second layer)	–	0.95	3.36	2	6
d_1	Distance between reinforcement bars (first layer)	mm	103.4	271.3	61.21	638.81
d_2	Distance between reinforcement bars (second layer)	mm	102.11	250.44	63	571.5

The next step consisted of preprocessing the selected database. This process began with the identification of the variables with the greatest influence on the axial capacity of the columns, based on literature references, linear correlation analyses among the variables, and the evaluation of feature importance using the Mean Decrease in Impurity (MDI) method, implemented in the Scikit-Learn library through the RandomForestRegressor. This method estimates the contribution of each variable from the average reduction of impurity in the tree splits, weighted by the fraction of affected samples, resulting in normalized values that sum to 1. Therefore, it represents an internal multivariate analysis based on the forest structure. The computation was performed using the $feature_importances$ routine, considering 100 estimators and $random_state = 42$.

The data preprocessing also involved the normalization of the input variables, considering the different physical units adopted, as well as the stratification of the dataset and its division into training and testing subsets, in proportions of 80% and 20%, respectively. From the training subset, 10% was automatically reserved for validation, a step employed to determine the optimal hyperparameters of the models. The training data were used for the adjustment and calibration of the machine learning algorithms, while the testing data, corresponding to 20% of the total, were used for the final evaluation of the models' performance. This validation strategy was adopted instead of the k-fold method due to the limited amount of available data.

After preprocessing, with the definition of the model input variables and parameters, the training of the predictive models was initiated. Two supervised learning methods were evaluated: artificial neural networks and tree/forest-based models, in which the dataset is labeled, meaning that the desired output variable is provided during training. To ensure consistency in the comparison, the same training dataset was used for both model classes, as well as for all architectures and hyperparameter variations within each class.

In the case of neural networks, a low-complexity architecture was chosen, consisting of two hidden layers with the number of neurons varying from 1 to 40 in each layer. The maximum number of iterations was set to 100,000, adopting an early stopping criterion after 10,000 iterations without performance improvement. In addition, a tolerance of 0.0001 was established. Regarding the activation function, based on the literature review and preliminary tests performed, the Rectified Linear Unit (ReLU) function was used, resulting in the generation of 1,600 architectures. Training was carried out using the Grid Search method. During the modeling process, the framework for both neural networks and tree-based models was defined, testing all proposed typologies: networks with two hidden layers (up to 40 neurons per layer) and forests with the number of trees ranging from 10 to 100.

[1]DOI: `https://doi.org/10.4231/D36688J50` ; available at the Data Center Hub: `https://datacenterhub.org/` (Accessed on July 24, 2025).

Subsequently, the five best architectures were analyzed in order to identify the topology that demonstrated the best performance in mapping the output variable. The selection was based on the highest coefficients of determination (R^2) obtained from the test data, in order to identify the networks with the greatest generalization capability. The values of the Mean Absolute Percentage Error (MAPE) and the Root Mean Squared Error (RMSE) were determined according to Equations eq. (1), eq. (2), and eq. (3), respectively, where y_i, $\bar{y}_i$, and $\hat{y}_i$ represent, respectively, the actual values, the mean of the actual values, and the predicted values.

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

$$MAPE = \frac{100\%}{n} \sum_{i=1}^{n} \left| \frac{y_i - \hat{y}_i}{y_i} \right| \tag{2}$$

$$RMSE = \sqrt{\frac{1}{n} \sum_{i=1}^{n} (y_i - \hat{y}_i)^2} \tag{3}$$

For modeling based on decision tree/forest algorithms, the RandomForestRegressor class available in the Scikit-learn library was used. The main hyperparameters adopted were: criterion=absoluteError, to minimize the influence of outliers; maxFeatures=log2, aiming to reduce correlation between trees; and maxDepth=30, to limit tree complexity. The only hyperparameter that was varied was the number of estimators (nEstimators), testing values from 10 to 100 in increments of 1, resulting in a total of 91 architectures evaluated. The resulting architectures were analyzed to identify those that exhibited the best performance in mapping the ultimate axial load. The selection of the best architectures was based on the previously described error metrics, ensuring the choice of the most appropriate model for prediction.

Finally, the most prominent architectures from each of the methods were compared in order to identify the one that achieved the most satisfactory performance, considering the characteristics of the dataset analyzed in this study.

3 Results

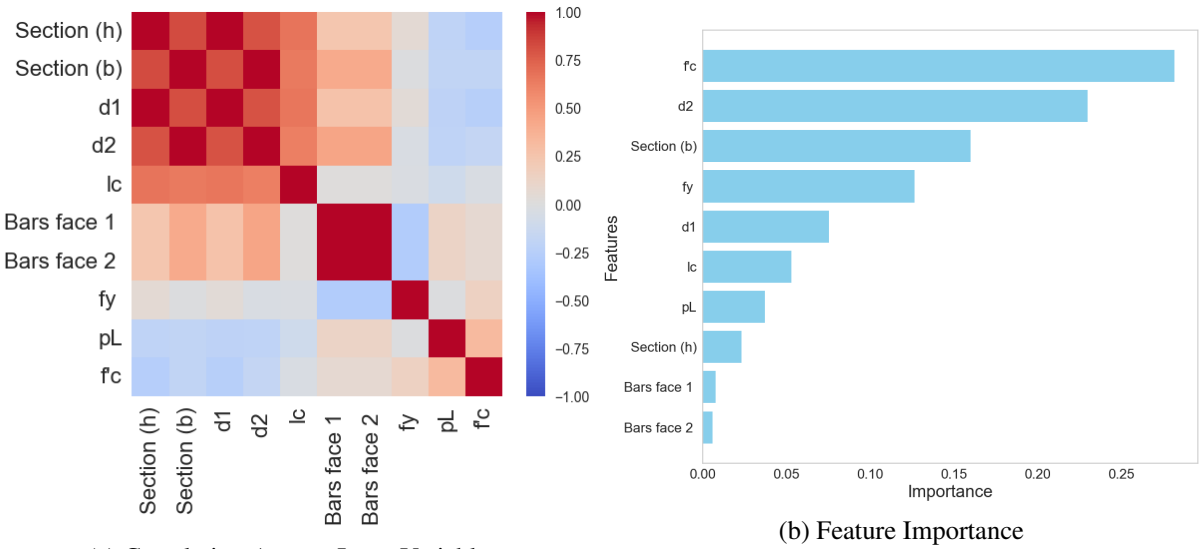
3.1 Preprocessing

The ten input parameters initially proposed in this study were analyzed for their mutual correlation. Figure 1(a) shows the resulting correlation matrix, where it can be observed that the geometric properties, such as the column's base and height, as well as the effective heights corresponding to each layer of longitudinal reinforcement, exhibit strong positive correlation. This behavior indicates that an increase in one of these variables tends to be accompanied by increases in the others. On the other hand, the variables related to concrete strength and steel yield stress show low correlation with the section's geometric parameters, suggesting that there is no direct linear relationship between these properties.

Figure 1 (b) shows the relative importance of the variables in predicting the axial load of the columns. It can be seen that, among the ten variables analyzed, the number of longitudinal reinforcement bars, in both the first and second layers, has little influence on determining the output variable. This finding is consistent with studies in the literature, such as Tran et al. [5], which investigated the axial capacity of tubular columns and highlighted the relevance of the column's geometric properties, as well as the strengths of the concrete and reinforcement, for predicting axial load. Additionally, Ali et al. [6], who also applied machine learning to predict the structural behavior of columns, emphasized the influence of other parameters, such as the steel ratios used in the columns, reinforcing the importance of properly considering these variables in predictive models.

Accordingly, based on the analysis presented in Figure 1, the variables listed in Table 2 were selected for training the models. It is worth noting that since the variables $Section(h)$ and d_1, as well as $Section(b)$ and d_2,

exhibited high correlation with each other, only the variables $Section(h)$ and $Section(b)$ were retained as model inputs. This choice is justified by the fact that the simultaneous presence of highly correlated variables may cause the model to assign disproportionate weights to one of them, thereby reducing its predictive capability.



(a) Correlation Among Input Variables

(b) Feature Importance

Figure 1. Database Features

Table 2. Input parameters of the models

Variable	Meaning	Unit
$Section(h)$	Column height	mm
$Section(b)$	Column base	mm
pL	Reinforcement ratio	%
f_c	Compressive strength	MPa
f_y	Yield strength	MPa
l_c	Column Length	mm

3.2 Artificial Neural Networks

The results obtained through modeling with Artificial Neural Networks (ANNs) are presented in Table 3, which highlights the five best-performing architectures among the 1,600 tested. The analysis indicates that, overall, the selected architectures achieved satisfactory performance, with high and comparable correlation coefficients between the training and testing sets. Furthermore, it is observed that, in most cases, the MAPE remained below 10%, while the RMSE stayed under 2.0 kN, values considered good given the range of forces in the database, which vary approximately between 15 and 33 kN.

The analysis of Table 3 shows that the best-performing architecture for modeling the ultimate axial load of reinforced concrete columns, based on the dataset used in this study, consists of 13 neurons in the first hidden layer and 34 neurons in the second. This configuration was selected based on the highest coefficient of determination achieved on the testing set, combined with its closeness to the training set coefficient, indicating good learning and generalization capabilities of the model. Furthermore, the observed errors were relatively low, considering the magnitude of the forces in the database, with MAPE of 6.57% and RMSE of 1.7402 kN.

These results align with the literature, recognizing that the magnitude of errors depends on the complexity of the dataset and the network architecture employed. However, there is evidence that errors below 10% indicate good predictive capability of the model, as demonstrated by Rafiq Joo and Ahmad Sofi [7], who reported average errors close to 8% in predicting the ultimate axial strength of columns. The authors concluded that the Artificial Neural Networks (ANNs) applied in their study showed high accuracy in estimating the axial load capacity of double-skin

steel tubular columns filled with concrete.

Table 3. Best architectures obtained with artificial neural networks

Layer 1	Layer 2	$R^2 train$	$R^2 test$	MAPE	RMSE
13	34	0.8804	0.8478	0.0657	1.7402
40	19	0.8875	0.8417	0.0641	1.7085
32	15	0.9141	0.8385	0.0570	1.5558
18	27	0.8664	0.8361	0.0671	1.8312
27	37	0.8680	0.8293	0.0657	1.8313

Figure 2 presents the scatter plot of the Predicted Axial Load (kN) versus the True Axial Load (kN), which demonstrates the performance of the correlation coefficient for all model data (training and testing). Good model accuracy can be observed, evidenced by the high concentration of data points around the identity line, which represents the ideal condition where predicted values are identical to true values. The proximity between the best fit line and the identity line reinforces the high correlation coefficient (0.874), confirming the model's robustness. However, the dispersion of some points far from the ideal line is noted, indicating the model's difficulty in correctly predicting certain values. These points may be considered potential outliers and warrant additional investigation to understand whether they represent noise in the data or specific model limitations.

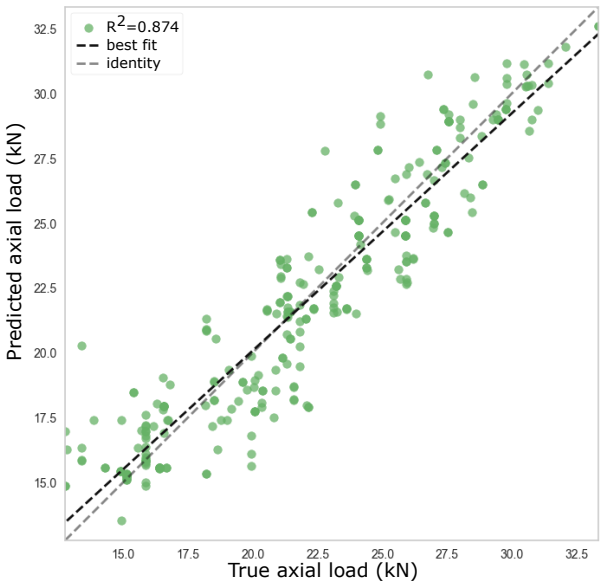


Figure 2. Relationship between Actual and Predicted Axial Load Values Using Neural Networks

3.3 Trees/Forests

For modeling with decision tree/random forest algorithms, a total of 91 architectures was evaluated by varying the number of estimators (nEstimators). The selection of the five best architectures, presented in Table 4, followed the same procedure adopted for Artificial Neural Networks. The data analysis highlights the satisfactory performance of the tested architectures, with MAPE error values below 10% and RMSE below 2.0 kN. Regarding the correlation coefficients, high values were observed in both the training and testing sets, indicating high model accuracy. However, a slightly better performance was noted in the training set, with coefficients approximately 0.1 higher than those obtained in the testing set. Despite this difference, the correlation coefficient for the testing set remained high, always above 0.83, demonstrating good predictive capability and generalization of the models.

In addition, Table 4 indicates that the optimal architecture consists of 68 trees.This configuration exhibited the highest correlation coefficients and the lowest error values, demonstrating its superior performance compared to

the other configurations. Consequently, Figure 3 presents the scatter plot of the model using all data (both training and testing). The data points are well aligned, with few outliers. Furthermore, the proximity between the best-fit line and the identity line confirms the model's high correlation coefficient and its robustness in predicting axial load. The concentration of points along the ideal line indicates the model's high predictive accuracy.

Table 4. Best architectures obtained with decision trees/forests

N. estimators	$R^2 train$	$R^2 test$	MAPE	RMSE
68	0.9566	0.8550	0.0665	1.8467
70	0.9568	0.8533	0.0669	1.8575
88	0.9573	0.8521	0.0673	1.8654
40	0.9557	0.8475	0.0675	1.9258
38	0.9552	0.8373	0.0682	1.9561

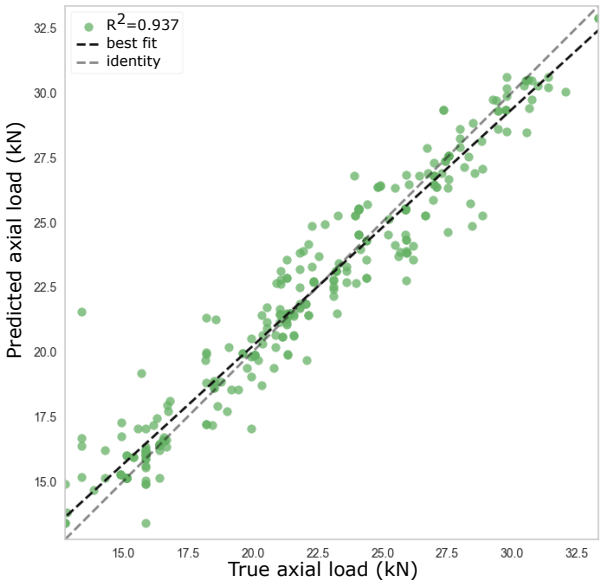


Figure 3. Relationship between Actual and Predicted Axial Load Using Tree/Forest Models

3.4 Comparison Between Predictive Models

Both the best architecture of the artificial neural networks and the optimal configuration of the tree and random forest model demonstrated satisfactory performance, highlighting the effectiveness of both approaches in the prediction task analyzed. However, a comparative analysis of the metrics indicates the superiority of the tree and forest-based model, evidenced by higher coefficients of determination along with error metrics comparable to those obtained by the neural network model. Furthermore, the analysis of the plots in Figures 2 and 3 shows less dispersion in the tree and forest model, reflecting greater consistency and robustness across the entire dataset. Despite a more pronounced difference between the training and testing coefficients, this model also maintained good generalization capability.

Similar results have been reported in previous studies, such as Yu et al. [8], who applied machine learning techniques to estimate the axial capacity of columns, highlighting the effectiveness of tree and forest-based models. This work demonstrates that relatively simple configurations, with fewer than 100 estimators, similar to that used in this study, are capable of generating consistent predictions with significantly low error metrics, reinforcing the efficiency of random forests in this type of application.

4 Conclusions

The results obtained in this article indicate that both models demonstrated satisfactory performance in predicting the ultimate axial load of rectangular reinforced concrete columns, confirming the potential of machine learning techniques for structural applications. The Artificial Neural Networks (ANNs) achieved coefficients of determination of 0.8804 and 0.8478 for the training and testing sets, respectively, with MAPE of 6.57% and RMSE of 1.7402 kN. Considering all data (training and testing), the overall correlation coefficient was 0.874.

The tree/forest-based model exhibited similarly strong performance, with correlation coefficients of 0.9566 for the training set and 0.8550 for the testing set, along with a MAPE of 6.65% and an RMSE of 1.8467 kN. The overall correlation coefficient (considering all data) was 0.937, and the scatter plot shows few dispersed data points. Even though the neural network achieved slightly lower error values, the Random Forest model stood out due to its greater consistency in predictions, as evidenced by the less dispersed scatter plot, as well as its robustness, lower sensitivity to outliers, and reduced need for hyperparameter tuning.

Although this study focuses on rectangular reinforced concrete columns, the results suggest the feasibility of extending the application of these techniques to elements with different geometries and materials, provided that appropriate data preprocessing and the possible exploration of other learning methods are employed.

Acknowledgements. The authors gratefully acknowledge the financial support provided by the Brazilian agencies FAPEMIG, CNPq and CAPES.

Authorship statement. The authors declare that they are solely responsible for the authorship of this work, ensuring that all content presented in the article is either their own property or used with the proper authorization from the respective owners.

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