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Deep Learning-Based Keras Network Formulation for Predicting the Shear Capacity of Squat RC Walls and Sensitivity Analysis

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Keywords:
Machine Learning; Squat RC walls; Shear strength; Keras; Deep learning.

Highlights:

- *Studying the creation of an efficient ML data-driven model to forecast the (Vn) of squat walls.*
- *Predict the shear strength of shear walls as a function of wall design parameters.*
- *Studying the applicability of the ML model, the accuracy of its analytical results, and their superiority to the results of empirical and theoretical models for predicting.*
- *Build the most comprehensive library of RC shear wall experimental datasets, containing (material properties, geometric dimensions, and reinforcement details).*

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Abstract: Squat-reinforced concrete (RC) shear walls with an aspect ratio of less than two are commonly used as lateral load-resisting buildings. It is frequently utilized in nuclear power plants and building structures due to its lateral strength and high stiffness. It is distinguished by its optimal cost and excellent performance. Nonetheless, precise assessment of the shear strength of squat shear walls is crucial for design specifications, and its computation can be exceedingly variable and intricate due to several efficient, expensive, and time-consuming constraining elements. The present study utilizes Keras deep learning techniques to develop a model for predicting the shear strength of squat RC walls to find a way to overcome these issues. The most comprehensive dataset of 1424 RC squat wall test specimens collected from the published literature to date has been used to develop the proposed deep learning model as well as three well-known machine learning models: RF, ANN, and LR. The results demonstrated that the Keras network exhibited a lower error rate and higher accuracy when predicting the shear strength of squat walls compared to earlier machine learning models, achieving 97.3% accuracy compared with the highest value in the RF algorithm, reaching 93.4%. Furthermore, parametric and sensitivity analyses were performed to verify that the algorithms can identify the most significant variables significantly influencing shear strength. The results showed that the (***hw***) was the most influencing factor on the peak shear strength of the squat shear wall as a ratio (6.36%), according to the results of the sensitivity analysis, followed by (***lw***) as a (5.10%), (***tf***) (4.96%), (f'_c) (4.69%), (***tw***) (4.06%), (***fy***) of the web as a ratio (3.94%), and (***ρh***) (3.89%). These results and analyses were obtained using the (KNIME) analytics platform software, characterized by its vital role in precise computing operations and simple handling without the need for codes to reduce costs and time, and it was supported for Python and R languages.

صياغة شبكة كيراس المستندة إلى التعلم العميق للتنبؤ بقدرة القص لجدران الخرسانية المسلحة القصيرة وتحليل الحساسية

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الخلاصة

تُستخدم جدران القص الخرسانية المسلحة (RC) ذات نسبة العرض إلى الارتفاع أقل من اثنين بشكل شائع كمقاومة للأحمال الجانبية للمباني. يتم استخدامه بشكل متكرر في محطات الطاقة النووية وهياكل البناء بسبب قوته الجانبية وصلابته العالية في مقاومة الأحمال الجانبية. ويتميز بتكلفته المثالية وأدائه الرائع. ومع ذلك، فإن التقييم الدقيق لقوة القص لجدران القص القصيرة أمر بالغ الأهمية لمواصفات التصميم، ويمكن أن يكون حسابه متغيرًا ومعقدًا للغاية بسبب العديد من العناصر المقيدة الفعالة والمكلفة والمستهلكة للوقت. تستخدم الدراسة الحالية تقنيات Keras للتعلم العميق لتطوير نموذج للتنبؤ بقوة القص لجدران RC القصيرة لإيجاد طريقة للتغلب على هذه المشكلات. تم استخدام مجموعة البيانات الأكثر شمولاًحتى الآن، ضمت ١٤٢٤ عينة اختبار لجدران القص تم جمعها من الدراسات السابقة لتطوير نموذج التعلم العميق المقترح Keras بالإضافة إلى ثلاثة نماذج الاكثر شيوعاً للتعلم الآلي: RF، ANN وLR. أظهرت النتائج أن شبكة التعلم العميق(Keras) حققت معدل خطأ أقل ودقة أعلى بنسبة بلغت ٩٧,٣٪ بالمقارنة مع نماذج التعلم الآلي الأكثر شيوعا حيث بلغت اعلى قيمة في RF بنسبة ٩٣,٤ ٪. علاوة على ذلك، تم إجراء تحليلات الحساسية لعوامل التصميم للتحقق من قدرة الخوارزميات على تحديد أهم المتغيرات التي لها تأثير كبير على قوة القص. أظهرت النتائج أن ارتفاع الجدار هو العامل الأكثر تأثيراً على قوة القص القصوى لجدار القص القصيرة بنسبة (٦,٣٦٪) حسب حساسيتها لقوة القص. يلي ذلك طول الجدار (٥,١٠٪)، وسمك الحافة (٤,٩٦٪)، وقوة الخرسانة (٤,٦٩٪)، وسمك الجدار (٤,٠٦٪)، ونسبة مقاومة خضوع لحديد التسليح (٣,٩٤٪)، وتفاصيل نسب التسليح (٣,٨٩٪). تم الحصول على هذه النتائج والتحليلات باستخدام برنامج منصة التحليلات (KNIME)، الذي يتميز بدوره الحيوي في عمليات الحوسبة الدقيقة، والتعامل البسيط دون الحاجة إلى أكواد لتقليل التكاليف والوقت، وقد تم دعمه للغتي Python و R.

الكلمات الدالة: تلوث الهواء، التعرض المشترك، نماذج التشتت، نظم المعلومات الجغرافية، تقنيات النمذجة. التلوث الضوضائي، بيانات المرور.

1.INTRODUCTION

Squat-reinforced concrete (RC) shear walls with an aspect ratio less than or equal to two are essential to constructing commercial and residential buildings and nuclear construction. They play a vital role in withstanding seismic-shock lateral loads and high winds lateral loads [1]. Shear capacity is a concept addressed in present-day construction requirements and is known to be beneficial [2]. Studies have shown that the European Committee for the Study of Provisions for Shear Walls (Eurocode 8) provides an overly cautious estimate of shear strength, and the American Concrete Institute (ACI) 318-19 does not address high-strength concrete shear walls and employs a low safety factor. An appropriate method for evaluating shear wall strength can replace these conclusions [3]. However, because rational techniques need an iterative computation to find the peak strengths of shear walls, using them may be challenging for structural engineers [4]. In recent decades, efforts have been made to develop mechanics of shear strength models for squat walls, such as the strut and tie (STM) model or the softened truss model [5]. These models' estimations contain some dispersion and bias because they simplify the complicated nonlinear responses of concrete [6]. New research avenues have arisen as an alternate remedy in structural and seismic engineering due to recent advancements in Machine Learning (ML) and deep learning techniques, increasing the breadth of structural and seismic engineering investigations [7, 8]. Due to the rapid and accurate ML algorithms being developed as well as the abundance of reliable experimental data [9, 10], these methods have been used in numerous studies recently throughout the structural engineering and optimization phases [11, 12]. Feng et al. [13] created a forecasting technique to anticipate the shear strength of squat walls made of reinforced concrete. Studies show that the XGBoost model resulted in an approximately 97% validation accuracy, which well exceeds current semiempirical models to predict shear strength and offers a respectable forecast. Moradi and Hariri Ardebili [14] employed an ANN model, and a library of shear wall datasets was created. In this database, they included thin-walled squats, in addition to rectangles and flanged cross-section shapes. Although their results demonstrated the ANN model's accuracy, the test and validation dispersion were still relatively large. Nguyen et al. [15] collected 369 test results of squat flanged RC walls from the literature. They used these results to develop an effective machine learning model, namely an artificial neural network (ANN), to predict the shear strength of squat flanged RC walls. Predictive models have been developed by Zhang et al. [16], employing a database of 429 RC wall trial data and various ML techniques to predict the seismic performance of reinforced concrete (RC) walls. The findings showed that the XGBoost and GB algorithms accurately predicted the failure modes of RC walls with an accuracy of 97%. The gradient boosting and random forest algorithms performed best in predicting the lateral strength and ultimate drift ratio of RC walls, with a mean predicted-to-tested strength ratio of 1.01 and a predicted-to-tested ultimate drift ratio of 1.08. In a study cited by Hemn Ahmed et al. [17]; using contemporary modeling techniques like Multi-Expression Programming (MEP), Full Quadratic (FQ), and ANN; it was possible to forecast the compressive strength (CS) of geopolymer concrete (GPC) reinforced with nanoparticles. Other ML techniques were also used to predict the CS of GPC. One variable was used as an output, and eleven significant variables were used as input model parameters; they were applied to 207 tested CS values. Due to the limited quantity of data and inputs, even though the ANN model was demonstrated to be more accurate than other models considering the CS of the GPC, more information about prediction and the influence of design factors needed to be gathered. A comprehensive dataset containing 558 samples of squat shear walls was used by Farzinpour et al. [6] to estimate the shear strength using three hybrid models: XGBoost, CatBoost, and LightGBM. These models combined genetic algorithms and boosting-based ensemble learning techniques. High prediction accuracy was demonstrated, with each of the three models having a coefficient of determination of at least 98.6%. Moreover, three models outperformed the semiempirical model and other genetic programming (GP)-based models in terms of performance. Lastly, to show that the models could determine the key factors that significantly affect shear strength, parametric and sensitivity analyses were conducted. Al-Bayati [18] used a large-scale database containing the results of 487 walls with a wide range of test parameters to forecast the ultimate shear strength of squat walls using an artificial neural network (ANN), the strut and tie (STM) method, and existing models. The ANN models provided the best correlation (R) with the considered database compared to the proposed (STM) model and those in existence. The results showed high prediction accuracy, with a correlation (R) of at least 98% for the walls with and without boundary elements. Similarly, sensitivity analysis using Garson's method revealed that horizontal reinforcement contributes the least to the ultimate shear strength of shear walls, while concrete strength is the most. The aforementioned studies showed how machine learning approaches may flourish in a variety of circumstances while overcoming obstacles, such as a lack of experimental data and an inability to expand the model. However, the shear strength of RC squat shear walls was not predicted by earlier studies using Keras deep learning models. In the present study, the Keras learning networks methodologies are used to estimate the shear strength of the RC squat shear walls. Additionally, it has not been investigated if input factors, such as reinforcement ratio, geometrical characteristics, concrete strength, and axial load, are relevant. The objective of this study is to test the effectiveness of the ensemble deep neural network models for determining the shear strength of the RC shear walls and to study the applicability of the key factors and their relationships with shear strength. To build the deep learning model, 1424 experimental tests were meticulously compiled considering 25 input variables to calculate the shear strength of squat RC walls, obtained after preprocessing the total data of 3159 samples and 45 design parameters, which included missing data, duplicate data, and outlier values. The data is then randomly split into training and testing sets using the traditional 80%-20% split. Deep learning networks (Keras), a highly efficient model, are employed to train a shear strength prediction model. The Keras deep learning model's results are then evaluated using the testing datasets. Its predictions are compared with those made by other conventional ML methods, including a Linear Regression (LR), an individual ML model as an Artificial Neural Network (ANN), and an ensemble ML model, a Random Forest (RF). The performances of models are assessed using four measuring metrics methods. The datasets of correlation matrix and statistical analysis are also generated. After performing sensitivity analysis to identify and explore the element most likely to affect shear strength, several results are drawn.

2.EXPERIMENTAL DATABASE FOR SQUAT RC WALLS

To create an optimum shear strength model for RC walls, a sizable experimental database is required. Due to this, data collected from 1424 tests from the literature of RC squat wall tests were utilized in this study [4, 13, 19-22]. 25 essential input factors must be considered to forecast the shear strength of the walls. A wide range of squat wall characteristics was included in the final database, improving the trained Keras model's prediction accuracy. The database's squat RC wall testing is shown in Fig. 1 in a conventional diagram with three distinct cross-section groupings: Walls might be rectangular, barbell-shaped, or flanged. The four types of input parameters, geometric dimensions, reinforcing configurations, material characteristics, and applied loads, are depicted in these figures. The main importance of this study is to use the artificial intelligence system (Keras deep learning algorithm) to estimate the shear strength of squat shear walls, which is considered the main factor in the design of these walls, as well as to study the effect and sensitivity of the factors that effect on it with high accuracy and to save time and cost compared to experimental, theoretical and laboratory equations that were characterized by high dispersion and inaccurate. The particular 25 input variables are the concrete strength $f'c$, vertical reinforcement ratio ρvbe and strength $fyv\ be$, horizontal reinforcement ratio ρhbe and strength $fyh\ be$, vertical web reinforcement ratio ρv, and strength fyv, horizontal web reinforcement ratio ρh and strength fyh, ultimate strengths of the vertical *fuv*, and horizontal *fuh* web reinforcement, the spacing of the vertical and horizontal web reinforcement *Sv* and *Sh*, longitudinal, and horizontal boundary diameter reinforcement *Dl be* and *Dh be*, vertical and horizontal web diameter reinforcement *Dwv* and *Dwh*, height *hw*, length *lw*, web thickness *tw*, flange height *bf*, flange thickness *tf*, and the applied axial load *P*. Simply expressed, the output is the actual shear strength *Vn*. The input variables are described in Table 1 along with their statistical features, which show how each variable is distributed using statistical functions including minimum, maximum, average, standard deviation (SD), and coefficient of variation (COV). It is important to remember that the abbreviations for these two concepts are standard deviation (SD) and coefficient of variation (COV). After data cleaning by conducting preprocessing data that included (removing duplicates, outliers, and missing data), 1424 experimental data were selected from 3159 total test samples from previous researchers and used to generate the histogram's distribution of 25 input variables, as illustrated in Fig. 2.

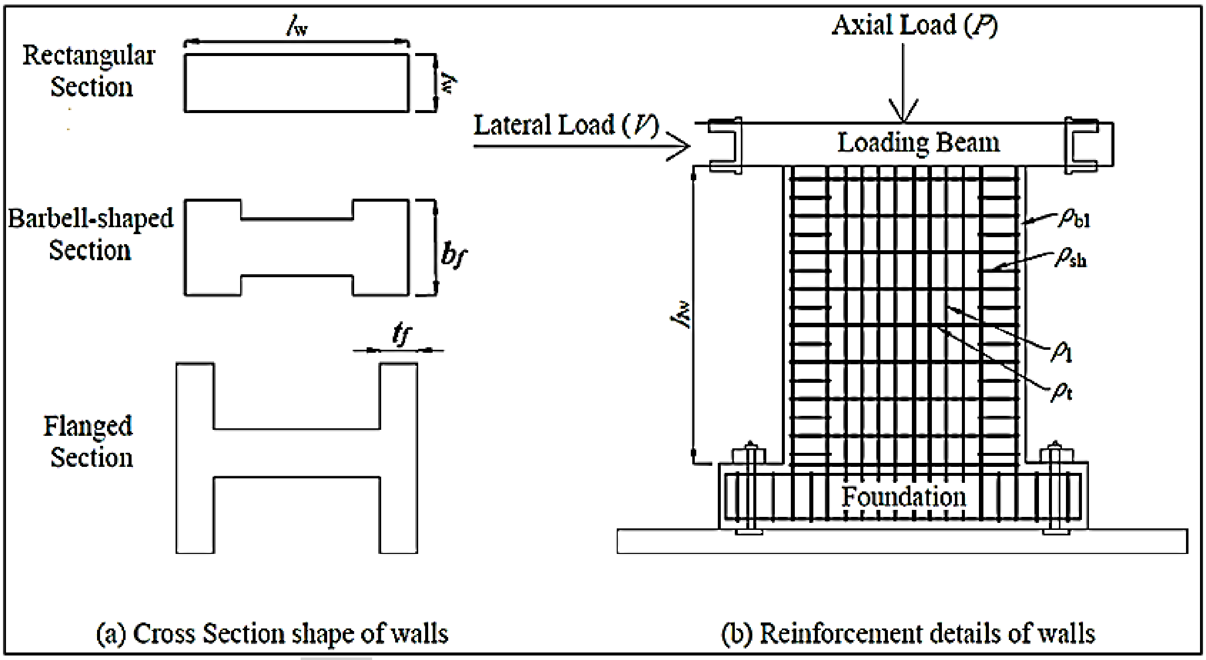
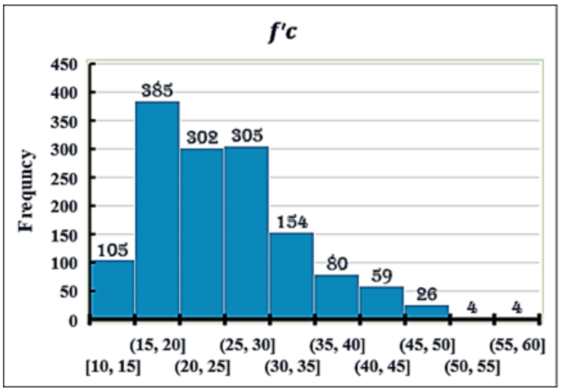


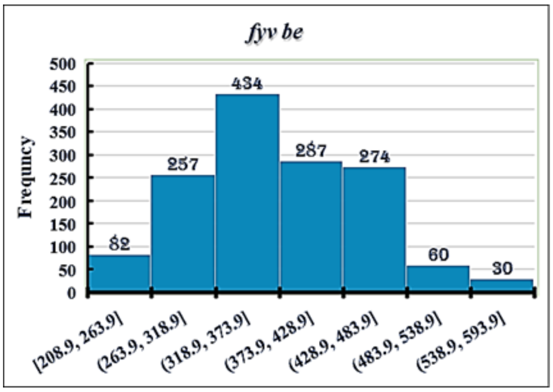
Fig. 1 Squat Walls' Geometric Cross-Section Shape.

Table 1 Statistical Properties of the Experiment Collection's Input Parameters.

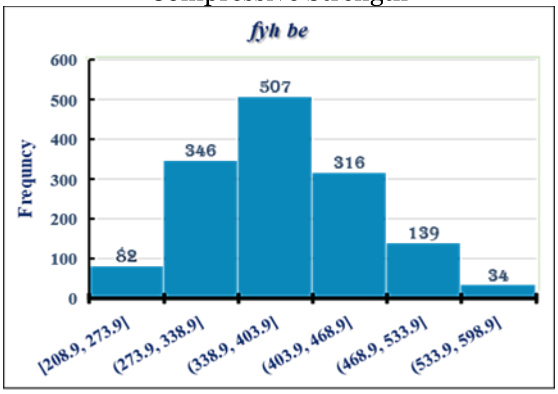
Variable	Unit	Minimum	Maximum	Mean	SD	COV	Type
f'c	MPa	10	56	25.07	8.38	0.33	Input 1
fyv be	MPa	208.90	585	375.05	73.83	0.20	Input 2
fyh be	MPa	160.87	529.60	364.22	54.64	0.15	Input 3
fyv	MPa	224	667.00	385.45	87.97	0.23	Input 4
fyh	MPa	222.10	667	386.61	89.10	0.23	Input 5
fuh	MPa	484.61	726.26	634.79	38.00	0.06	Input 6
fuv	MPa	509.09	699.51	635.90	33.77	0.05	Input 7
ρvbe	%	0	8.90	3.09	1.93	0.62	Input 8
ρhbe	%	0	0	0	0	0	Input 9
ρv	%	0	1.63	0.52	0.34	0.66	Input 10
ρh	%	0	1.63	0.54	0.36	0.66	Input 11
ρvall	%	0.30	0.30	0.30	0	0	Input 12
sv	mm	229	229	229	0	0	Input 13
sh	mm	203	203	203	0	0	Input 14
Dl be	mm	9.5	9.5	9.5	0	0	Input 15
Dh be	mm	4.95	4.95	4.95	0	0	Input 16
Dwv	mm	6.35	6.35	6.35	0	0	Input 17
Dwh	mm	6.35	6.35	6.35	0	0	Input 18
lw	mm	254	3329.50	1223.55	611.65	0.50	Input 19
hw	mm	150	2760	918.43	535.08	0.58	Input 20
tw	mm	20	203	107.38	29.48	0.27	Input 21
tf	mm	30	260	120.97	58.05	0.48	Input 22
bf	mm	30	610	144.53	98.31	0.68	Input 23
tweb	mm	16	160	69.31	36.93	0.53	Input 24
P	kN	0	830	125.62	197.04	1.57	Input 25
Vn	kN	0	2668	354.85	373.73	1.05	Output



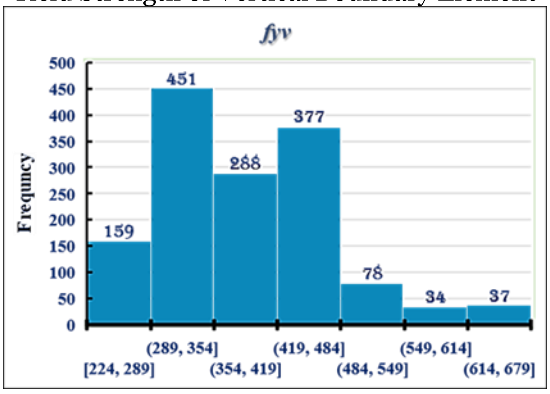
Compressive Strength



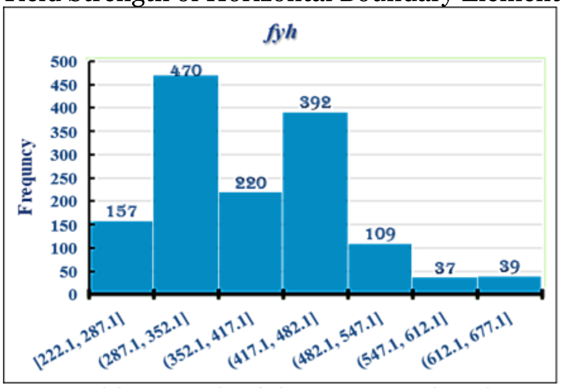
Yield Strength of Vertical Boundary Element



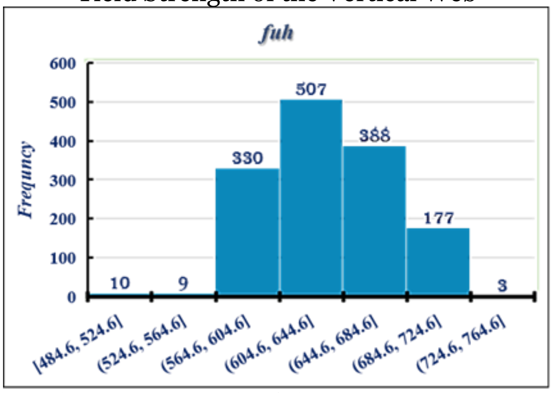
Yield Strength of Horizontal Boundary Element



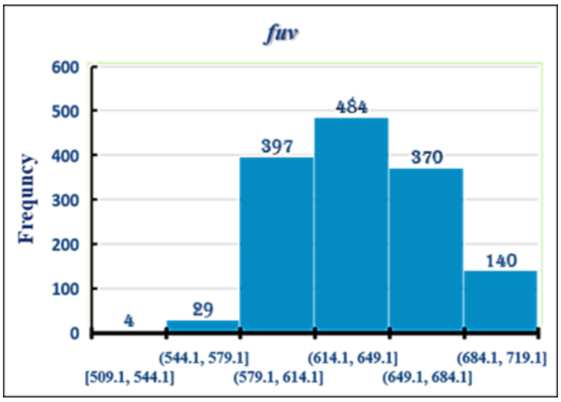
Yield Strength of the Vertical Web



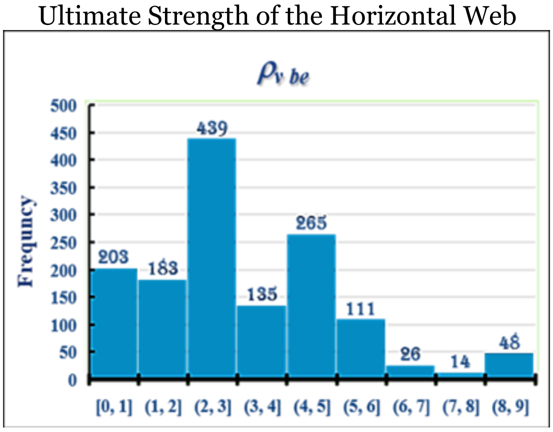
Yield Strength of the Horizontal Web



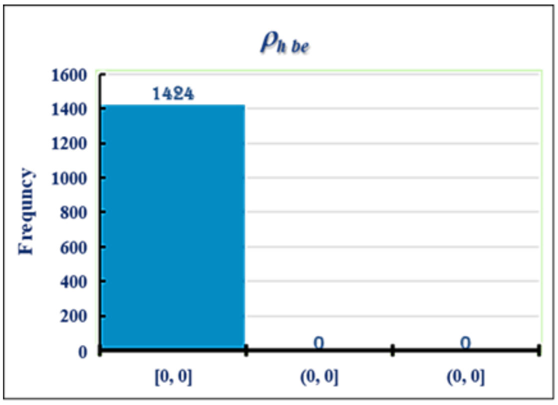
Ultimate Strength of the Horizontal Web



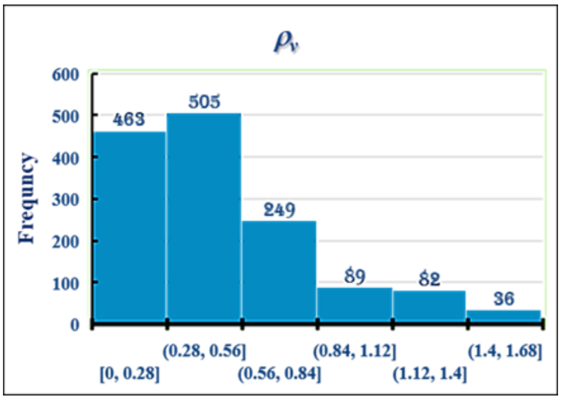
Ultimate Strength of the Vertical Web



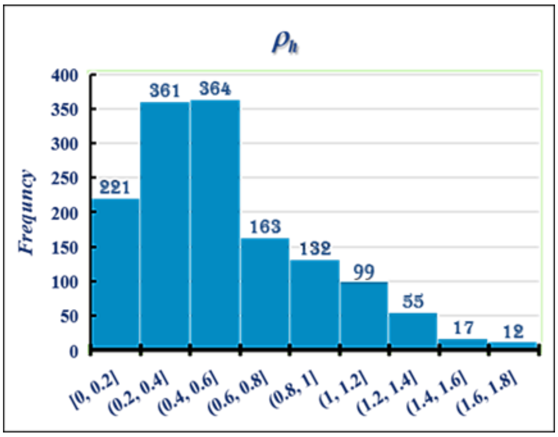
Reinforcement Ratio of Vertical Boundary Element



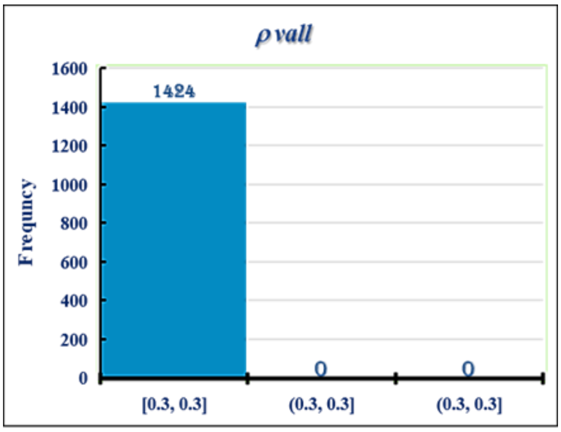
Reinforcement Ratio of Vertical Boundary Element



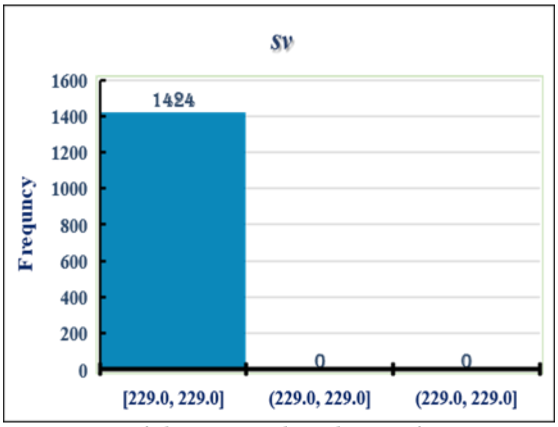
Reinforcement Ratio of Vertical Web



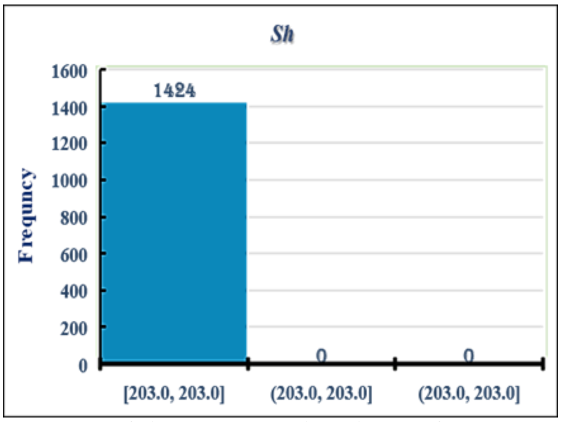
Reinforcement Ratio of Horizontal Web



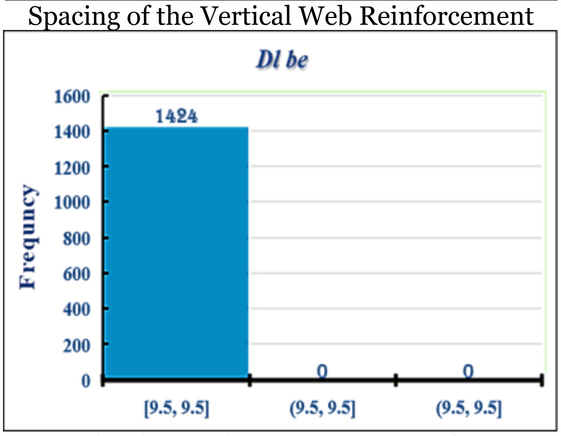
The Ratio of all Vertical Reinforcement



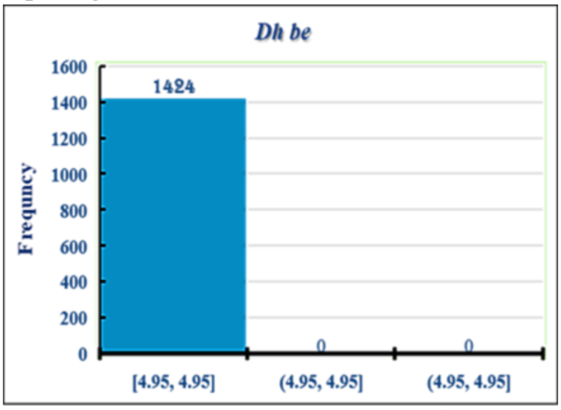
Spacing of the Vertical Web Reinforcement



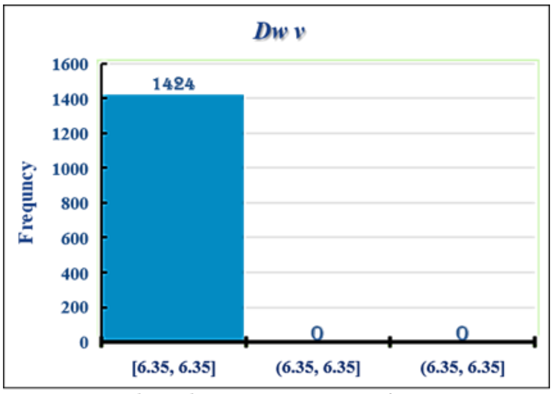
Spacing of the Horizontal Web Reinforcement



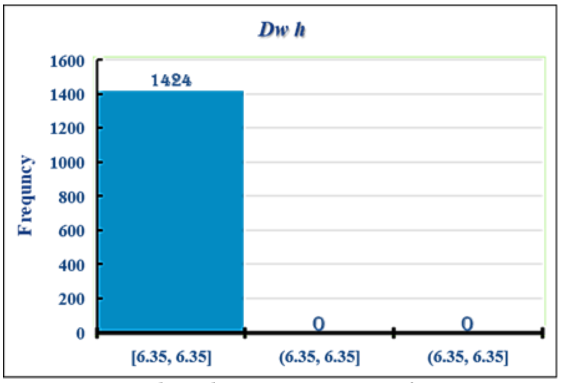
Longitudinal Boundary Diameter Reinforcement



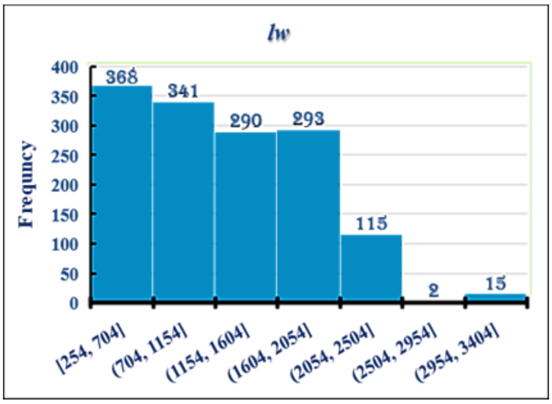
Horizontal Boundary Diameter Reinforcement



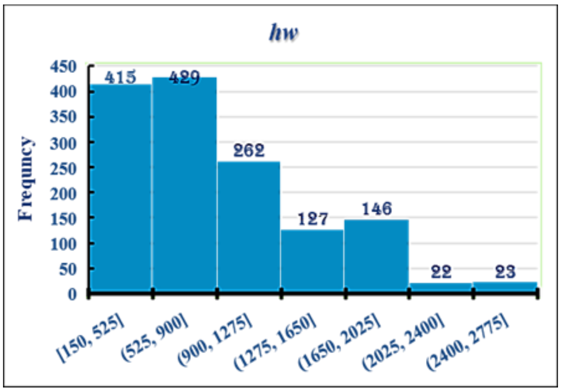
Vertical Web Diameter Reinforcement



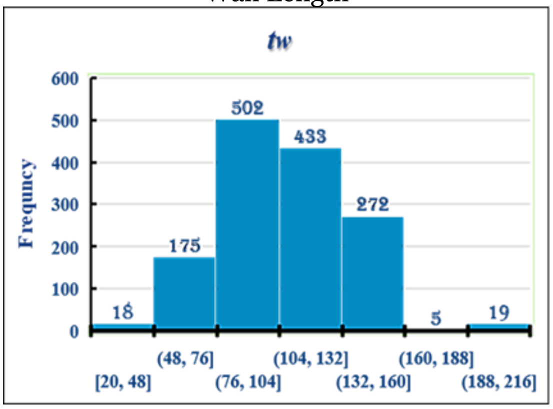
Horizontal Web Diameter Reinforcement



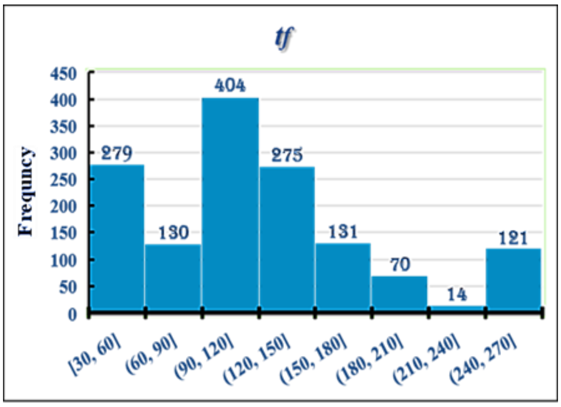
Wall Length



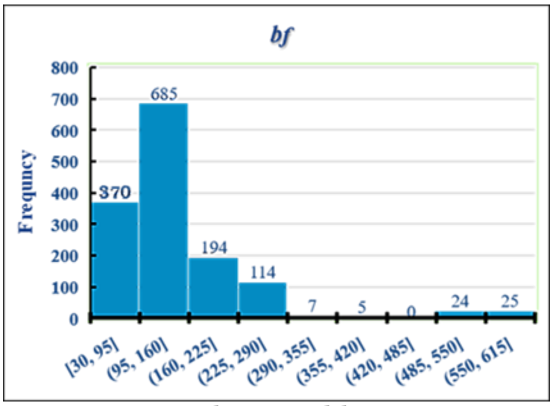
Wall Height



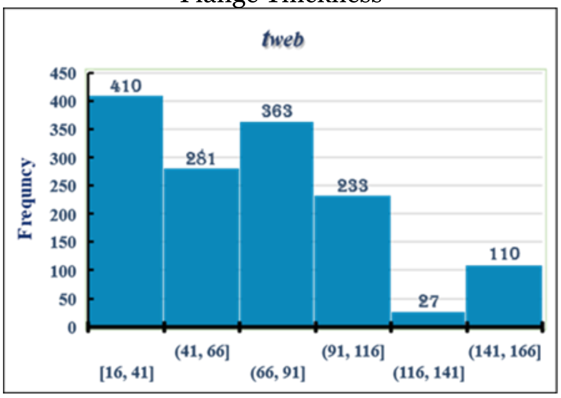
Wall Width



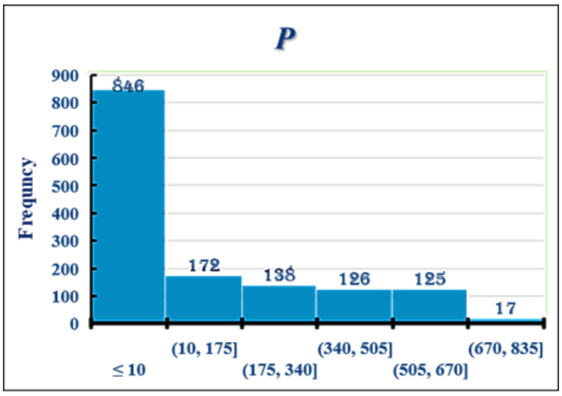
Flange Thickness



Flange Width



Web Thickness



Axial load

Fig. 2 Histograms of the Input Parameters Based on 1424 Experimental Data.

The linear correlation between two variables is usually identified utilizing the Pearson correlation coefficient [4]. Whose value ranges from -1 to +1. Whereas 0 means no linear correlation, +1 denotes a perfect linear positive correlation, and -1 suggests a perfect linear negative correlation. A coefficient value between ±0.50 and ±1 is assumed to indicate a significant association. A heatmap of the correlation coefficient between the variables in pairs is shown in Fig. 3. It shows that although certain parameters have strong relationships, others have poor correlations. For example, the correlation factor between (*ρh*) and (*ρv*) was 0.794, indicating that the relation is positive and strong with each other. The correlation between (*fyv*) and (*fyh*) was 0.807; the correlation between (*P*) and (*tweb*) was 0.588. As for the shear strength (Vn), it was revealed that there was a substantial correlation with (*lw*) only; it was 0.704. Yet, there was a weak association between it and the other factors, such as (*hw*), (*fyh be*), (*sv*), (*bf*), and (*f□c*) were 0.251, -0.112, N/A, 0.415, and 0.254, respectively. The statistical analysis of data, histograms, and relationships between variables is known as data exploration, often referred to as exploratory data analysis. It is the method of comprehending and evaluating data via statistical and visual techniques. This technique aids in identifying trends in a dataset. Finding patterns in data distributions, identifying the features of individual variables, and identifying correlations between variables are the three fundamental aims of data exploration. Histograms and charts are used to visually represent data as part of visualization techniques, making it easier to comprehend the data's many connections and structures, an action above.

		f ′c	ρv	ρh	fyv be	ρvbe	fyv	lw	hw	tf	fyh	tw	bf	P	ρhbe	tweb	fyh be	fuh	fuv	sv	sh	DL be	Dh be	Dwv	Dwh	ρvall	Vn
1	f ′c	1																									
2	ρv	0.287	1																								
3	ρh	0.221	0.794	1																							
4	fyv be	0.297	0.021	-0.035	1																						
5	ρvbe	0.090	0.032	0.067	0.059	1																					
6	fyv	0.321	0.113	0.050	0.404	-0.072	1																				
7	lw	-0.055	-0.080	-0.034	0.135	-0.193	0.220	1																			
8	hw	0.204	-0.070	-0.065	0.063	0.044	0.297	0.414	1																		
9	tf	0.035	0.009	0.053	0.268	-0.090	0.151	0.455	0.170	1																	
10	fyh	0.332	0.108	0.066	0.372	-0.057	0.807	0.215	0.286	0.153	1																
11	tw	0.075	-0.015	0.032	-0.204	-0.085	0.140	0.211	0.296	-0.008	0.129	1															
12	bf	0.186	0.026	0.078	0.115	-0.130	0.181	0.330	0.252	0.051	0.163	0.355	1														
13	P	0.287	0.020	0.062	0.004	-0.021	0.203	0.203	0.351	0.205	0.225	0.217	0.305	1													
14	ρhbe	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	1												
15	tweb	0.009	-0.072	-0.018	-0.192	0.075	0.081	0.199	0.372	0.084	0.092	0.147	0.212	0.588	0.322	1											
16	fyh be	0.026	0.014	0.007	-0.380	0.023	0.045	-0.111	0.230	-0.126	0.036	0.185	0.016	0.126	0.562	0.277	1										
17	fuh	0.073	0.060	0.011	-0.175	-0.150	0.128	0.052	0.245	-0.091	0.207	0.172	-0.127	0.053	0.273	0.010	0.259	1									
18	fuv	0.082	0.063	0.017	-0.198	-0.144	0.179	0.053	0.274	-0.106	0.144	0.195	-0.123	0.059	0.300	0.039	0.273	0.941	1								
19	sv	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	1							
20	sh	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	1						
21	DL be	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	1					
22	Dh be	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	1				
23	Dwv	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	1			
24	Dwh	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	1		
25	ρvall	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	1	
26	Vn	0.2547	0.1248	0.1883	0.2611	-0.075	0.301	0.7043	0.2514	0.422	0.287	0.2934	0.4153	0.3482	N/A	0.1872	-0.112	0.0599	0.0587	N/A	N/A	N/A	N/A	N/A	N/A	N/A	1

Correlation Coefficient (R): -1, -0.5, -0.4, -0.3, -0.2, 0, 0.2, 0.3, 0.4, 0.5, 1

Fig. 3 Correlation Analysis Matrix.

3.KERAS DEEP LEARNING MODEL FOR SHEAR STRENGTH OF RC WALLS

Artificial neural networks provide the foundation for learning models in deep learning, a subset of machine learning and artificial intelligence. The number of layers in a neural network is referred to as the "deep" in deep learning. The structure and function of the human brain were modeled for a series of algorithms collectively referred to as "deep learning." Using a massive amount of structured and unstructured data, it successfully trains computers and makes predictions. Where machine learning and deep learning technologies vary most in how the data is presented. As one of the deep learning programming interfaces that can handle huge amounts of data and several layers, Keras is used in the present study. High-level deep learning Application Programming Interface (API) Keras was developed with people in mind and is easy to use. It is created in Python and may be used to create any type of neural network. Only two of many deep learning frameworks are TensorFlow and Theano, and Keras is built on top of both of them. It emphasizes being fundamental, modular, and expandable to speed up experimenting with creating deep neural networks and provides comprehensive, expert-level knowledge regarding deep learning [23]. The baseline models are built using separate deep neural networks. Keras describes a model as a set of layers. Each layer's nodes are neurons. The learning rate, activation functions, optimizer, and number of neurons per layer are selected using the Keras-Tuner package, which also assists in choosing the best set of deep neural network hyperparameters. A streamlined version of the deep learning workflow is shown in Fig. 4.

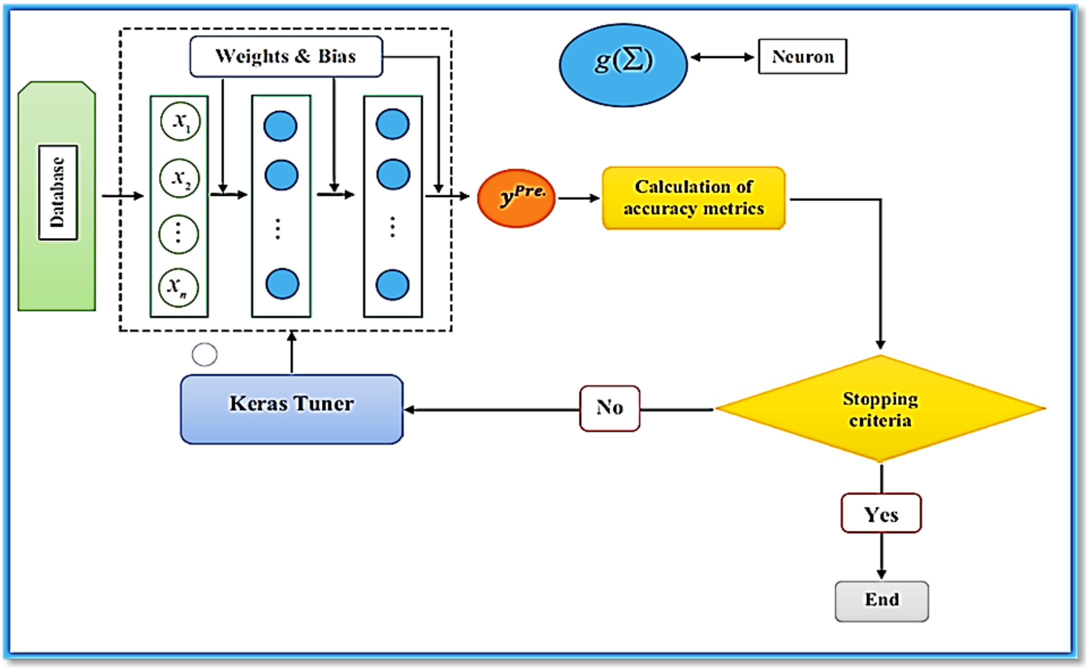


Fig. 4 Keras Deep Learning Network model process.

The Keras tuner considers six activation functions: Sigmoid, Relu, Softplus, Tanh, Selu, and Elu. Regressions should only make use of Relu. The optimizer is a critical component of the training process. The optimizer function aids the network in determining how to change the weights to lessen the loss. The eight optimization algorithms used are Adaptive Moment Estimation (Adam), Adaptive Delta (Adadelta), Stochastic Gradient Descent (SGD), Root Mean Square Prop (RMSProp), Nadam (Adam with Nesterov momentum), and Follow-the Regularized Leader (Ftrl). Adamax is an Adam variant based on the infinity norm. When setting up a Keras learning network, (RMSProp) and (Adam) are used for regression. Based on the test results, each fundamental model's efficacy will be determined for this study. Reliance is put on the more precise final base model (sub-model) data. There are five fundamental methods and strategies for creating deep learning models using Keras [24]. The breakdown of each method is shown below.

1- Describe the Keras network learner. This step should include the number of layers, neurons, and connections between each layer, as well as any regularization strategies that can be utilized to avoid overfitting.

2- Building the model network learner involves describing the metrics for measuring the correctness of the model, the optimizer that reduces loss, and the loss function that determines losses in a model.

3- Introducing the batch size, epoch size, and validation split are required to fit the model network learner. Make a model out of this that matches the data, then train it with the data.

4- Evaluating the Keras model network Executor: To assess the model using the test data set and show the plots, one must first ascertain and analyze the model's level of accuracy once it has been fitted to data.

5- Make forecasts: Predict the probability for the test data set using the model prediction Executor (Keras) [25].

4.VALIDATION CRITERIA

In this study, the coefficient of determination (R^2), root mean square error (RMSE), mean absolute percentage error (MAPE), and scatter index (SI) were utilized as metrics to assess the effectiveness of the proposed prediction models. Eqs.1-4 give form to these indications.

$$R^2 = \left(\frac{n\sum_{i=1}^{n} yi\hat{y}i - \sum_{1=1}^{n} yi \sum_{i=1}^{n} \hat{y}i}{\sqrt{(n\sum_{i=1}^{n} yi^2 - (\sum_{i=1}^{n} yi)^2)(n\sum_{i=1}^{n} \hat{y}i^2 - (\sum_{i=1}^{n} \hat{y}i)^2)}}\right) \quad (1)$$

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(yi - \hat{y}i)^2} \quad (2)$$

$$MAPE = \frac{100\%}{n} \sum_{i=1}^{n} \left|\frac{(yi - \hat{y}i)}{yi}\right| \quad (3)$$

$$SI = \frac{RMSE}{\frac{1}{n}\sum_{i=1}^{n} yi} \quad (4)$$

where n is the number of datasets, yi is the actual value of the ith dataset, and $\hat{y}i$ is the predicted value of the ith dataset. The value of R^2 was used to measure the variation between predicted and experimental data. Meanwhile, the RMSE value represents the mean of errors. Moreover, the MAPE is a percentage residual error between the actual and forecasted values, and SI, i.e., the percentage of error, measures how dispersion the error is relative to the mean of the dataset. In general, better accuracy and effective performance of the model are indicated by higher R^2, lower RMSE, and lower MAPE values. Concerning the SI parameter, it may be claimed that a model performs poorly when SI > 0.3, fairly well when 0.2 < SI < 0.3, good performance when 0.1< SI < 0.2, and excellent performance when SI < 0.1 [26].

5.RESULTS AND DISCUSSIONS

5.1.Model Implementation

Four phases generally structure the execution of the proposed deep learning model. The collected database were split into training (80%) and testing (20%) data sets as the first phase [27]. All inputs were normalized to lie inside the same range to prevent the scaling effect. A 10-fold cross-validation (CV) strategy was used throughout the training phase to decrease the bias introduced by the training set's random selection, and the grid search method was used to find the ideal hyperparameters. The four metrics tools mentioned above were used to evaluate the model's performance on the testing set (20%), used to determine the model's efficacy. The KNIME Analytics platform, version 4.7.7, a programming tool recognized as one of the most recent data science and artificial intelligence programs that support the Python and R languages, was used in the present study.

5.2.The Keras Network Model's Prediction Results

The subsequent steps will explain the shear strength results for squat shear walls as predicted by the Keras model. To maximize the forecast accuracy of the shear strength value and reduce the error rate by achieving the maximum R^2 and lowest RMSE values, numerous attempts were made to adjust the model's hyperparameters. Table 2 shows the set hyperparameters and the highest values obtained.

Table 2 Keras Network Package Tunning of Hyperparameters.

Model	Parameter	Value
Keras Network Learner	Epochs	270
	Training batch size	60
	Loss functions	Mean Square Error
	Activation functions- Denes Hidden layer	ReLU
	Activation functions- Output layer	Linear
	Optimizer functions	Adam
	Learning rate	0.01
	Keras Denes Layer- Hidden layer	2
	No. units (Nodes) of each Denes Layer	150

The Keras model has been assessed using the testing set after identifying the hyperparameters. More specifically, the model's other three statistical metrics were R^2 = 0.973, MAPE = 17.6%, and SI = 0.171, demonstrating a high level of precision in predicting the shear strength based on the highest R^2 value and the lowest RMSE. Figure 5 compares the results of the measured shear strengths to what the model predicted for the test sets. The ideal line (y=x) is represented by the dashed line, while the solid line depicts the linear regression of the scatterplots. The outcome is predicted more precisely the more closely the dispersion follows the ideal line y=x. It has been shown that the suggested deep learning model in this work significantly reduced dispersion. The data's linear regression line also had the lowest MAPE score of 17.6%, almost equal to the ideal line y=x. It should be mentioned that the model, in this instance, is assessed based on the outcomes of the program's training. Figure 6 displays a flowchart of every data processing step, including preprocessing, normalization, and partitions. The algorithm is then given the dataset to produce the results.

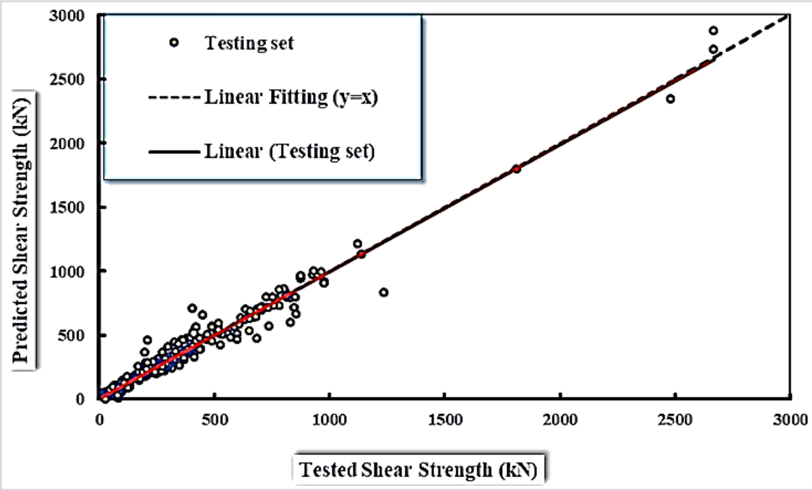


Fig. 5 Tested Values Versus Predicted Values by the Keras Model.

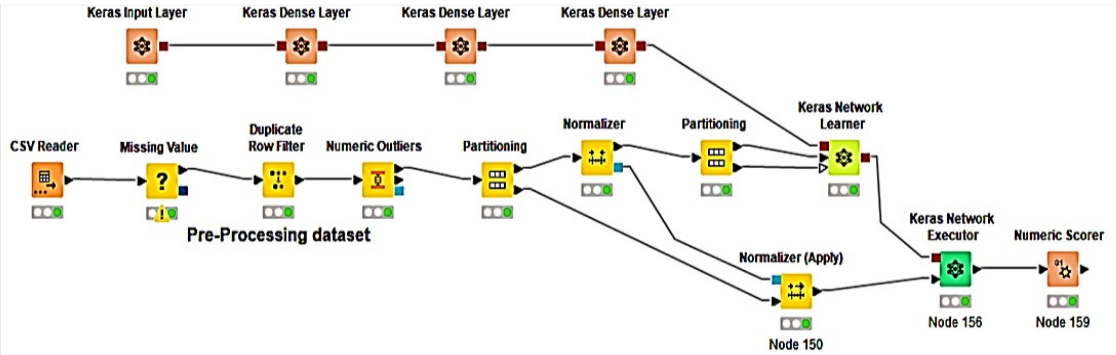


Fig. 6 Flowchart Diagram of Every Operation Performed on the Keras Model Data.

5.3.Comparison with Other ML Models

To further emphasize the better performance of the Keras-based prediction model, three popular ML models, RF, ANN, and LR, were also employed as comparisons. One of the most well-known machine learning methods, ANN employs linked nodes or neurons in a layered structure modeled after the way the human brain processes information. A dependent variable and one or more independent variables can be correlated linearly using the supervised machine learning model LR. Upon being trained on labeled datasets, it maps data into the most efficient linear formulae. RF is a machine learning technique that uses ensemble learning techniques to merge several distinct ML models, often Decision trees. An approach to machine learning called RF uses ensemble learning methods to combine various ML models, most frequently a Decision tree. A member of the bagging crew is RF. RF develops each distinct model in parallel using the bootstrap technique before averaging them all. Similar methods were used to determine the best hyperparameters for different models, such as partitioning the dataset into training (80%) and testing (20%), normalization scale [0,1], grid search, and the tenfold CV [13]. After preprocessing, the dataset goes through all these steps, such as addressing missing values, duplicate values, and outliers, before being fed into an algorithm. Obtaining the outcome of the forecast, Fig. 7 shows the results of the proposed machine learning models. Table 3 provides the precise metrics values demonstrating the models' performance. It has been revealed that the Keras model performed the best, while the LR model performed the worst. Additionally, it should be emphasized that RF and ANN all outperform LR since these techniques are ensemble learning techniques, which are more accurate and dependable than individual learning approaches (like LR). Figure 8 displays the SI assessment parameter values for the tested versions of the generated models. As shown in Fig. 8, the values for SI for LR, RF, Keras, and ANN are 0.382, 0.287, 0.171, and 0.365, respectively. Under this statistical assessment tool, the Keras model had good precision for the testing dataset, whereas the ANN and LR models had poor performance. While the RF model's performance was fair. Compared to the LR, RF, and ANN models, the SI values of the Keras model were 123%, 68%, and 113% lower, respectively. The outcomes of the scatter interval for residual errors of all developed models are displayed in Fig. 9. Furthermore, Keras outperforms LR, RF, and ANN, whose MPEs were (45%), (24%), and (26%), respectively, to attain the lowest error ratio (MAPE) of 17.6%. Figure 10 shows a histogram that compares the MAPEs of the suggested models. In terms of expected accuracy, the Keras model performs better than the other three models. Figures 8 - 10 demonstrate that the predicted and actual shear strength values for the Keras model are closer to one another, indicating the Keras model's superior performance than that of the other three models.

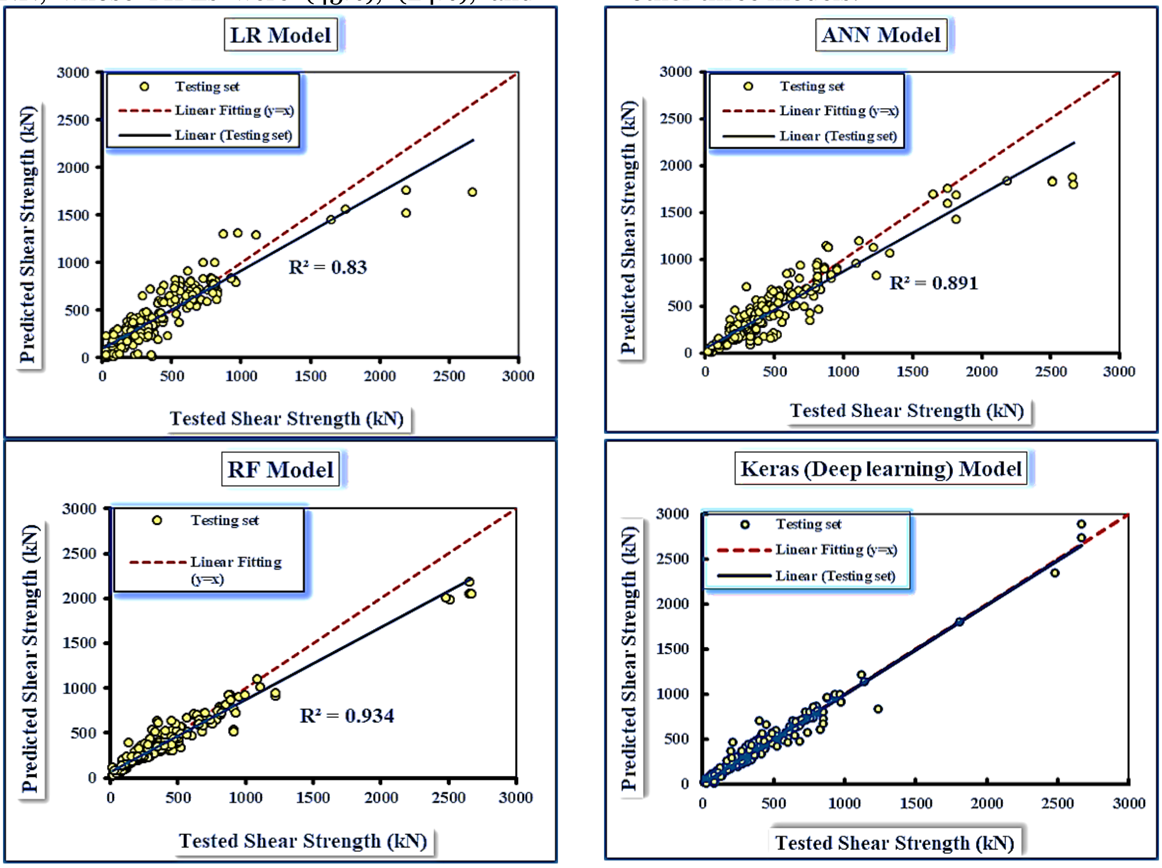


Fig. 7 Outcomes of Shear Strength Estimation via ML Models LR, ANN, RF, RF, and Keras.

Table 3 Comparison Results for Different Proposed Models.

Models	Sets	Measures			
		R^2	RMSE (kN)	MAPE (%)	SI
Keras	Testing	0.973	61.01	17.6	0.171
RF	Testing	0.934	103.13	24	0.287
ANN	Testing	0.891	142.59	26	0.365
LR	Testing	0.83	146.35	45	0.382

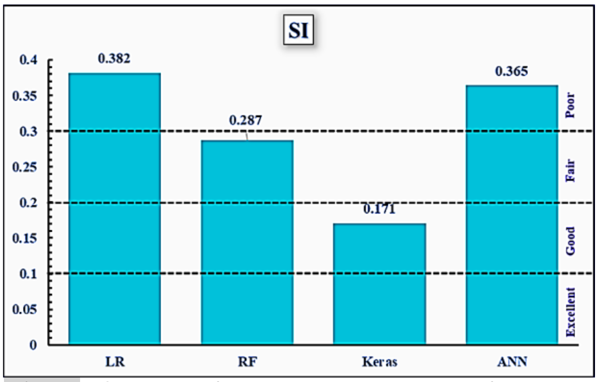


Fig. 8 The SI Performance Parameters of Various Developed Models Comparison.

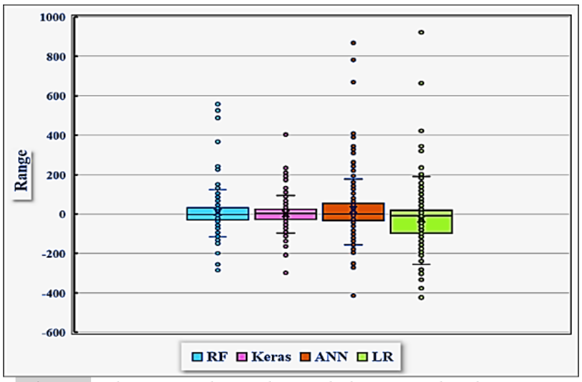


Fig. 9 The Developed Models' Residual Errors' Scatter Interval.

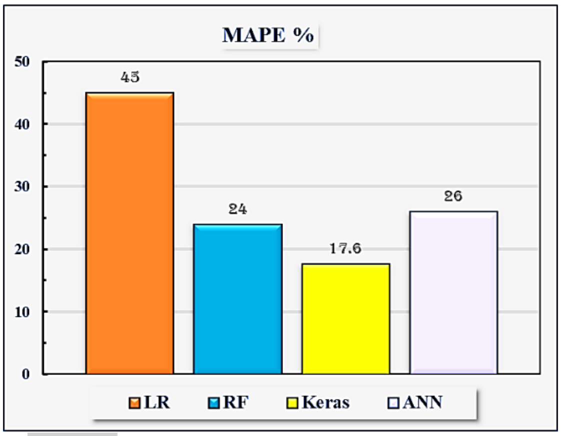


Fig. 10 MAPEs of the Developed Proposed Models.

5.4. *Sensitivity Analysis*

In this part, to identify the effects of input factors on the shear strength of the walls, a sensitivity analysis study was performed. Based on Keras' most accurate results predictions, the way the model reacts to changes in the input data reveals how well it is doing and, consequently, how well it can correctly reflect reality. Various sets of training data from multiple sources were employed in the sensitivity analysis. When the model was trained, just one variable from each set was omitted, and the RMSE was calculated separately for each training dataset. The omitted variable in the experiment with the highest RMSE for the set has the most impact on forecasting shear strength [28]. Table 4 summarizes the outcomes of the sensitivity analysis for the most crucial variables.

Table 4 Parametric Analysis Employing Keras-Based Model.

Sr.no	Removed Parameter	R^2	RMSE	Ranking
	None	0.973	61.01	–
1	*f'c*	0.953	82.55	5
2	*fyv be*	0.977	59.99	23
3	*fyh be*	0.969	61.22	22
4	*fyv*	0.974	58.67	24
5	*fyh*	0.964	69.38	8
6	*fuh*	0.962	69.61	7
7	*fuv*	0.971	62.48	**20**
8	*ρvbe*	0.942	87.37	4
9	*ρhbe*	0.959	65.70	15
10	*ρv*	0.975	58.45	25
11	*ρh*	0.971	68.43	10
12	*ρvall*	0.972	62.36	21
13	*sv*	0.968	66.38	13
14	*sh*	0.968	65.59	16
15	*Dl be*	0.968	65.71	14
16	*Dh be*	0.97	64.11	18
17	*Dwv*	0.97	63.11	19
18	*Dwh*	0.967	66.80	12
19	*lw*	0.947	89.85	2
20	***hw***	**0.885**	**112.01**	**1**
21	*tw*	0.958	71.56	6
22	*tf*	0.964	87.42	3
23	*bf*	0.957	68.14	11
24	*tweb*	0.969	65.57	17
25	*P*	0.966	68.60	9

It is clear from the results that the geometric properties were the most sensitive and influential in predicting the shear strength of shear walls, represented by the wall height (*hw*), which is considered one of the design parameters that most influence the shear strength; however, its effect is inverse, and it is located in the twentieth row in bold line, followed by wall length (*lw*), flange thickness (*tf*), and wall thickness (*tw*). The material properties after wall dimensions represented by compressive strength (*f'c*) significantly impacted the shear strength, afterward its reinforcement ratio (*ρh*), and yield strength (*fyh*) of the horizontal web in terms of impact and sensitivity. Figure 11 displays the results of the sensitivity evaluation based on the optimal Keras model, which shows the proportion of model input parameter contribution computed following sensitivity analysis.

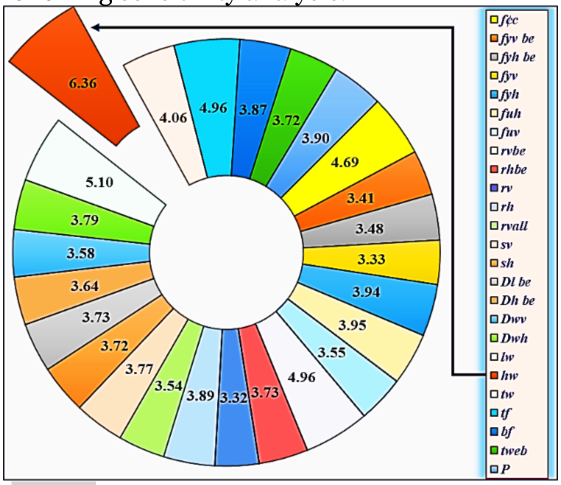


Fig. 11 Sensitivity Analysis Employing Keras-Based Model.

According to the proportionality results, derived from the most effective model (Keras deep learning) are evident in the figure. The geometric dimensions of the wall have the most significant influence on shear strength, followed by compressive force, details, and reinforcement properties. These variables are the most sensitive in predicting shear strength. This result aligns with other experimental investigations and earlier studies that have been concluded and disseminated in the literature [19, 29-31].

6. CONCLUSIONS

The present investigation's data set was assembled from 1424 tests and experimental results. In this study, the shear strength of squat reinforced concrete walls was effectively predicted using the deep learning model embodied by Keras. 80% and 20% of the data were randomly selected for training and testing in the grid search method to find the optimal Keras hyperparameters. The prediction outcomes of the recommended model were compared with those of other well-known machine learning models. The present study allows for deducting the following conclusions:

- When comparing the outcomes of the numerical and experimental programs, there was a noticeable level of convergence. The result was the KNIME Analytics Platform. It may be used in the fields of machine learning and data science because of its vital role in precise computing processes, simplicity of handling without the need for codes, support from the Python and R languages, and capacity to keep up with new techniques for handling and analyzing data.

- Using the largest shear wall database, which included 3159 test specimens, in this work is novel compared to previous studies.
- When designing the wall, consider the 25 most important and influential design parameters and shear strength as a parameter that has not been previously used in previous studies in terms of number.
- Estimating the wall shear strength using deep learning instead of traditional machine learning algorithms, obtaining high accuracy, reaching 97% and an error rate of 17.6, which has not been achieved yet.
- The established Keras predicted the shear strength of squat-RC walls with the lowest error and the highest accuracy. The performance measurement standards for the testing set were R2 = 0.973, RMSE =62.01 kN, MAPE = 17.6%, and SI = 0.171.
- The Keras model was compared with the ANN, LR, and RF ML models. Ensemble learning techniques (Keras and RF) significantly outperformed individual learning strategies (ANN and LR), with Keras attaining the best overall performance.
- As a consequence of 0.1< 0.171<0.2, it can be said that a model performs well (Good). The results for Keras showed that the predicted and actual shear strength values were very close, indicating that the degree of scattering of the test data around the ideal line (y = x) was lowest based on the scatter index value, which was (SI=0.171).
- The height of the wall was the factor that most influences the peak shear strength of the squat shear wall as a ratio (6.36%), according to the results of the sensitivity analysis, followed by the wall length (5.10%), the flange thickness (4.96%), the concrete strength (4.69%), the wall thickness (4.06%), the yield strength of the web as a ratio (3.94%), and the reinforcement ratio information (3.89%). This result consents with the findings of the previous experiments.
- The shear strength of squat walls can be predicted faster and more precisely using a machine-learning approach than with experimental or theoretical models. This method considers all the necessary variables for designing shear walls in buildings and constructions, and its results can be used to save time and money on current design work.

ACKNOWLEDGEMENTS

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NOMENCLATURE

ACI	*American Concrete Institute*
Adadelta	*Adaptive Delta*
Adam	*Adaptive Moment Estimation*
Adamax	*Adam variant based on the infinity norm*
ANN	*Artificial Neural Network*
API	*Application Programming Interface*
bf	*flange height*
COV	*coefficient of variation*
CS	*compressive strength*
Dh be	*horizontal boundary diameter reinforcement*
Dl be	*longitudinal boundary diameter reinforcement*
Dwv	*vertical web diameter reinforcement*
Dwh	*horizontal web diameter reinforcement*
f´c	*concrete strength*
FQ	*Full Quadratic*
Ftrl	*Follow-the Regularized Leader*
fuh	*Ultimate Strength of the Horizontal Web*
fuv	*ultimate strengths of the vertical*
fyh	*Yield Strength of the Horizontal Web*
fyh be	*Yield Strength of Horizontal Boundary Element*
fyv be	*Yield Strength of Vertical Boundary Element*
fyv	*Yield Strength of the Vertical Web*
GB	*gradient boosting*
GPC	*geopolymer concrete*
hw	*Wall height*
LR	*Linear Regression*
lw	*Wall length*
MAPE	*mean absolute percentage error*
MEP	*Multi-Expression Programming*
ML	*Machine Learning*
n	*number of datasets*
Nadam	*Adam with Nesterov momentum*
P	*applied axial load*
R^2	*coefficient of determination*
RC	*Squat-reinforced concrete*
RF	*Random Forest*
RMSE	*root mean square error*
RMSProp	*Root Mean Square Prop*
SD	*standard deviation*
SGD	*Stochastic Gradient Descent*
Sh	*the spacing of the horizontal web reinforcement*
SI	*scatter index*
Sv	*the spacing of the vertical web reinforcement*
tf	*flange thickness*
tw	*Wall thickness*
Vn	*actual shear strength*
yi	*actual value of the ith dataset*
$\hat{y}i$	*predicted the value of the* i^{th} *dataset*
	Greek symbols
ρh	horizontal web reinforcement ratio
ρhbe	horizontal reinforcement ratio
ρv	vertical web reinforcement ratio
ρvbe	vertical reinforcement ratio

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