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Integrating Machine Learning and Genetic Expression Programming for Enhanced Punching Shear Strength Prediction

#	Name	Email Address	Degree	Country	Affiliation
1	Mahmoudian, Alireza	amahmoudian1997@sru.ac.ir	MSc	Iran	Department of Civil Engineering, Shahid Rajaee Teacher Training University, Tehran, Iran
2	Tajik, Nima	nimataji@buffalo.edu	Ph.D. Candidate	United States of America	1-Department of Civil, Structural and Environmental Engineering, State University of New York at Buffalo, Buffalo, NY, USA 2-School of Civil Engineering, College of Engineering, University of Tehran, Iran
3	Darabi, Amirhossein	amir_darabi@civileng.iust.ac.ir	MSc	Iran	School of Civil Engineering, Iran University of Science & Technology, Tehran, Iran
4	Mohammadzadeh Taleshi, Mostafa	mostafam@unr.edu	Ph.D. Candidate	United States of America	Civil and Environmental Engineering Department, University of Nevada, Reno
5	Marmarchinia, Saba	sabamarm@buffalo.edu	Ph.D. Candidate	United States of America	1-Department of Civil, Structural and Environmental Engineering, State University of New York at Buffalo, Buffalo, NY, USA 2-School of Civil Engineering, College of Engineering, University of Tehran, Iran
6	Asghari, Abazar	abazar.asghari@ut.ac.ir	Ph.D.		School of Civil Engineering, College of Engineering, University of Tehran, Iran
7	Mirghaderi, Seyed Rasoul	rmirghaderi@ut.ac.ir	Ph.D.	Iran	School of Civil Engineering, College of Engineering, University of Tehran, Iran

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Abstract

Estimating the punching shear strength of reinforced concrete (RC) flat slabs is critical in structural engineering due to potential catastrophic failures. This study introduces advanced data-driven methods, including machine learning (ML), deep learning (DL), and genetic expression programming (GEP), to improve predictions of punching shear strength. Analyzing a dataset of 380 test samples, the research evaluates various models such as linear regression, stochastic gradient descent, ridge regression, decision trees, K-nearest neighbors, random forests, adaptive boosting, extreme gradient boosting (XGBoost) for ML, alongside artificial neural networks (ANNs) for DL, and GEP for deriving explicit equations. Significant enhancements in model performance were achieved through rigorous hyperparameter tuning, notably with the XGBoost model, which attained an R^2 (coefficient of determination) score of 0.98, surpassing other models and existing code-based predictions. The study uses SHapley values to interpret model predictions, highlighting the significant impact of slab depth on punching shear strength, especially in the XGBoost model. Additionally, the GEP method derives explicit equations that accurately represent the relationship between input features and punching shear strength. This research highlights the advantages of advanced computational models and offers new insights into the factors influencing punching shear strength in RC slabs.

Keywords

Machine learning, Artificial neural networks, Extreme gradient boosting, Punching shear strength, Genetic expression programming

1. Introduction

Concrete structures are the most prevalent types of structures worldwide, with extensive research conducted on the load capacity of concrete elements such as beams, columns, and slabs . Flat slabs, critical elements in reinforced concrete structures, are directly supported by concrete columns without any intervening beams. These slabs are deemed cost-effective due to the reduced construction time compared to traditional slabs and are particularly advantageous in scenarios where higher headroom or lower story heights are required. Ensuring the structural safety of various components is paramount in structural engineering, highlighting the importance of detecting visible signs of failure before the actual collapse of members. However, reinforced concrete (RC) flat slabs, lacking beams as a primary load path between slabs and columns, are prone to brittle punching failures, often occurring without prior visible warning signs and resulting in sudden collapses a situation that is critically concerning for civil engineers. This vulnerability is primarily attributed to the concentrated column reactions in the flat slabs. The collapse of RC flat slabs typically results from a combination of concrete crushing and the extensive spread of flexural fractures and punching shear.

Experimental tests conducted in the literature have led to the derivation of several punching shear strength formulations, which serve as the primary method for designing RC flat slab punching shear strength. However, the accuracy of these models, as proposed in various codes, has not been thoroughly investigated, casting doubts on their reliability (ACI Committee 318, 2019; Canadian Standards Association, 2014; European Committee for Standardization, 2004; Standards Australia, 2011).

The literature on the punching shear behavior of reinforced concrete slabs has primarily investigated the influence of various parameters, including the compressive strength of concrete, type of concrete, yield strength of reinforcement, reinforcement ratio, slab configurations, and conditions of support and load (Birkle & Dilger, 2008; Elstner & Hognestad, 1956; Guandalini et al., 2009; Ozden et al., 2006; Regan, 1986; Rizk et al., 2011; Theodorakopoulos & Swamy, 2002). Notably, (Liang et al., 2023) proposed a hybrid model known as the Symbolic Regression MCFT (SR-MCFT) to estimate the punching shear resistance of Fiber Reinforced Polymer (FRP)-reinforced concrete slabs, utilizing results from 154 experimental samples. Similarly, (Liu et al., 2024) developed an explainable XGBoost model to predict the punching shear strength of flat slabs constructed from various types of fiber-reinforced concrete (FRC), based on a comprehensive database of 251 flat slabs that include normal strength, high-performance, and ultra-high-performance FRC slabs. Furthermore, (Alotaibi et al., 2021) assessed the performance of several machine learning algorithms, including Artificial Neural Networks (ANN) and Support Vector Machines (SVM), for estimating the punching shear capacity of fiber-reinforced concrete slabs. The results show that ANN-based models perform best, with the slab's effective depth being the most influential factor. Consequently, these studies provide a vast amount of datasets which are beneficial for having a data-driven insight into the problem.

Nowadays, the integration of computer science skills such as machine learning (ML), gene expression programming (GEP), finite element analysis (FEM), and probability analysis with other fields of expertise like structural engineering has proven to be successful (Al-Bayati, 2023; Anjali et al., 2023; Li & Li, 2023; Marmarchinia et al., 2024; Palomino Ojeda et al., 2023; Tavasoli, 2023), and there have been various models in numerous studies which have been conducted for damage assessment in structures (Afzali et al., 2023; Aminian et al., 2011; Bypour et al., 2024; Gandomi et al., 2015; Hamidia et al., 2024; Jamshidian & Hamidia, 2023; Mirzahosseini et al., 2019; Naderpour et al., 2024; Tajik et al., 2023; Taleshi et al., 2024; Zaker Esteghamati, 2024; Zaker Esteghamati & Huang, 2023). However, investigating the punching shear strength of RC flat slabs without transverse reinforcement has not been taken seriously in the literature over the years. For instance, in the study of (Abambres & Lantsoght, 2020), only the important parameters in a structure on the shear capacity prediction of one-way slabs under concentrated loads which are the width of the slab, effect of the beam span-to-depth ratio, and concrete compressive strength have been introduced.

According to the literature, some deep learning models have been developed with acceptable accuracies, such as the deep learning models of (Tran & Kim, 2021); where a total number of 218 sample data were used to develop the ANN models for predicting the punching shear strength of two-way reinforced concrete slabs, where the R^2 score of the implemented model was 0.995. Mangalathu et al., (2021) investigation of machine learning models revealed that the R^2 score accuracy of the XGBoost model (one of the well-known ML models that have been used in predicting the punching shear capacity) is 0.98 for estimation of punching shear capacity of RC slabs. Additionally, some studies focus on implementing machine learning and metaheuristic methodologies into flat slab design, such as the work by (Alkhawaldeh, 2024). which combined the Light Gradient Boosting Machine (LGBM) and Locust Swarm Algorithm (LSA) to improve punching shear strength predictions in flat slabs.

This study addresses a crucial gap in the current understanding and prediction of punching shear strength in RC flat slabs. While traditional code-based methods offer a standardized and generally reliable approach, their predictive accuracy, although good, can still be significantly enhanced. This limitation presents an opportunity for improvement in ensuring infrastructure safety, underscoring the need for more precise and robust predictive models. The primary goal of this research is to develop and validate advanced data-driven models, including machine learning (ML), deep learning (DL), and genetic expression programming (GEP) techniques, to predict punching shear strength with higher accuracy than current code formulations. By comparing these models' performance against existing codes, this study aims to demonstrate the superiority of modern computational methods in capturing the complex interactions that govern punching shear failure. It has been tried to use the grid-search method for tuning the hyperparameters of the ML model (Jiang & Xu, 2022) for capturing higher accuracy of prediction for the existing 380 experimental sample dataset. Then, to propose an explicit formula to calculate the punching shear capacity of conventional concrete slab, genetic expression programming is implemented, which provides the function between inputs and outputs in a given dataset.

The first section of this study aims to present and describe various ML models suitable for certain applications, highlighting the advantages and disadvantages of each algorithm. Following this, the study delves into the utilized dataset and describes the implemented methods, including linear regression, stochastic gradient descent, ridge regression, support vector machine, K-nearest neighbors, decision tree, random forest, adaptive boosting, extreme gradient boosting, and artificial neural networks (ANNs). This section also introduces the evaluation metrics used to measure the accuracy of these models. Given the opaque nature of machine learning and deep learning algorithms, subsequent sections endeavor to demystify the impact of each model feature on the final predictions through the use of Shapley values. Additionally, the study explores the generation of mathematical equations for predicting the target value using GEP. A separate section is dedicated to comparing the outputs generated by ML algorithms with those of conventional design codes and formulations, demonstrating the effectiveness of these modern tools. Finally, the study concludes with a summary and remarks on the findings presented in the last section.

2. Overview of machine learning

2.1. Machine learning and deep learning methods

Machine learning methods are now widely used to make logical predictions for unseen datasets by training with a limited amount of data. Civil engineers have seized this opportunity, striving to enhance their research by incorporating these techniques. Among these, linear regression is a well-known algorithm that trains a model as a linear combination of dependent variables. This study investigates nine linear regression models, including linear regression, stochastic gradient descent (SGD), ridge regression, support vector machine (SVR), K-nearest neighbors (KNN), decision tree (DT), random forest (RF), adaptive boosting (AdaBoost), and extreme gradient boosting (XGBoost), to predict the final punching shear capacity of reinforced concrete flat slabs without transverse reinforcement.

In the case of simple linear regression, just one feature and one target are involved. However, multiple linear regressions are used since the dataset has several features and a single dependent variable. But in the famous machine learning libraries in Python programming language, linear regression specifically means using the normal equation for regression tasks. As in equation (1), the normal equation is a closed-form solution used to determine the parameters (W) that minimize the cost function.

$$W = (X^T X)^{-1}.(X^T y) \tag{1}$$

Stochastic gradient descent is a numerical method used to decrease the amount of loss function. In fact, SGD works as an optimizer for a model that helps to converge the model. Moreover, SGD is based on trial and error, which is why it has relatively high calculation costs and errors. Support vector regression is one of the reputed regression algorithms used to predict independent variables (Parbat & Chakraborty, 2020). K-nearest neighbors are a popular machine learning non-parametric algorithm, and the output is estimated as the weighted average of the

KNN (Mangalathu et al., 2021). Model ensembling is another method that refers to the process of employing several models to gets an improved prediction performance. In ensemble models like random forests, each base model is a decision tree, and the result of the random forest model is the aggregate output of these decision trees. In random forests, all the base models are constructed independently using different subsamples of the data (see ***Fig. 1***). The RF model efficiently handles tabular data with numerical or categorical features that have fewer than hundreds of categories. Unlike other linear models, RF can capture nonlinear interactions between features and targets. Adaptive boosting is an ensemble of many decision tree models, each of which is a weak learner and is slightly better than random guessing. However, the adaptive AdaBoost algorithm carries the gradient of previous trees to the next ones to improve the error of the previously mentioned trees. Thus, this subsequent learning of trees at each step builds up a strong learner. Final prediction is the weighted average of the predictions given by each tree. Because of high adaptability, AdaBoost is more sensitive to outliers data which is a key requirement in the case of this study (Patil et al., 2018). In XGBoost, trees are grown sequentially, and continuous scores are allocated to each leaf (Chen & Guestrin, 2016). In addition to the mentioned models, in this study, the artificial neural networks (ANNs) models are also being used to improve the accuracy of punching shear strength prediction in the flat slabs. ***Fig. 2***. shows the inter-relationship between ANNs and ML. Consider ANN as a subset of deep learning, which is a subset of machine learning, which is a branch of artificial intelligence.

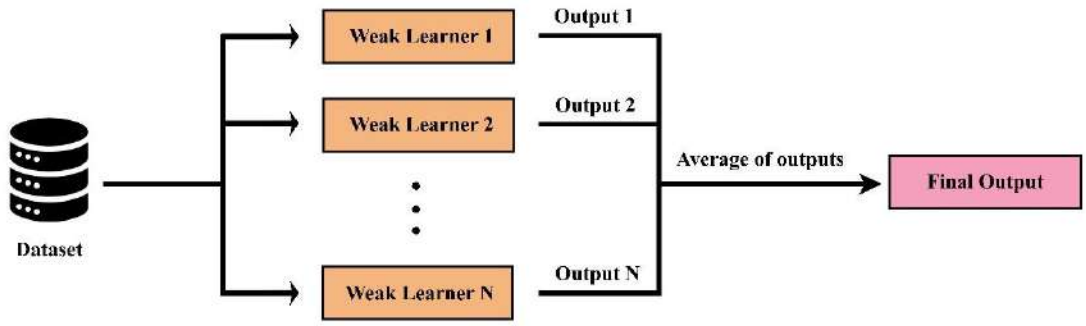


Fig. 1. Schematic of random forest model.

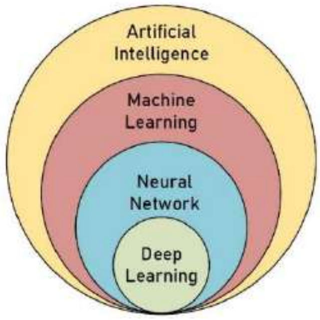


Fig. 2. AI vs. machine learning vs. neural network vs. deep learning.

It should be noted that ANNs are usually used for large datasets due to their increased model capacity. However, depending on the model type, sometimes it can be useful for small datasets. The main concept behind using the ANN approach is that it learns adaptively from experience and extracts various functions, each appropriate for its purpose. ANN has the ability to operate on large quantities of data and learns complex model functions from examples by training on a set of inputs and the corresponding outputs. ANNs can take into account the nonlinear and complex interactions that take place among the variables of a system without the need for assuming the form of the relationship that exists between the independent variables and those that are dependent is the primary advantage that ANN has over more conventional modeling techniques (Soleimani-Babakamali & Zaker Esteghamati, 2022; Tran & Kim, 2021). An ANN model is a mathematical tool for imitating human brain functions like learning, reasoning, and performing heavy parallel computations. The smallest unit that makes up an ANN model is referred to as a neuron, and it is developed in three distinct levels (Mehrzad et al., 2023). These layers are the input layer, the hidden layer, and the output layer (Tran & Kim, 2021). As the grid search parameters in neural networks were reviewed in previous sections, the aforementioned parameters were implemented with the dataset studied in this research, and the following results were achieved.

There are various metrics to evaluate the accuracy of a model (A. Habib & Yildirim, 2022; M. Habib et al., 2023), which MSE (mean squared error) being the most common. This method which is shown in equation (2), considers the average squared difference between the actual and predicted values as the error. However, the problem with this method is that the MSE value is not understandable to users, so another method shown in equation (3), called R^2 score is used. R^2 score is a statistical measure representing the proportion of the variance for a dependent variable explained by an independent variable or variables in a regression model.

$$MSE = \frac{\sum (y_i - \hat{y}_i)^2}{n} \tag{2}$$

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

2.2. Overview of Genetic Expression Programming (GEP)

In artificial intelligence, GEP is a robust and advanced evolutionary algorithm, motivated by natural selection and genetics concepts. Like the process of gene expression in natural living organisms, GEP mimics their process to solve complicated problems. Since Ferreira (Ferreira, 2001), initially presented it, it has grown in popularity due to its effectiveness and adaptability. GEP algorithm can be used to achieve a mathematical function between the features and the targets. In this function, logical operators (AND, IF, …), algebraic operators (+ - * /), and algebraic functions such as trigonometric, exponential, etc., could be used.

In order to implement the GEP framework, first a linear chromosome population needs to be formed, which can be single or multi-gene (***Fig. 3*** depicts a chromosome example with N genes). One of the variables, targets, or guessed mathematical operators may be placed in each gene position of this chromosome. Some rules have been established by the inventor of the algorithm for choosing the length of the gene and the placement of these variables:

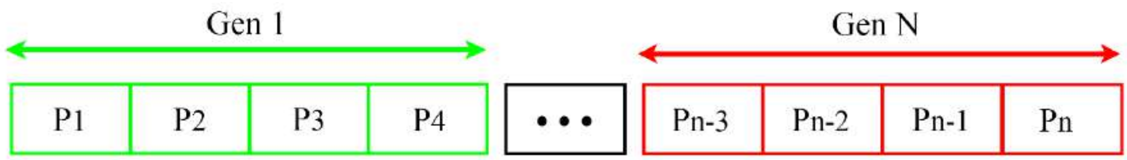


Fig. 3. An example of a chromosome.

- Every gene has a head and a tail section, and the functions of a gene cannot be assigned to the tail part.
- As seen in equation (4), the maximum number of function parameters (n) determines the tail section length (t), while the head section length (h) is user-specified.

$$t = h(n - 1) + 1 \quad (4)$$

Then, it's time to assess each chromosome's fitness in the generation after chromosomes have been created and inserted into their proper locations. For this purpose, in the GEP algorithm, chromosomes are expressed as Tree Expression (TE), enabling the algorithm to assess and evolve the most promising solutions within each generation. Because of its creative methodology and adherence to genetic principles, GEP is recognized as a strong and trustworthy instrument for handling challenging problems in a variety of intersecting fields (Ferreira, 2001; Mansouri et al., 2021). The flowchart of GEP process is shown in ***Fig. 4.***

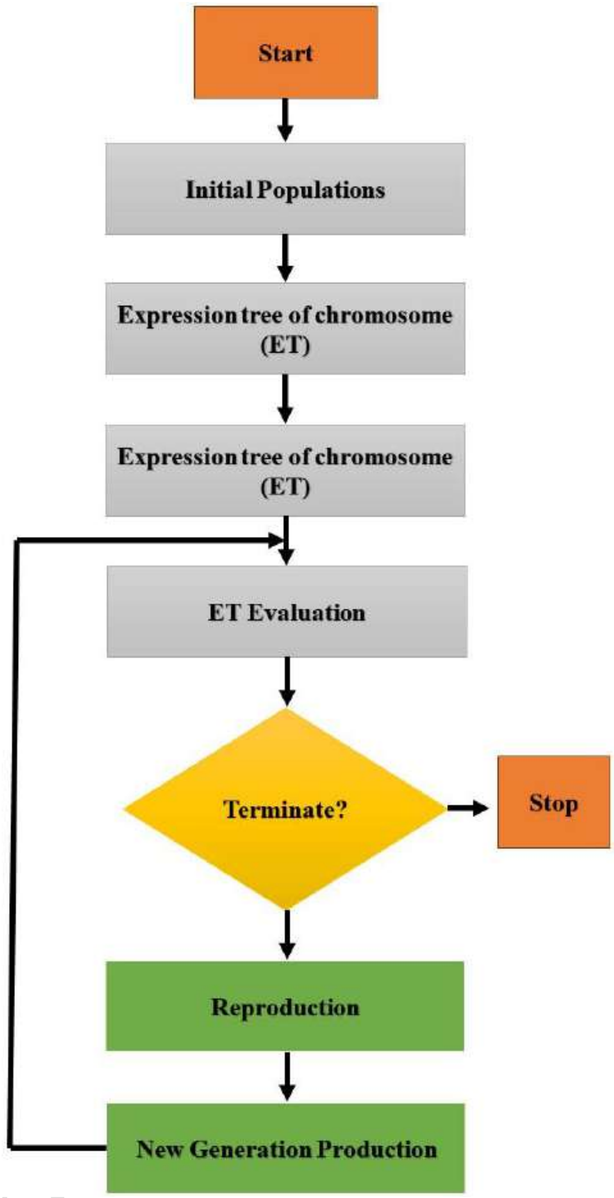


Fig. 4. Flowchart of GEP process.

2.3. SHapley values

Machine learning models have been increasingly utilized to address a wide range of problems, yet the manner in which results are derived from these models often remains scrutinized. To aid in the interpretation of results produced by machine learning models, techniques such as SHapley values have proven to be effective. Based on the principles of game theory, SHapley values significantly enhance the interpretability of machine learning models. The SHAP (Shapley Additive exPlanations) method, which is grounded in the Shapley value theory from cooperative game theory, was initially introduced by Lundberg and Lee (Lundberg & Lee, 2017). This method has since been recognized for its ability to provide clear explanations for the output of machine learning models, making it a pivotal tool in understanding and justifying the decision-making processes of these models.(see ***Fig. 5***)

The SHAP method employs two key equations to facilitate the interpretation of machine learning models through an additive feature attribution approach. This approach decomposes a model's output into the sum of contributions from its input variables, enhancing interpretability. equation (5), outlines the basic form of the explanation model, g(x'), which uses a simplified version of the input, x', to approximate the original model's behavior, f(x). In this equation (Lundberg & Lee, 2017):

$$f(x) = g(\acute{x}) = \varphi_0 + \sum_{i=1}^{M} \varphi_i x_i' \tag{5}$$

- x', represents the simplified input variables, derived from the original input variables.
- M denotes the total number of features.
- φ_0 is the constant value indicating the model's output in the absence of all inputs.
- φ_i signifies the attributed contribution of each individual variable to the model's output.

Equation (6), provides a formula for calculating the contribution of each feature. The parameters in this equation include (Lundberg & Lee, 2017):

$$\varphi_i(f, x) = \sum_{Z' \subseteq x'} \frac{|z'|!\ (M - |Z'| - 1)!}{M!} [f_x(z') - f_x(z' \backslash i)] \tag{6}$$

- $|z'|$ represents the count of non-zero elements within Z', indicating the number of active features in the subset .

- $Z' \sqsubseteq x'$ signifies all instances of Z' vectors where their non-zero elements correspond to a subset of the non-zero elements found in x', focusing on specific combinations of features.

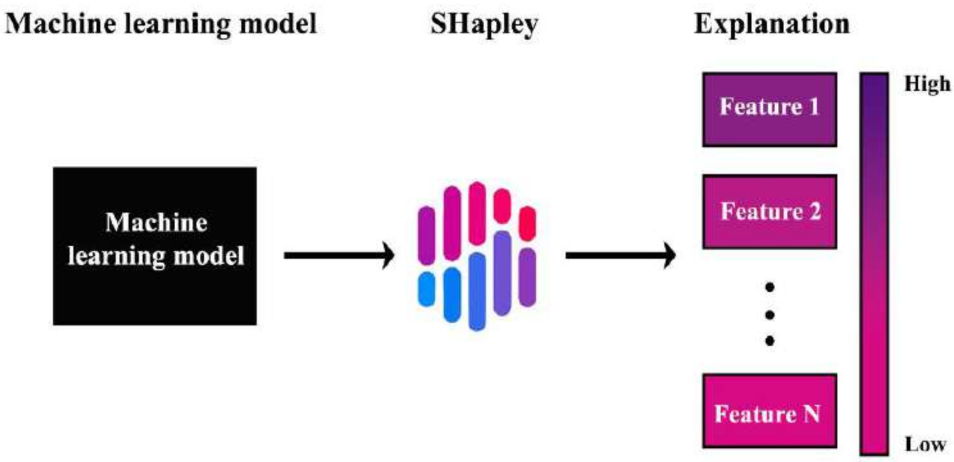


Fig. 5. Shematic of SHapley values method.

2.2. Dataset

Achieving a precise machine learning model entails having a clean dataset. Dataset plays a vital role in machine learning models. The preprocessing of the dataset is more significant than the dataset itself, which requires great accuracy. In this study, 380 samples, each with six independent variables and one dependent variable, have been investigated (Mangalathu et al., 2021). Since the target variable under study is a discrete variable, it is clear that regression-based models should be used, and these algorithms are briefly introduced in the previous section. To evaluate the model effectively, not all available data is presented to it during training. A portion of the dataset, typically 10-30%, is reserved as test data. This allows for the evaluation of the model's performance after the learning process is complete. It is crucial that the test data be randomly selected to ensure it is representative of the entire dataset, facilitating a comprehensive evaluation of the model. The normal distribution, also known as the Gaussian distribution, is a symmetric probability distribution centered around the mean, which indicates that data points close to the mean are more common than those far from it. This study presents the normal distribution of each feature and target to highlight this aspect, as shown in ***Fig. 6***.

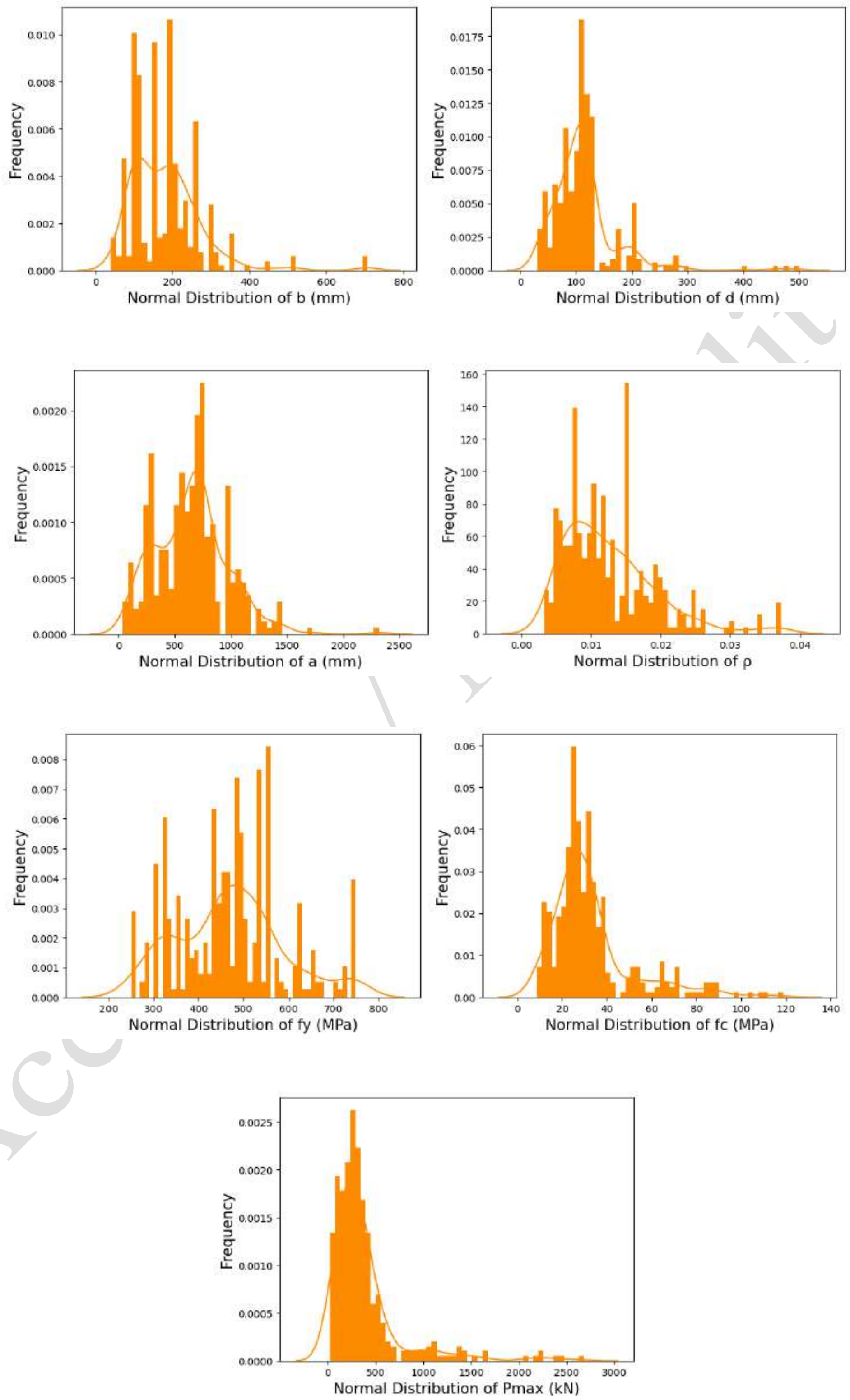


Fig. 6. Normal distribution of features and outputs.

2.3. Grid search

Grid search is designed to conduct hyperparameter tuning systematically by automatically going through a possible set of hyperparameter values during learning. In a grid search, each hyperparameter is given a series of values, and the program will then iterate through every hyperparameter value combination possible to train models (Jiang & Xu, 2022). We applied hyperparameter tunning and grid search to optimize model performance in this study, which helped us achieve high accuracy in our machine-learning models (see ***Fig. 7***). It should be noted that not all parameters of a model are considered hyperparameters. However, the most important ones, which probably significantly impact the model's accuracy, are considered hyperparameters.

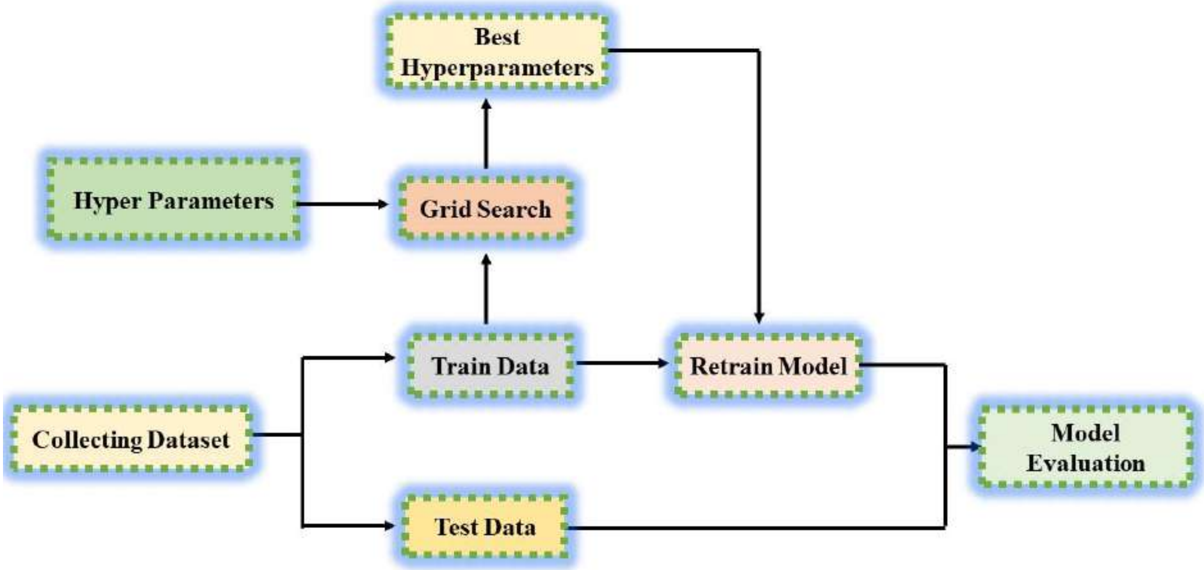


Fig. 7. Flowchart of grid search.

In the SGD model, 81 models used different values for the four arguments in **Table 1**. Among them, the penalty argument that prevents model overfitting and the learning rate determining the speed of reaching the minimum point in the cost function are more important.

Table 1. SGD grid search parameters.

penalty	max_iter	learning_rate	alpha
l1	1000	constant	0.0001
l2	1500	optimal	0.001
elasticnet	2000	invscaling	0.01

As shown in **Table 2**, 120 different models have been tested for KNN; the most important argument of KNN is the number of neighbors in predicting punch shear strength values. It should be noted that selecting a small number of neighbors, such as one or two, leads to model overfitting.

Table 2. KNN grid search parameters.

neighbors	weights	algorithm	p
3	uniform	auto	1
4	distance	Ball_tree	2
5	-	Kd_tree	3
6	-	brute	-
7	-	-	-

Table 3 and **Table 4** show that 50 different models have been used for DT and RF algorithms, each having different values for the arguments mentioned. Criterion is the function to measure the quality of a split, and max_depth expresses the maximum depth of a decision tree in which the chosen numbers are suitable and widely used. Also, n_estimators is the number of trees used in the random forest.

Table 3. DT grid search parameters.

criterion	splitter	max_depth
squared_error	best	5
friedman_mse	random	10
absolute_error	-	15

Table 4. RF grid search parameters.

n_estimators	criterion	max_depth
100	squared_error	5
200	absolute_error	10
300	-	15
400	-	20

Table 5 and **Table 6** show that 648 models for XGBoost and 60 models for AdaBoost with different values for the mentioned arguments have been tested. The number of trees in the ensemble often increased until no further improvements were seen. The boost parameter specifies the type of learner. In most cases, this is either a tree or a linear function. In the case of trees, the model will consist of an ensemble of trees.

Table 5. AdaBoost grid search parameters.

n_estimators	Learning_rate	loss
50	0.001	linear
80	0.01	square
100	0.1	exponential
150	1	-
250	-	-

Table 6. XGBoost grid search parameters.

n_estimators	max_depth	Bace_score	learning_rate
100	2	0.4	0.05
200	4	0.5	0.1
400	6	0.6	0.2
600	8	0.7	-
800	10	0.8	-
1000	15	1	-

As shown in **Table 7**, 162 models with different parameters for different arguments have been used in artificial neural networks. The first and second columns show the number of neurons in each layer. Another important parameter is the batch size, which indicates how much data is entered into the model in each iteration. Then, the type of optimizer, the most well-known of which is adam, is specified, and finally, the activation function is added to the model after the last layer.

Table 7. ANNs grid search parameters.

Layer1	Layer2	batch size	optimizer	active function
16	16	64	adam	relu
32	32	128	SGD	linear
64	64	256	RMSprop	-

3. Machine learning and deep learning models of punching shear strength

3.1. Features

The important parameters used in this study to calculate the punching shear strength (V_n) are divided into two categories: (I) Parameters related to materials include compressive strength of slab concrete and slab flexural reinforcement yield strength. (II) Parameters related to geometry include the effective flexural depth of slab (d), which expresses the average value of the effective flexural depth of the slab in two orthogonal directions, the shear span (a), which shows the distance between the slab supports and the face of the column, the slab reinforcement ratio (ρ), which is an estimate of the slab reinforcement ratio it is orthogonal in two directions and the equivalent width of the column (b). Because punching shear occurs in a critical perimeter (b_0), it is necessary to find this value using different codes. The critical perimeter is located at a certain distance from the face of the column, for which different codes have stated different values. For example, ACI-318-14, CSA A23.3-19, and AS 3600 consider the critical section at half of the effective flexural depth of the slab from the face of the column, while Eurocode 2 considers it twice the depth from the face of the column. However, this study follows ACI-318-14.

For a better understanding of the relation between the features, ***Fig. 8*** is used. This scatter plot indicates that the closer the slope of the regressor is to the angle of 45 degrees, the more the two features are related to each other. Also, The exact relation is expressed through the correlation matrix shown in ***Fig. 9***. To be more precise, the slope of the regressor drawn in the scatter plot shows that the relationship between d and P_{max} is close to an angle of 45 degrees, indicating the strong relation between these two features.

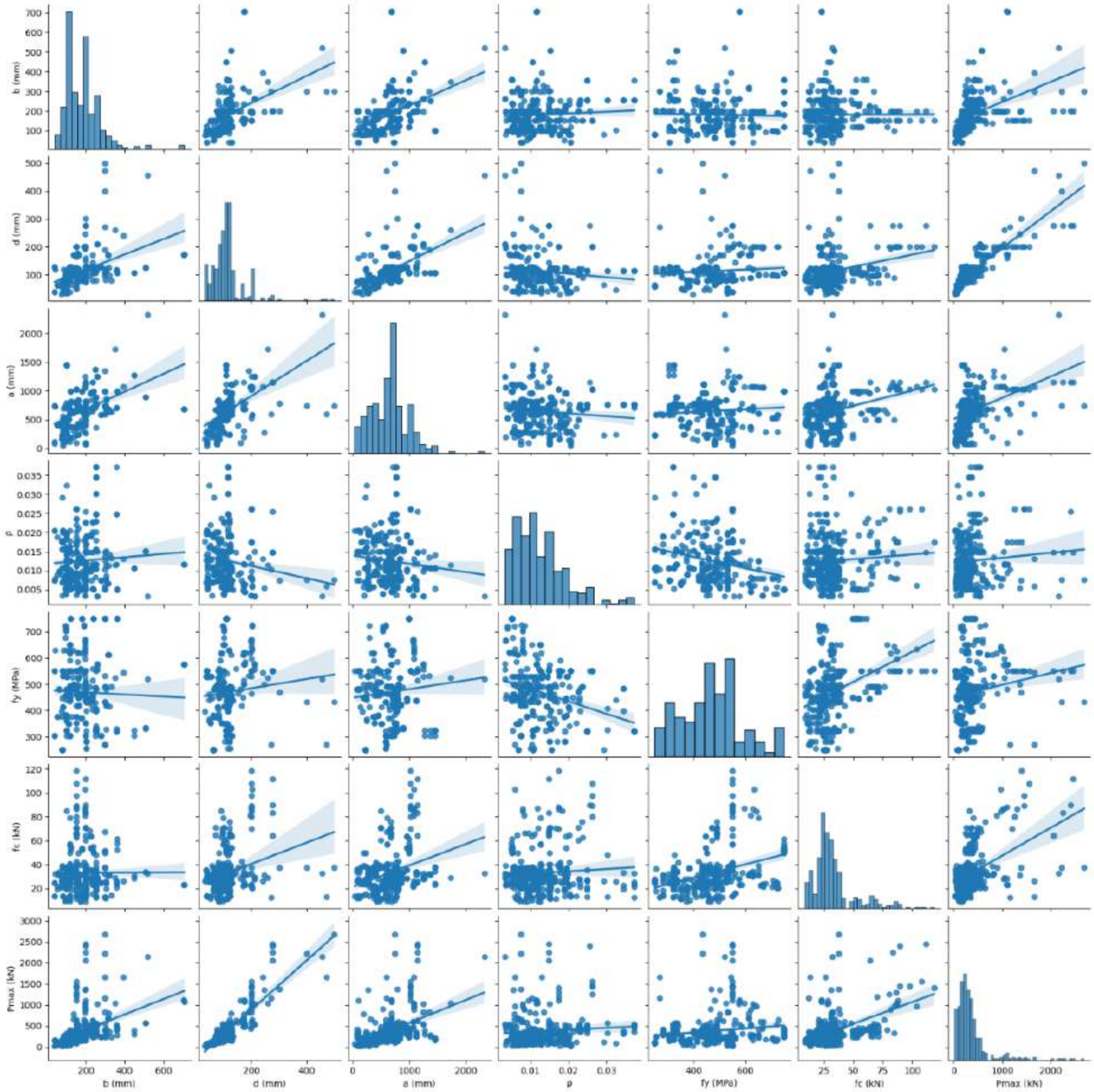


Fig. 8. Scatter plot and regression of features and output.

A correlation matrix is a matrix that shows the relationship and correlation of dataset features with each other. This matrix's number of rows and columns equals the number of features of the dataset. Each cell is marked with a color ranging from minus one to plus one. The closer this number is to minus one, it means that these two features are inversely related to each other, and the closer this number is to plus one, it means that two features are directly related to each other. This matrix is symmetric, and the main diagonal of this matrix is equal to one because each feature naturally has a maximum correlation with itself. In this study, the correlation matrix is a matrix that has seven rows and seven columns. For example, in ***Fig. 9***, the maximum compressive strength that enters the column (P_{max}) has a positive correlation (+0.88) with the effective depth of the slab (d) and is marked with red color. This shows that when d increases, so does P_{max}.

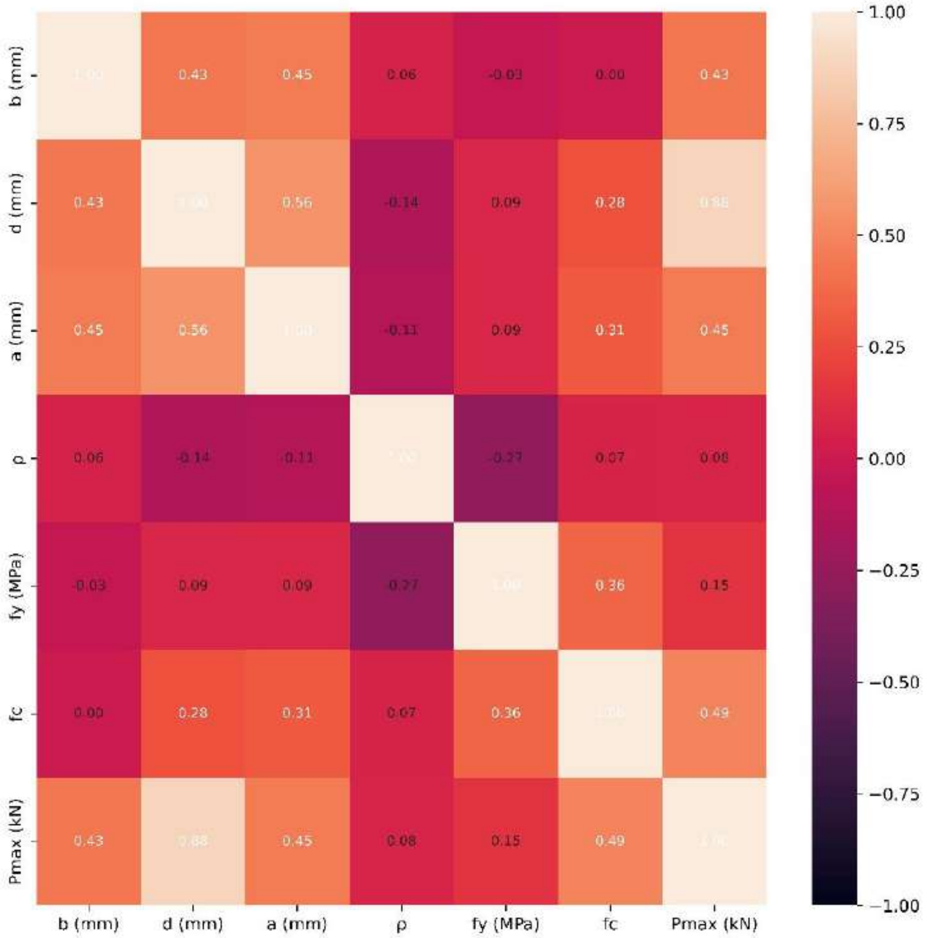


Fig. 9. Features and output correlation matrix.

3.2. Machine learning and deep learning with grid search results

The first method used in this study is linear regression based on a normal equation shown in ***Fig. 10***. Because this method is derived from an explicit equation, there is no need for trial and error and special hyperparameter tuning. Of course, it can achieve different accuracies by changing the training data size or the normalization method, but the difference in these accuracies is insignificant in this study. With a train size of 0.8 and the StandardScaler normalization method, the accuracy of this model on test data has been achieved at 0.88, as shown in ***Fig. 10***.

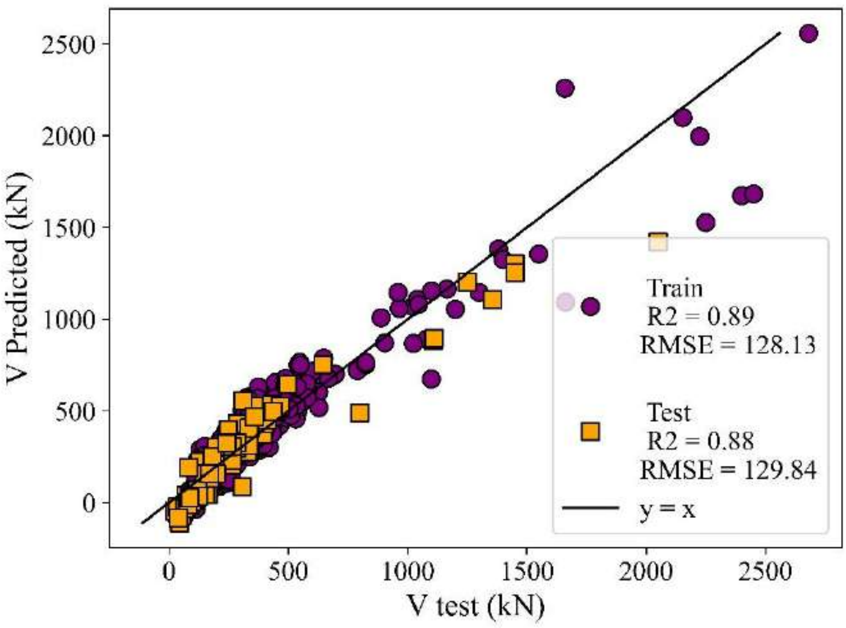


Fig. 10. The best linear regression model results.

The next method used in this article is the SGD method. This method is based on trial and error and has various hyperparameters that can be changed, especially the learning rate. This method's best possible accuracy can be achieved by evaluating different hyperparameter values using a grid search, as shown in **Table 8** and ***Fig. 11***.

Table 8. Results of grid search for SGD.

R^2_score Train	R^2_score Test	alpha	penalty	learning_rate
0.89	0.88	0.1	l1	constant

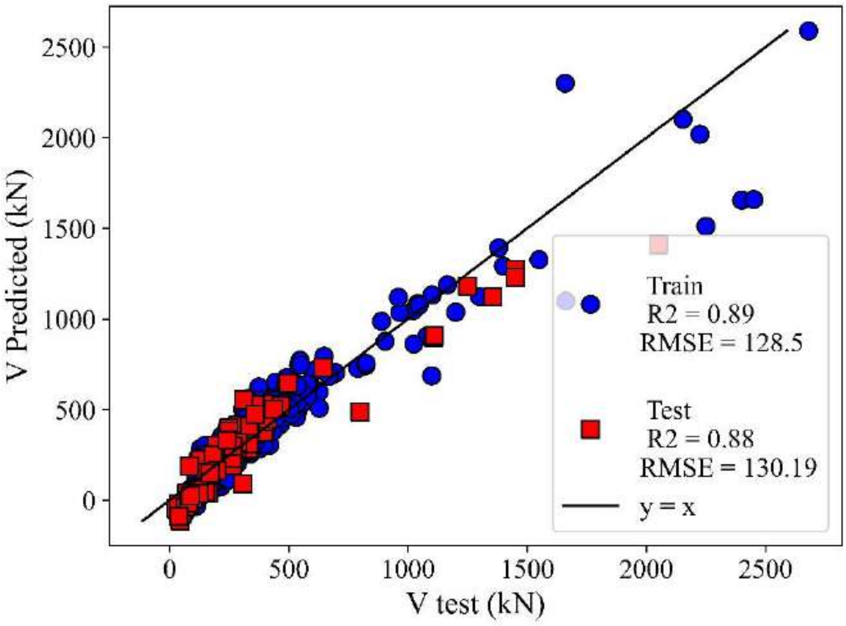


Fig. 11. The best SGD regression model results.

Although KNN is mostly used for classification tasks, it is also used in regression problems. As demonstrated in ***Fig. 12***, applying an appropriate grid search, shown in **Table 9**, to this model can achieve high accuracy. In this model, according to the number of neighbors and type of distance, desired neighbors are selected, and their average label is considered the output label. According to the KNN grid search results in **Table 9**, the optimal number of neighbors in this dataset is four, and the power distance (p) type is one. The decision tree model usually works very well in train samples, but its test sample accuracy is not the same as train sample accuracy. Actually, this does not imply that overfitting has occurred in this model; rather, it indicates that its accuracy on train data is much higher.

Table 9. Results of grid search for KNN.

R^2_score Train	R^2_score Test	neighbors	weights	algorithm	p
1	0.93	2	distance	auto	2

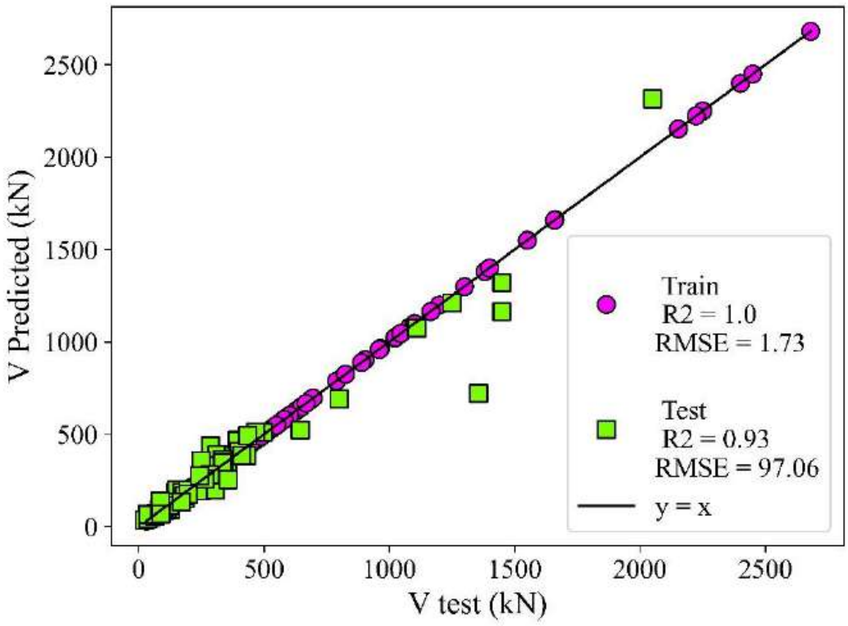


Fig. 12. The best KNN regression model results.

The grid search results in the DT model showed that the max_depth would probably not have a remarkable effect on the accuracy achieved in this dataset, as shown in **Table 10**. Furthermore, applying the grid search method for the DT model resulted in an accuracy of 0.93, as shown in ***Fig. 13***.

Table 10. Results of grid search for DT.

R^2_score Train	R^2_score Test	criterion	splitter	max_depth
1	0.95	friedman_mse	random	15

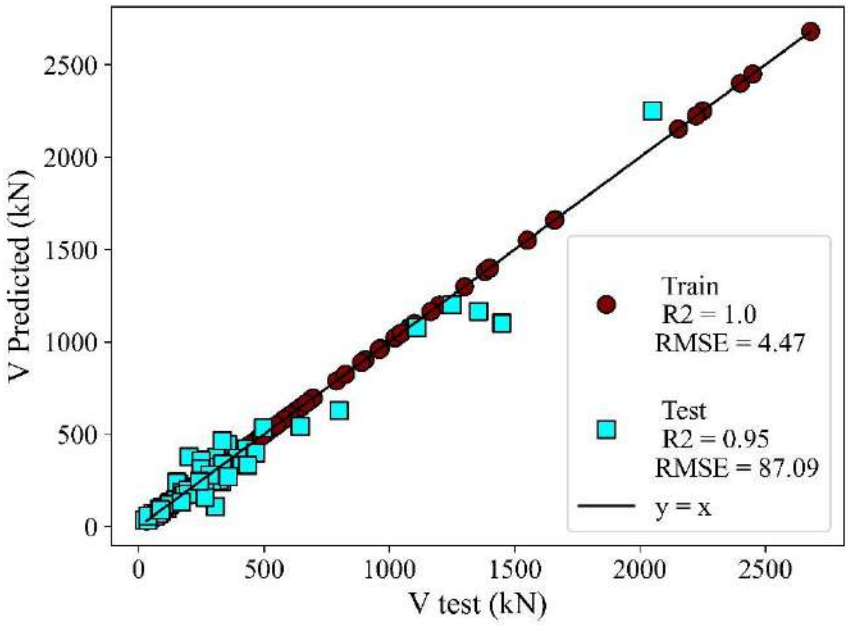


Fig. 13. The best DT regression model results.

Random forest, AdaBoost, and XGBoost models are based on ensemble learning. In this field, techniques have been proposed that use several models in a combined and simultaneous way to make decisions to increase the model's power in estimating the data output. As demonstrated in **Table 11**, similar to DT, the max_depth parameter in RF models has little effect; however, this data set clearly shows that squared_error is the best criterion value, and applying the grid search method to the RF model resulted in an accuracy of 0.95, as shown in ***Fig. 14***.

Table 11. Results of grid search for RF.

R^2_score Train	R^2_score Test	n_estimators	criterion	max_depth
0.99	0.95	100	squared_error	10

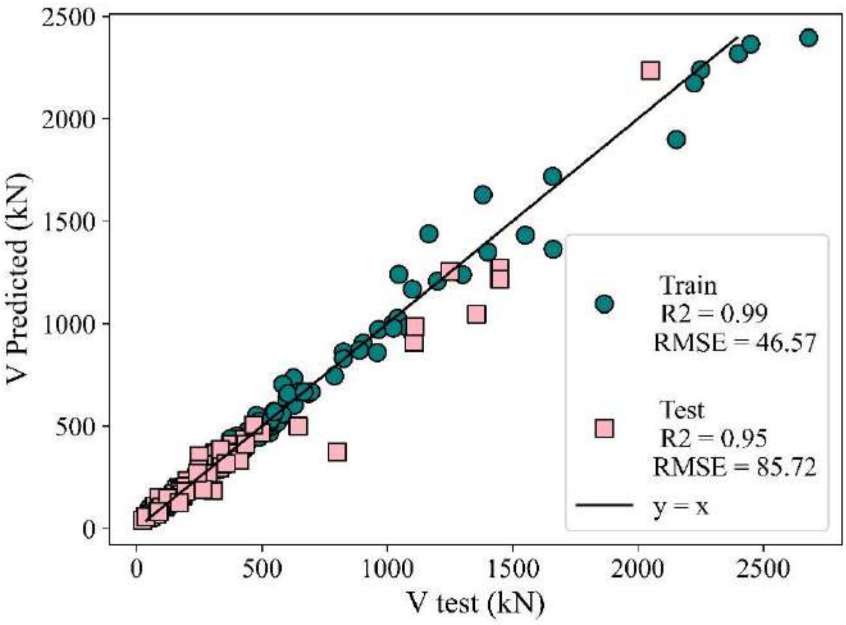


Fig. 14. The best RF regression model results.

Applying grid search has led to various results in the AdaBoost models, as shown in **Table 12**, but it is easy to understand that the best value for the learning rate is 0.1. As shown in ***Fig. 15***, the grid search method achieved the best AdaBoost model accuracy of 0.91.

Table 12. Results of grid search for AdaBoost.

R^2_score Train	R^2_score Test	n_estimators	learning_rate	loss
0.94	0.91	150	0.1	exponential

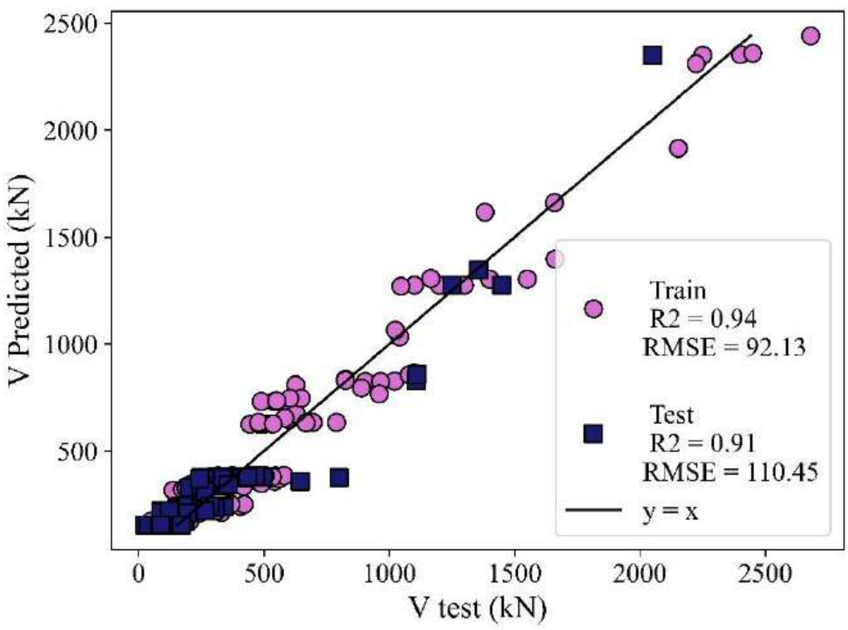


Fig. 15. The best AdaBoost regression model results.

In the XGB algorithm, as many models as possible have been tested to achieve the best results. After seeing the results in **Table 13**, it can be concluded that the best input values for the arguments of max_depth, Base_score, and booster are 2, 1, and 5, dart, respectively. As seen in ***Fig. 16***, the best accuracy achieved in XGB is 0.98.

Table 13. Results of grid search for XGB.

R^2 score Train	R^2 score Test	n_estimators	max_depth	learning_rate
0.9975	0.9802	300	2	0.05

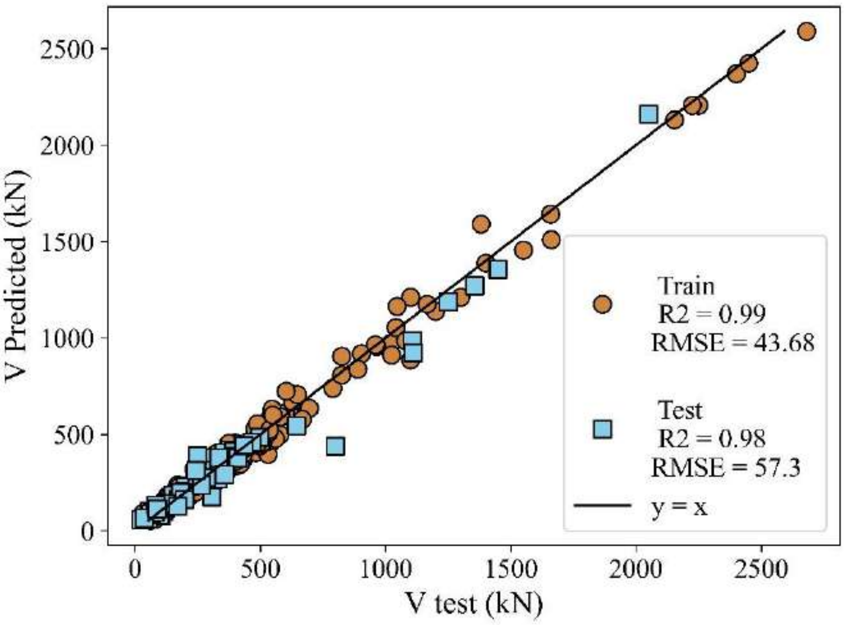


Fig. 16. The best XGB regression model results.

The findings from these models demonstrate that the XGBoost (XGB) model outperforms the Artificial Neural Networks (ANNs), exhibiting higher accuracy on this specific dataset. Despite achieving commendable accuracy with machine learning models, further investigations were conducted using neural network models varying in neuron counts, activation functions, and optimizers. According to the results presented in **Table 16** and ***Fig. 17,*** and ***Fig. 18***, the accuracy attained by neural networks falls short of that achieved by the best machine learning model. It was also determined that the Adam optimizer and the relu activation function are the most effective for this dataset.

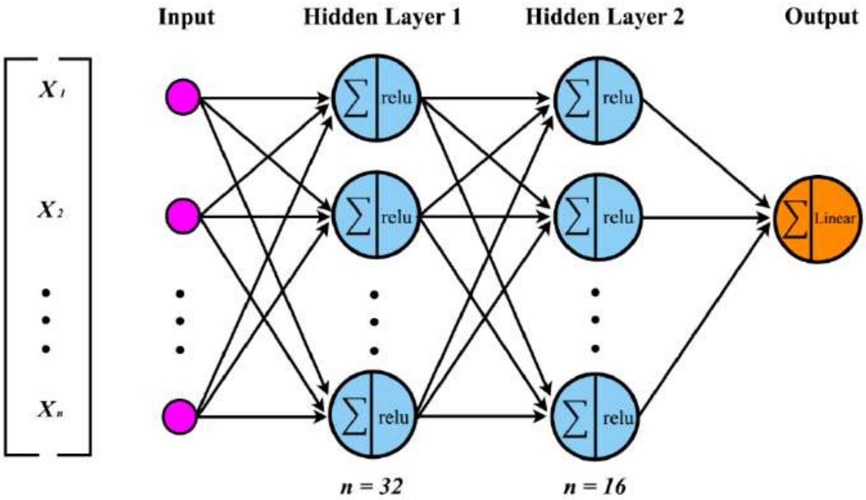


Fig. 17. The architecture of ANNs regression model.

Table 14. Results of grid search for ANNs.

R^2_score Train	R^2_score Test	Layer1	Layer2	Batch size	optimizer	activatefuntion
0.97	0.96	32	64	32	adam	relu

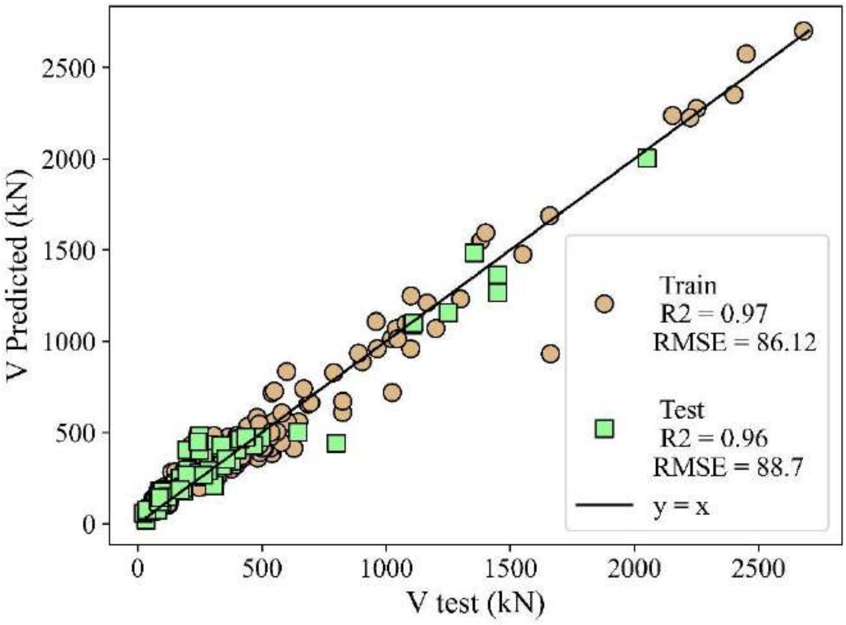


Fig. 18. The best ANNs regression model results.

3.3. GEP model proposal

A section of this study proposes a precise model for predicting the punching shear strength of reinforced concrete flat slabs, using the GEP approach. The model inputs adhere to the standards commonly employed in machine learning practices. Through the application of the GEP technique, an empirical model was constructed to forecast the punching shear strength of reinforced concrete flat slabs, as elucidated in equation (7).

$$V = V_1 + V_2 + V_3 + V_4$$

$$V_1 = d_3(d_4 + d_1 - d_2) + \frac{d_5 d_1}{39.25}$$

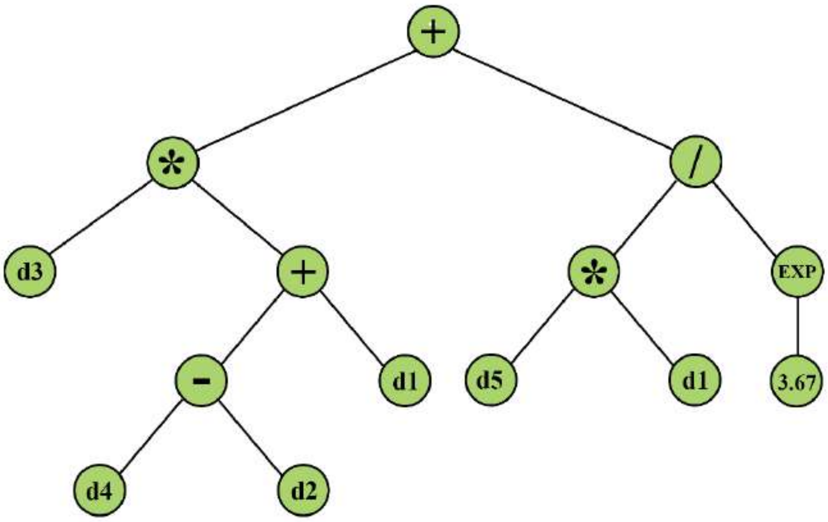
$$V_2 = d_3(d_4 + d_0 - 3.67) + \frac{d_5}{10.69} \tag{7}$$

$$V_3 = -8.91 d_3 d_1 + \frac{d_0}{e^{d_0}}$$

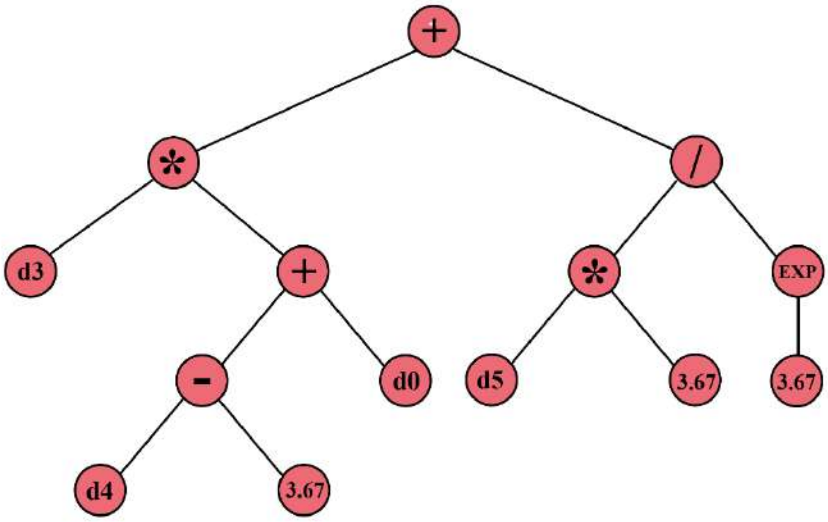
$$V_4 = d_3 {d_1}^2 + \frac{d_0 d_1}{247.15}$$

Fig. 19 shows the expression tree of the estimation model, ***Fig. 20*** demonstrates it’s results, and **Table 17** details the operational and functional specifics of the proposed model. It is crucial to highlight that the selection of parameters greatly influences GEP's generalization ability.

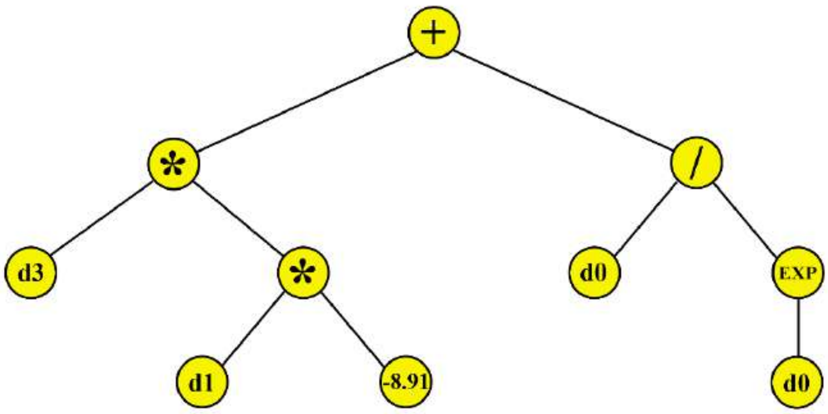
Sub-ET 1



Sub-ET 2



Sub-ET 3



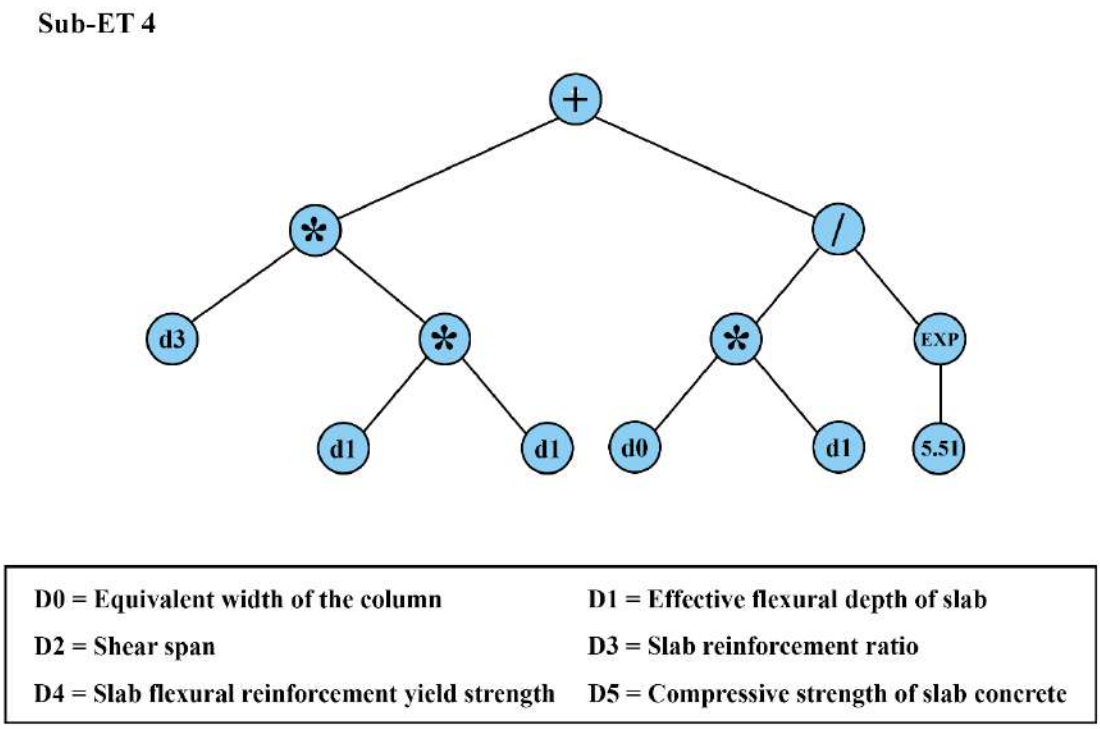


Fig. 19. Expression tree (ET) of GEP model proposed.

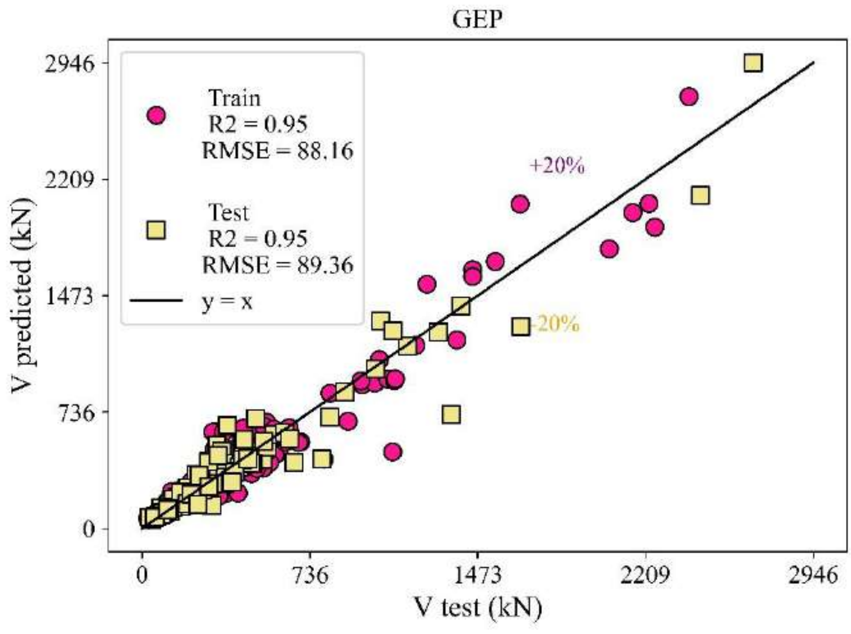


Fig. 20. GEP model results.

Table 17. GEP model parameters.

Function	(+ - * /), pow, sqrt, Exp, Ln, Sin, Arctan, Tanh, Not
Number of generations	63919
Chromosomes	30
Head size	8
Number of genes	3
Linking function	Addition
Mutation	0.44
IS Transposition	0.1
RIS Transposition	0.1
One-point recombination rate	0.2
Two-point recombination rate	0.3
Gene recombination	0.2
Gene transposition	0.1

3.4. Feature importances

In order to identify the black box of ML models, especially the XGB model, which exhibits the highest accuracy among the models in this study, SHapley values are employed. ***Fig. 21*** and ***Fig. 22*** reveal that the slab depth (d) is the most significant feature in this model, whereas the feature fy (MPa) ranks lowest in terms of importance. While ***Fig. 21*** presents the SHapley values separately, ***Fig. 22*** shows the average impact of each feature on the model's predictions.

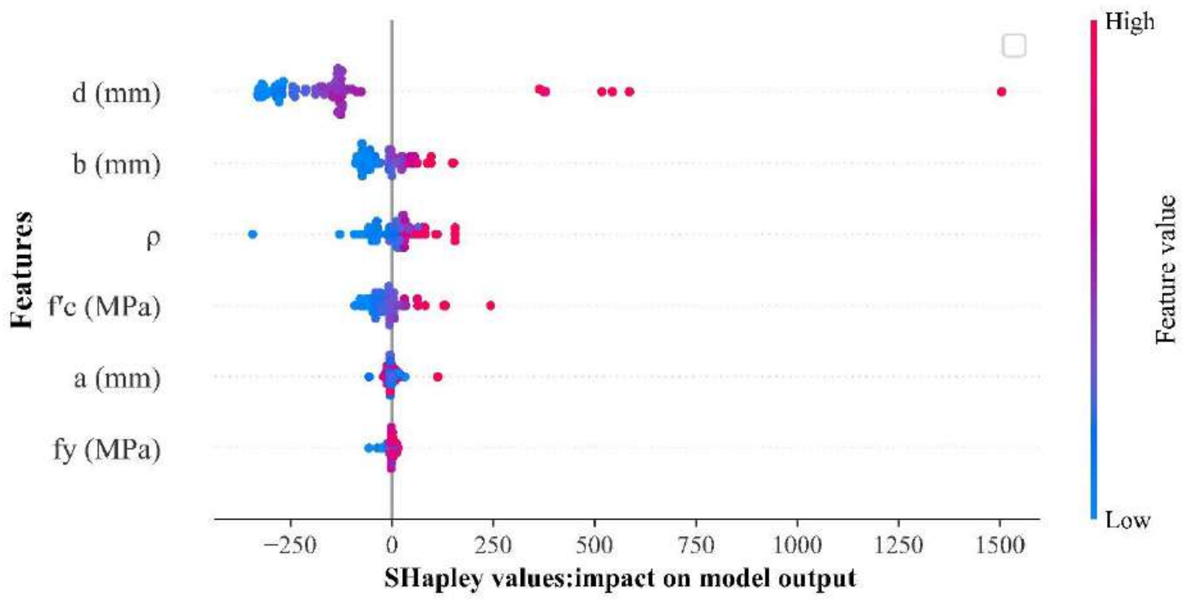


Fig. 21. The SHapley values of XGB model.

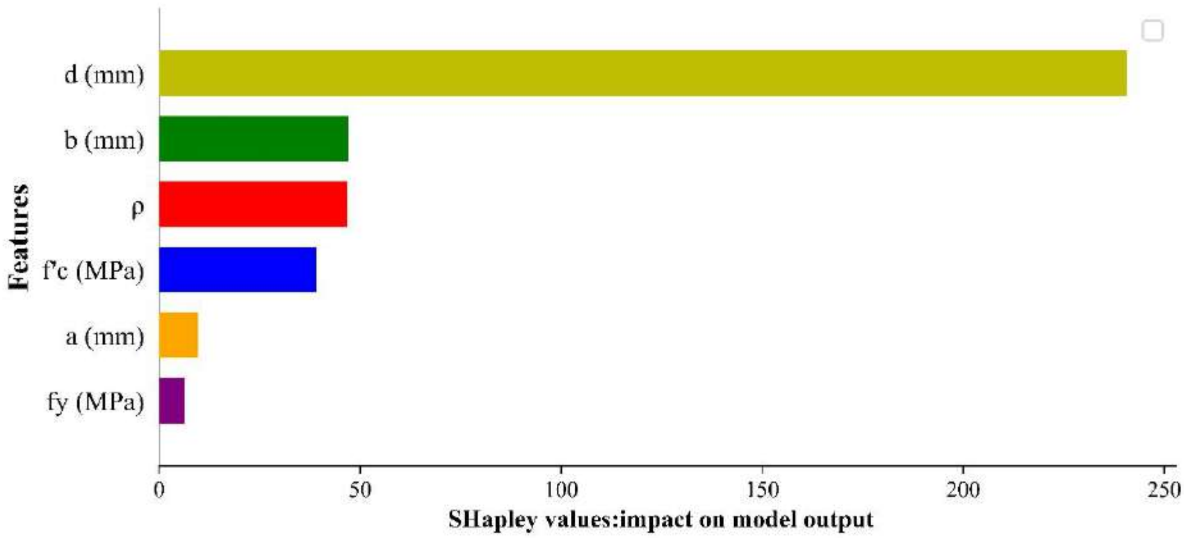


Fig. 22. The mean SHapley values of XGB model.

3.4. Empirical design code equations

The codes used in this study to calculate punching shear strength in two-way slabs without transverse reinforcement are ACI 318-14, ACI 318-19, ACI 440.1R-06, Eurocode 2, and CSA A23.3-14 (ACI Committee 318, 2014, 2019; ACI Committee 440, 2006; Adom-Asamoah & Kankam, 2008; European Committee for Standardization, 2004). In ACI 318-14, the following equation (8) is used to find the punching shear strength, where b_0 (mm), d (mm), f_c' (MPa) have an effect.

$$V_n = \frac{1}{3}\sqrt{f_c'}\, b_0 d \tag{8}$$

Based on ACI 318-19, equation (9) is an updated form of the equation (8) with three other parameters called α_s (a constant dependent on supporting column location and its value is 40 for interior columns, 30 for edge columns, and 20 for corner columns; since this study considers only interior columns, α_s = 40), β (The ratio of the long side to the short side of the column, concentrated load, or reaction area) and λ_s (which follows: $\lambda_s = \sqrt{2/(1+0.004d)} \leq 1$)

$$V_n = min[\frac{1}{3}, \frac{1}{6}\left(1+\frac{2}{\beta}\right), \frac{1}{12}\left(2+\frac{\alpha_s d}{b_0}\right)]\, \lambda_s \sqrt{f_c'}\, b_0 d \tag{9}$$

ACI 440.1R-06, using the variable k in equation (10), also enters the ratio of the modulus of elasticity of steel to concrete:

$$V_n = 0.8\sqrt{f_c'}\,kb_0d \tag{10}$$

Where $k = \sqrt{(n\rho)^2 + 2n\rho} - n\rho$, $n = E_s/E_c$

In equation (11), Eurocode 2 uses f_{ck} instead of f_c' as the indicator of characteristic cylinder strength ($f_{ck} = f_c' - 1.6$).

$$V_n = 0.18\,\xi\,\sqrt[3]{100\rho f_{ck}}\;b_0d \tag{11}$$

It also introduces a new variable related to geometry, and this variable and its limit is as follows:

$$\xi = \left(1 + \sqrt{\frac{200}{d}}\right) \leq 2$$

CSA A23.3-14 (Canadian Standards Association, 2014) also uses the normal density of concrete (for normal density concrete, $\lambda = 1$) in relation to punching shear strength in two-way slabs without transverse reinforcement with equation (12):

$$V_n = min[\,0.38\;, 0.19\left(1 + \frac{2}{\beta}\right), \left(0.19 + \frac{\alpha_s d}{b_0}\right)]\,\lambda\phi_c\sqrt{f_c'}\,b_0d \tag{12}$$

Where $\phi_c = 0.65$ and $\alpha_s = 4$ for interior columns, 3 for edge columns, and 2 for corner columns; since this study considers only interior columns, $\alpha_s = 4$. After introducing the above equations, the R^2 score graphs of punching shear strength test values (V test) and punching shear strength results from codes equations (V predicted) are shown in ***Fig***

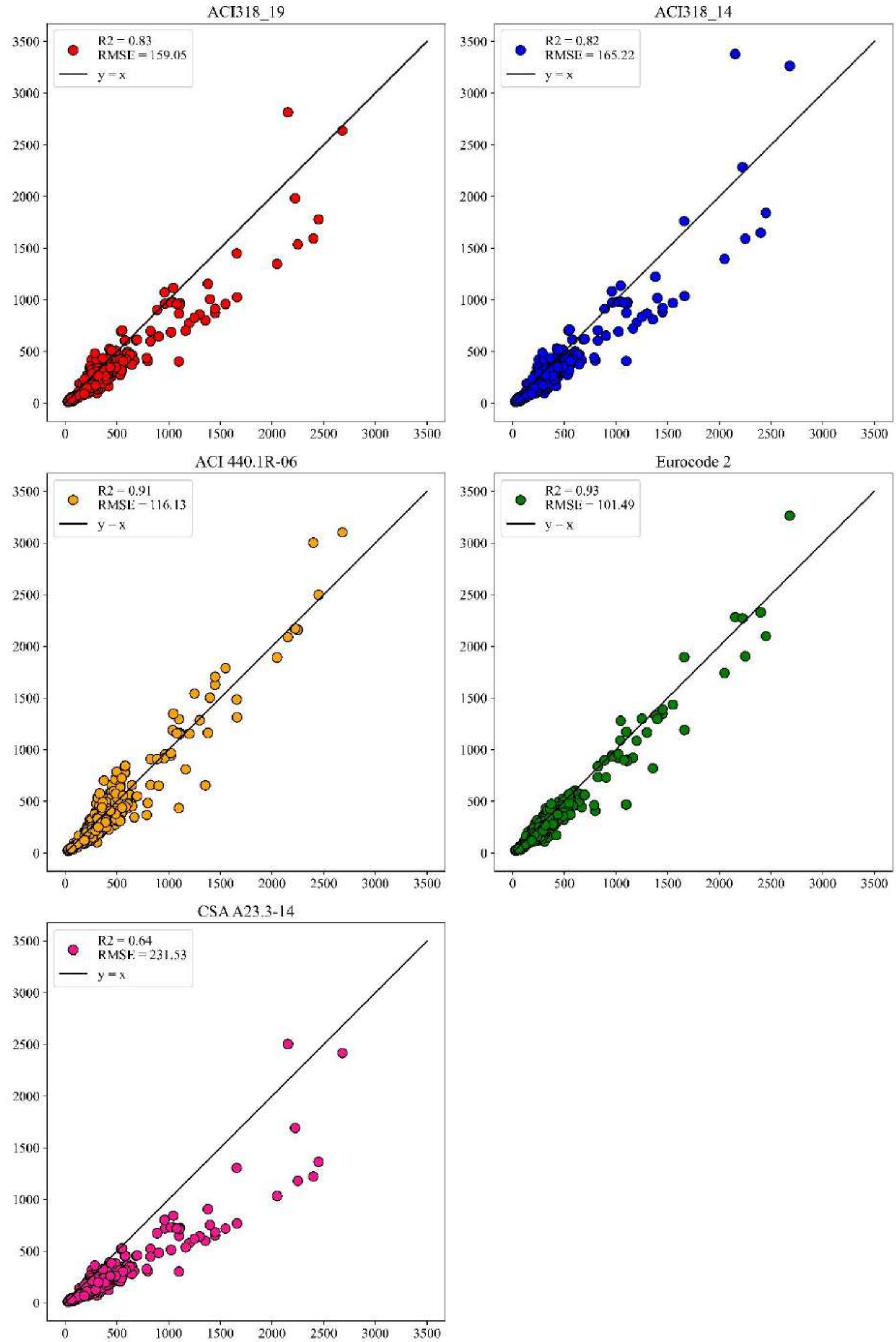

ACI318_19
R2 = 0.83
RMSE = 159.05
y = x
ACI318_14
R2 = 0.82
RMSE = 165.22
y = x
ACI 440.1R-06
R2 = 0.91
RMSE = 116.13
y = x
Eurocode 2
R2 = 0.93
RMSE = 101.49
y = x
CSA A23.3-14
R2 = 0.64
RMSE = 231.53
y = x
0
500
1000
1500
2000
2500
3000
3500

Fig. 23. Comparison of the R^2 score graphs of the punching shear strength test values (V test) vs. punching shear strength results from codes equations (V predicted): ACI 318-19, ACI 318-14, ACI 440.1R-06, Eurocode 2, and CSA A23.3-14.

4. Conclusions

Several experimental and few machine learning investigations have been conducted due to the significance of the brittle punching shear failure of reinforced concrete flat slabs without transverse reinforcement. However, the improvement of machine learning models, which have a lower cost of computations (time and hardware) than deep learning models, has not been investigated in the studies of machine learning models or deep learning models. Therefore this study aims to provide improved machine learning and deep learning models with grid search for punching shear strength prediction in reinforced concrete flat slabs without transverse reinforcements to make supplementary design proposals. In addition, GEP is impelemeted in this study in order to propose a explicit formula to calculate the punching shear strength of concrete slabs.

The following are the conclusions derived from this study:

1. This study aimed to optimize the accuracy of machine learning and deep learning models by applying a grid search to various algorithm parameters. In this effort, 959 machine learning models and 162 artificial neural network models were evaluated to identify the most effective model. Due to the limited number of experimental tests available, the methodology of this study—utilizing a range of models and refining their hyperparameters with optimization tools—provides a more accurate estimation of the punching shear strength of slabs compared to similar studies.
2. Each model has a unique accuracy on the test data and a unique accuracy on the training data, but in ranking the best models, one should pay attention to the accuracy of the test data and rank the models accordingly. This is because the test data did not affect the training of the model, and the model did not see them. Therefore, it can be a good

criterion for evaluating the model. In this study, the best model achieved from the test data is the XGB model with an R^2 score of 0.98; therefore, the XGB model is introduced as the best model in this study.

3. An expilicit formula based on Genetic expression programming (GEP) for calculating punching shear strength of concrete slabs is proposed, which its R^2 score on test data obtained 0.95.
4. After comparing the punching shear obtained from Eurocode 2, ACI, and Canadian codes with the actual values of punching shear strength available in the dataset, the best R^2 score achieved in Eurocode 2 was 0.93, followed by ACI 440.1R-06 with 0.91, while the best R^2 score of machine learning and deep learning models, was achieved XGB accounting for 0.98. Therefore, the values obtained from the codes are far from the actual values of the punching shear strength compared to machine learning and neural networks models. Therefore, it is suggested that in the new editions of these codes, more statistical calculations should be performed on the actual data of punching shear strength in order to achieve a better formula closer to reality.

References

Abambres, M., & Lantsoght, E. O. L. (2020). Neural network-based formula for shear capacity prediction of one-way slabs under concentrated loads. *Engineering Structures*, *211*, 110501. https://doi.org/10.1016/j.engstruct.2020.110501

ACI Committee 318. (2014). Building Code Requirements for Structural Concrete and Commentary. In *American Concrete Institute*. American Concrete Institute.

ACI Committee 318. (2019). Building Code Requirements for Structural Concrete and Commentary. In *American Concrete Institute*. American Concrete Institute.

ACI Committee 440. (2006). Guide for the Design and Construction of Concrete Reinforced with FRP Bars. In *American Concrete Institute*. American Concrete Institute.

Adom-Asamoah, M., & Kankam, C. K. (2008). Behaviour of reinforced concrete two-way slabs using steel bars milled from scrap metals. *Materials & Design*, *29*(6), 1125–1130. https://doi.org/10.1016/j.matdes.2007.06.001

Afzali, M., Hamidia, M., & Safi, M. (2023). Data-driven strength-based seismic damage index measurement for RC columns using crack image-derived parameters. *Measurement*, *218*, 113155. https://doi.org/10.1016/j.measurement.2023.113155

Al-Bayati, A. F. (2023). Shear Strength of Reinforced Concrete Squat Walls. *Civil Engineering Journal*, *9*(2), 273–304. https://doi.org/10.28991/CEJ-2023-09-02-03

Alkhawaldeh, S. M. A. (2024). Enhancing flat slab design: machine learning and metaheuristic approaches to predict punching shear strength. *Asian Journal of Civil Engineering*, *25*(3), 2459–2469. https://doi.org/10.1007/s42107-023-00919-4

Alotaibi, E., Mostafa, O., Nassif, N., Omar, M., & Arab, M. G. (2021). Prediction of Punching Shear Capacity for Fiber-Reinforced Concrete Slabs Using Neuro-Nomographs Constructed by Machine Learning. *Journal of Structural Engineering*, *147*(6). https://doi.org/10.1061/(ASCE)ST.1943-541X.0003041

Aminian, P., Javid, M. R., Asghari, A., Gandomi, A. H., & Esmaeili, M. A. (2011). A robust predictive model for base shear of steel frame structures using a hybrid genetic programming and simulated annealing method. *Neural Computing and Applications*, *20*(8), 1321–1332. https://doi.org/10.1007/s00521-011-0689-0

Anjali, K., Yesilyurt, S. N., Samui, P., Yildirim Dalkilic, H., & Mert Katipoglu, O. (2023). Determination of DBTT of Functionally Graded Steels Using Artificial Intelligence. *Civil Engineering Infrastructures Journal*, *57*(1), 189–203.

Birkle, G., & Dilger, W. H. (2008). Influence of Slab Thickness on Punching Shear Strength. *ACI Structural Journal*, *105*(2). https://doi.org/10.14359/19733

Bypour, M., Mahmoudian, A., Tajik, N., Taleshi, M. M., Mirghaderi, S. R., & Yekrangnia, M. (2024). Shear capacity assessment of perforated steel plate shear wall based on the combination of verified finite element analysis, machine learning, and gene expression programming. *Asian Journal of Civil Engineering*, *25*(7), 5317–5333. https://doi.org/10.1007/s42107-024-01115-8

Canadian Standards Association. (2014). Design of concrete structures. In *Canadian Standards Association*. Canadian Standards Association.

Chen, T., & Guestrin, C. (2016). XGBoost. *Proceedings of the 22nd ACM SIGKDD International Conference on Knowledge Discovery and Data Mining*, 785–794. https://doi.org/10.1145/2939672.2939785

Elstner, R. C., & Hognestad, E. (1956). Shearing Strength of Reinforced Concrete Slabs. *ACI Journal Proceedings*, *53*(7). https://doi.org/10.14359/11501

European Committee for Standardization. (2004). Eurocode 2: Design of Concrete Structures-Part 1.1: General Rules and Rules for Buildings. In *European Committee for Standardization*. European Committee for Standardization.

Ferreira, C. (2001). Gene Expression Programming: a New Adaptive Algorithm for Solving Problems. *Complex Systems*, *13*(2), 87–129.

Gandomi, A. H., Faramarzifar, A., Rezaee, P. G., Asghari, A., & Talatahari, S. (2015). NEW DESIGN EQUATIONS FOR ELASTIC MODULUS OF CONCRETE USING MULTI EXPRESSION PROGRAMMING. *Journal of Civil Engineering and Management*, *21*(6), 761–774. https://doi.org/10.3846/13923730.2014.893910

Guandalini, S., Burdet, O. L., & Muttoni, A. (2009). Punching Tests of Slabs with Low Reinforcement Ratios. *ACI Structural Journal*, *106*(1). https://doi.org/10.14359/56287

Habib, A., & Yildirim, U. (2022). Estimating mechanical and dynamic properties of rubberized concrete using machine learning techniques: a comprehensive study. *Engineering Computations*, *39*(8), 3129–3178. https://doi.org/10.1108/EC-09-2021-0527

Habib, M., Bashir, B., Alsalman, A., & Bachir, H. (2023). Evaluating the accuracy and effectiveness of machine learning methods for rapidly determining the safety factor of road embankments. *Multidiscipline Modeling in Materials and Structures*, *19*(5), 966–983. https://doi.org/10.1108/MMMS-12-2022-0290

Hamidia, M., Kaboodkhani, M., & Bayesteh, H. (2024). Vision-oriented machine learning-assisted seismic energy dissipation estimation for damaged RC beam-column connections. *Engineering Structures*, *301*, 117345. https://doi.org/10.1016/j.engstruct.2023.117345

Jamshidian, S., & Hamidia, M. (2023). Post-earthquake damage assessment for RC columns using crack image complexity measures. *Bulletin of Earthquake Engineering*, *21*(13), 6029–6063. https://doi.org/10.1007/s10518-023-01745-4

Jiang, X., & Xu, C. (2022). Deep Learning and Machine Learning with Grid Search to Predict Later Occurrence of Breast Cancer Metastasis Using Clinical Data. *Journal of Clinical Medicine*, *11*(19), 5772. https://doi.org/10.3390/jcm11195772

Li, B., & Li, X. (2023). Study on the Test Error of Silt Dynamic Characteristic and Its Influence on the Peak Ground Acceleration. *HighTech and Innovation Journal*, *4*(1), 65–74. https://doi.org/10.28991/HIJ-2023-04-01-05

Liang, S., Shen, Y., Gao, X., Cai, Y., & Fei, Z. (2023). Symbolic machine learning improved MCFT model for punching shear resistance of FRP-reinforced concrete slabs. *Journal of Building Engineering*, *69*, 106257. https://doi.org/10.1016/j.jobe.2023.106257

Liu, T., Cakiroglu, C., Islam, K., Wang, Z., & Nehdi, M. L. (2024). Explainable machine learning model for predicting punching shear strength of FRC flat slabs. *Engineering Structures*, *301*, 117276. https://doi.org/10.1016/j.engstruct.2023.117276

Lundberg, S., & Lee, S.-I. (2017). *A Unified Approach to Interpreting Model Predictions*.

Mangalathu, S., Shin, H., Choi, E., & Jeon, J.-S. (2021). Explainable machine learning models for punching shear strength estimation of flat slabs without transverse reinforcement. *Journal of Building Engineering*, *39*, 102300. https://doi.org/10.1016/j.jobe.2021.102300

Mansouri, I., Güneyisi, E. M., & Mosalam, K. M. (2021). Improved shear strength model for exterior reinforced concrete beam-column joints using gene expression programming. *Engineering Structures*, *228*, 111563. https://doi.org/10.1016/j.engstruct.2020.111563

Marmarchinia, S., Ghiami Azad, A. R., Mirghaderi, S. R., & Karney, B. (2024). A Novel Modular System for Pipe Racks Using Slip-Friction Connections. *SSRN*.

Mehrzad, A., Darmiani, M., Mousavi, Y., Shafie-Khah, M., & Aghamohammadi, M. (2023). A Review on Data-Driven Security Assessment of Power Systems: Trends and Applications of Artificial Intelligence. *IEEE Access*, *11*, 78671–78685. https://doi.org/10.1109/ACCESS.2023.3299208

Mirzahosseini, M., Jiao, P., Barri, K., Riding, K. A., & Alavi, A. H. (2019). New machine learning prediction models for compressive strength of concrete modified with glass cullet. *Engineering Computations*, *36*(3), 876–898. https://doi.org/10.1108/EC-08-2018-0348

Naderpour, H., Abbasi, M., Kontoni, D.-P. N., Mirrashid, M., Ezami, N., & Savvides, A.-A. (2024). Integrating Image Processing and Machine Learning for the Non-Destructive Assessment of RC Beams Damage. *Buildings*, *14*(1), 214. https://doi.org/10.3390/buildings14010214

Ozden, S., Ersoy, U., & Ozturan, T. (2006). Punching shear tests of normal- and high-strength concrete flat plates. *Canadian Journal of Civil Engineering*, *33*(11), 1389–1400. https://doi.org/10.1139/l06-089

Palomino Ojeda, J. M., Cayatopa-Calderón, B. A., Quiñones Huatangari, L., Piedra Tineo, J. L., Milla Pino, M. E., & Rojas Pintado, W. (2023). Convolutional Neural Network for Predicting Failure Type in Concrete Cylinders During Compression Testing. *Civil Engineering Journal*, *9*(9), 2105–2119. https://doi.org/10.28991/CEJ-2023-09-09-01

Parbat, D., & Chakraborty, M. (2020). A python based support vector regression model for prediction of COVID19 cases in India. *Chaos, Solitons & Fractals*, *138*, 109942. https://doi.org/10.1016/j.chaos.2020.109942

Patil, S., Patil, A., & Phalle, V. M. (2018). Life Prediction of Bearing by Using Adaboost Regressor. *SSRN Electronic Journal*. https://doi.org/10.2139/ssrn.3398399

Regan, P. E. (1986). Symmetric punching of reinforced concrete slabs. *Magazine of Concrete Research*, *38*(136), 115–128. https://doi.org/10.1680/macr.1986.38.136.115

Rizk, E., Marzouk, H., & Hussein, A. (2011). Punching Shear of Thick Plates with and without Shear Reinforcement. *ACI Structural Journal*, *108*(5). https://doi.org/10.14359/51683215

Soleimani-Babakamali, M. H., & Zaker Esteghamati, M. (2022). Estimating seismic demand models of a building inventory from nonlinear static analysis using deep learning methods. *Engineering Structures*, *266*, 114576. https://doi.org/10.1016/j.engstruct.2022.114576

Standards Australia. (2011). Reinforced Concrete Design : in accordance with AS 3600-2009. Sydney, N.S.W : Cement & Concrete Aggregates Australia . In *Standards Australia*. Standards Australia.

Tajik, N., Mahmoudian, A., Mohammadzadeh Taleshi, M., & Yekrangnia, M. (2023). Explainable XGBoost machine learning model for prediction of ultimate load and free end slip of GFRP rod glued-in timber joints through a pull-out test under various harsh environmental conditions. *Asian Journal of Civil Engineering*. https://doi.org/10.1007/s42107-023-00764-5

Taleshi, M. M., Tajik, N., Mahmoudian, A., & Yekrangnia, M. (2024). Prediction of pull-out behavior of timber glued-in glass fiber reinforced polymer and steel rods under various environmental conditions based on ANN and GEP models. *Case Studies in Construction Materials*, *20*, e02842. https://doi.org/10.1016/j.cscm.2023.e02842

Tavasoli, M. (2023). *Web-based intelligent packaging evaluation (WIPE) platform*. Michigan State University.

Theodorakopoulos, D. D., & Swamy, R. N. (2002). Ultimate punching shear strength analysis of slab–column connections. *Cement and Concrete Composites*, *24*(6), 509–521. https://doi.org/10.1016/S0958-9465(01)00067-1

Tran, V.-L., & Kim, S.-E. (2021). A practical ANN model for predicting the PSS of two-way reinforced concrete slabs. *Engineering with Computers*, *37*(3), 2303–2327. https://doi.org/10.1007/s00366-020-00944-w

Zaker Esteghamati, M. (2024). Leveraging machine learning techniques to support a holistic performance-based seismic design of civil structures. In *Interpretable Machine Learning for the Analysis, Design, Assessment, and Informed Decision Making for Civil Infrastructure* (pp. 25–49). Elsevier. https://doi.org/10.1016/B978-0-12-824073-1.00008-3

Zaker Esteghamati, M., & Huang, Q. (2023). Evaluating the impact of higher-mode and inelastic dynamic responses of concrete frames on the performance of seismic intensity measures. *Structures*, *56*, 105029. https://doi.org/10.1016/j.istruc.2023.105029