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Machine Learning-Based Model for Predicting the Shear Strength of Slender Reinforced Concrete Beams without Stirrups

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Abstract: The influence of concrete mix properties on the shear strength of slender structured concrete beams without stirrups (SRCB-WS) is a widespread point of contention. Over the past six decades, the shear strength of SRCB-WS has been studied extensively in both experimental and theoretical contexts. The most recent version of the ACI 318-19 building code requirements updated the shear strength equation for SRCB-WS by factoring in the macroeconomic factors and the contribution of the longitudinal steel structural ratio. However, the updated equation still does not consider the effect of the shear span ratio (a/d) and the yield stress of longitudinal steel rebars (F_y). Therefore, this study investigates the importance of the most significant potential variables on the shear strength of SRCB-WS to help develop a gene expression-based model to estimate the shear strength of SRCB-WS. A database of 784 specimens was used from the literature for training and testing the proposed gene expression algorithm for forecasting the shear strength of SRCB-WS. The collected datasets are comprehensive, wherein all considered concrete properties were considered over the previous 68 years. The performance of the suggested algorithm versus the ACI 318-19 equation was statistically evaluated using various measures, such as root mean square error, mean absolute error, mean absolute percentage error, and the coefficient of determination. The evaluation results revealed the superior performance of the proposed model over the current ACI 318-19 equation. In addition, the proposed model is more comprehensive and considers additional variables, including the effect of the shear span ratio and the yield stress of longitudinal steel rebars. The developed model reflects the power of employing gene expression algorithms to design reinforced concrete elements with high accuracy.

Keywords: gene expression algorithms; shear strength; slender reinforced concrete; building construction

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1. Introduction

The cost-efficient design of reinforced concrete (RC) beams is challenging due to the complex interaction between the mechanical properties of concrete and longitudinal steel rebars. Although the constructed RC buildings must comply with the code design limitations, the code design requirements overestimate the strength of RC members, which may not be considered optimum options. Researchers have utilized cutting-edge technologies and state-of-the-art software to solve this gap by building decision-making aids that improve cost-effectiveness [1–29].

The design optimization of the shear strength of RC beams can be achieved in two ways. The first method uses the empirical equation, semi-empirical formulas, differential equations based on finite element evaluation, and mechanics-based methodologies. Empirical models represent models that use the experimental database to establish models for determining the shear strength of RC beams [30,31]; the main drawback of these models is that they present the best-fitting models, based on the investigated database. These models might not be accurate if they were used to predict the outputs of a new database. Conversely, models that are based on the materials' fundamental mechanics are described as mechanics-based methods [32,33]. Still, these models cannot easily quantify the non-homogeneous nature of concrete, which makes them inadequate for predicting the shear strength of RC beams. The semi-empirical models combine the mechanics-based concept with some fitted coefficients to improve the prediction accuracy of the shear strength of experimentally tested specimens in the literature [34,35], making them more accurate in predicting the behavior of RC beams. Moreover, several studies have used finite element analysis [36,37] to investigate more details about the tested beams, such as the distribution of stresses and strains, beam deflection, and local failures.

The second method deploys artificial intelligence algorithms to accurately estimate the shear strength of RC beams. Recently, a boost in machine-learning algorithm involvement has been witnessed in various civil engineering applications, such as smart cities, green buildings, high-performance concrete, etc. The high volume of the experimental databank in structural engineering helps the structural engineers to build sophisticated algorithms that learn from the experimental database, while satisfying a certain statistical performance to predict the desired outputs for certain problem input parameters accurately. Although machine-learning algorithms have high predictive precision compared to other methodologies, it is inconvenient for structural engineers to use algorithms in the daily-based design process in the design office. In addition, these algorithms need highly skilled engineers to run them, making it uneconomical to benefit from the advantages of machine learning tools. To present a solution to this problem, a closed-form solution model is more practical for adoption by the practitioners. In this regard, the gene expression (GEP)-based model [38,39] in structural engineering is becoming more popular for building machine learning models creating closed-form solutions. Considering the abundant availability of a database of RC beams, using GEP to estimate the shear strength and other desired performance measures would greatly improve the design of optimized RC beams.

The following two models, ACI 318-19 [40] and the system developed by Gandomi et al., 2014 [41], will be explained in detail as they will be used in this study for comparison purposes.

1.1. ACI 318-19

The ACI318-19 [40] specifies an empirical-based equation to determine the shear strength of non-prestressed structured concrete beams with no shear structure in one direction as shown in Equation (1).

$$V_C = 0.66\lambda\lambda_s(\rho_w)^{1/3}\sqrt{f'_c}b_w d \quad (1)$$

In this Equation, λ_s is the impact of the size factor, while λ is a factor that considers the type of concrete, which equals 1.0 and 0.75 for normal-weight and lightweight concrete, respectively. Also, ρ_w is the longitudinal steel reinforcement ratio and $\lambda_s = \sqrt{(2/(1+0.004\text{d}))} \leq 1.0$.

1.2. The Gandomi Model

The linear gene expression (LGP) method was used to put together the shear strength of RC beams [41]. A literature-based database was utilized for building the algorithm. The suggested design equation evaluated the shear strength of RC beams without stirrups. The LGP simulation gives better predictions than the existing building codes. The parameterized sensitivity assessments reflect the finding that the proposed shear strength equation can capture their fundamental physical behavior. The shear stress, v_u, is estimated by Equation (2):

$$v_u = \frac{2d}{a}\sqrt{\frac{d}{8a}(3 - a_g)\rho + f'_c\sqrt{\frac{3\rho}{z}}} \quad (2)$$

where z = 0.9d and a_g is the maximum size of coarse aggregate and is assumed to be 19 mm, if the aggregate size is not given.

1.3. Gene Expression (GEP) Model

The GEP models have the advantage of tracing the nonlinear interaction of various variables, which improves the prediction accuracy compared to the LGP-based models. Although the GEP modeling was successfully used in various fields of structural engineering [38,39], it is necessary to estimate the shear strength of SRCB-WS because the interaction between components of the shear transfer mechanism is complex. The high volume of the experimental database in the literature helps to train, validate, and test sophisticated GEP models to predict the shear strength.

Estimating the shear strength of slender reinforced concrete beams with no stirrups (SRCB-WS) is among the most difficult issues to understand in reinforced concrete (RC) buildings. The SRCB-WS are commonly used on various RC members, such as shallow beams, RC slabs, and concrete panels, where the applied shear forces are less than the shear strength of SRCB-WS. On the other hand, RC members must be strengthened if the external shear forces will exceed the shear strength of SRCB-WS. There are various options to enhance the shear capacity of SRCB-WS, to accommodate shear stresses that exceed its strength, such as providing stirrups with adequate spacing, adding steel fibers of at least 0.75%, and strengthening the concrete using wraps of fiber-reinforced polymers (FRP). However, these options require additional labor and increase the overall cost of constructing RC buildings. Therefore, an accurate estimate of SRCB-WS shear strength is critical to deciding if the shear strength must be improved. Several equations have been proposed in the literature to estimate the shear strength of SRCB-WS. However, these models have a large discrepancy in terms of the estimation of shear strength because identifying the relevance degree of the primary regulating factors is quite difficult. In general, once the shear crack develops at the web of the SRCB-WS, the shear forces are resisted by: (1) shear stresses that are resisted by the entire compressive region; (2) the dowel action provided by the longitudinal steel reinforcement; (3) the aggregate interlock that results from the friction between the irregular crack sides, working to transfer the shear forces from one side to the other; and (4) the size effect, which refers to the action of shear stress reduction in beams with high beam depth compared to shallow beams, even if the beams have the same mechanical properties of steel and concrete. The four factors above are difficult to directly estimate using the mechanics-based models. In addition, the interaction between these four factors has not been quantified. Therefore, most design codes use empirical models to correlate the shear strength with basic properties of beams, such as the beam section area, concrete compressive strength, longitudinal reinforcement ratio, shear span ratio, and other concrete and steel properties.

Various variables have recently been recognized as having a considerable effect on the shear strength of SRCB-WS effects, such as the compressive strength of concrete, the size effect, shear span ratio, longitudinal steel reinforcement ratio, axially compressed or tensioned beams, and so on. Additional significant aspects include test-setup settings and loading design. Generally, the shear capacity of SRCB-WS increases as the concrete compressive strength increases. In contrast, the ACI 318-19 and European Union design codes relate the shear strength of the SRCB-WS to $(f'_c)^{1/2}$ and $(f'_c)^{1/3}$, respectively. This implies that the concrete compressive strength is being utilized as a critical parameter. The current version of ACI 318-19 [40] limits the concrete compressive stress to 42 MPa. However, recent advancements in concrete technology and the use of superplasticizers have helped to produce high-strength concrete, where concrete with a compressive strength of 70 MPa is commonly used to reduce the cross-sectional area of RC members and resist the high stresses developed in the lower stories of high-rise buildings. Therefore, shear strength models shall consider the shear strength improvement of SRCB-WS that are made of high-strength concrete.

Moreover, the size effect was experimentally observed many years ago, in 1967 [31]; this phenomenon is due to the interaction of several factors, such as the loss of the aggregate interlock contribution if the beam depth is increased [42] and the decrease in compression zone ratio, which is a major variable in the shear strength of RC beams [42–44]. The experiments conducted by Kani [45] regarding the impact of size in 1967 and the tests by Shioya et al. [46] have successfully explained this effect. While Bazant et al. [34] justified the impact of size using the concepts of the fracture mechanics of concrete, Collins et al. [44] and Reineck [43,47] have described the size effect as a decrease in shear transmission at the contact point, due to the bigger crack sizes taking place in reinforced concrete that are associated with high effective depth.

RC beams can be categorized into two groups, based on the proportionality of a/d, where slender beams have a value of $a/d > 2$, while short beams have a value of $a/d \leq 2.5$. The short beams can be found on RC bridge girders and transfer girders in RC buildings, which transfer loading from the upper stories to the supporting columns, corbels, ledge girders, deep beams, and nodal loading within a distance from the supports that is less than twice the beam depth. This effect is important in SRCB-WS structures where the a/d proportion is lower than 2.5, since part of shear forces might be transferred directly to the support by the strut-and-tie mechanism. As a result, it would be more effective to use the strut-and-tie models rather than the beam theory to accurately estimate the shear strength of SRCB-WS with an a/d of less than 2.5; this phenomenon is called arch action. Generally, the arch action has only a minor effect in slender beams with a shear span-to-effective depth (a/d) of more than 2.5. Slender beams are more widely used than short beams; they are seen in slab panels, RC slab systems, and RC girder bridges with long spans. Several realistic expressions for determining shear strength involving the a/d ratio to account for the effect of a/d on SRCB-WS have been carried out. It is worth mentioning that every test database suggested for the proposed study has a/d proportions that are larger than 2.5.

In SRCB-WS, flexural stresses and strains in steel rebars rise when the longitudinal steel ratio decreases. Thus, the crack widths become larger, and the shear strength of SRCB-WS is decreased. In addition, as the longitudinal steel reinforcement ratio decreases, the dowel action also reduces. Furthermore, when the SRCB-WS parts are exposed to tension in the axis, the shear strengths of SRCB-WS reduce. On the other hand, if the axial compression stresses rise, the area of the uncracked compression region increases, thus improving the shear transfer.

Extensive experimental programs have been conducted over the past six decades, enabling the researchers to use various machine learning tools, the primary focus of which is predicting the shear strength of structured concrete beams. Cladera and Mari [48,49] and Jung and Kim [50] used experimental data to train and test an artificial neural network (ANN)-based model to estimate the shear strength of RC beams. Ashour et al. [1] proposed a gene expression (GEP)-based model that can calculate the RC beams' shear strength. Although the ANN-based models are considered to offer a significant improvement compared to the available ACI 318-19 [40] code equations, the main disadvantage of using ANN is the lack of a closed-form solution to estimate shear strength where ANN models only provide solution algorithms. With the limited capabilities of the currently available design tools, it is not possible for practitioners to smoothly evaluate the shear strength.

It is imperative to develop an accurate and practical shear strength evaluation tool to overcome these evaluation limitations. Thus, the current study investigated the use of gene expression algorithms to improve the efficiency of evaluating the shear strength of SRCB-WS. The developed model is superior to the available shear evaluation tools; it is generic and can be employed by practitioners without the need for the big data availability that is required for training and testing purposes. In addition, a closed-loop gene expression-based solution can be generated with less uncertainty. Furthermore, the developed model considers one-of-a-kind and the most influential features (i.e., the shear span ratio and the yield stress of longitudinal steel rebars).

Additionally, the non-linearity of the proposed model empowers its evaluation accuracy by tracking the interaction among the interconnected features and their individual impact on the shear strength. Moreover, the experimental database used in this study to build the gene expression model is the largest in the literature, including data from 1953 to the present. The data collection effort was huge, wherein over 100 hundred references from prestigious academic journals within the field were investigated over one year. Thus, the developed model can be considered a generic and useful support decision tool for practitioners within the building construction arena. The adopted research methodology is outlined in Figure 1.

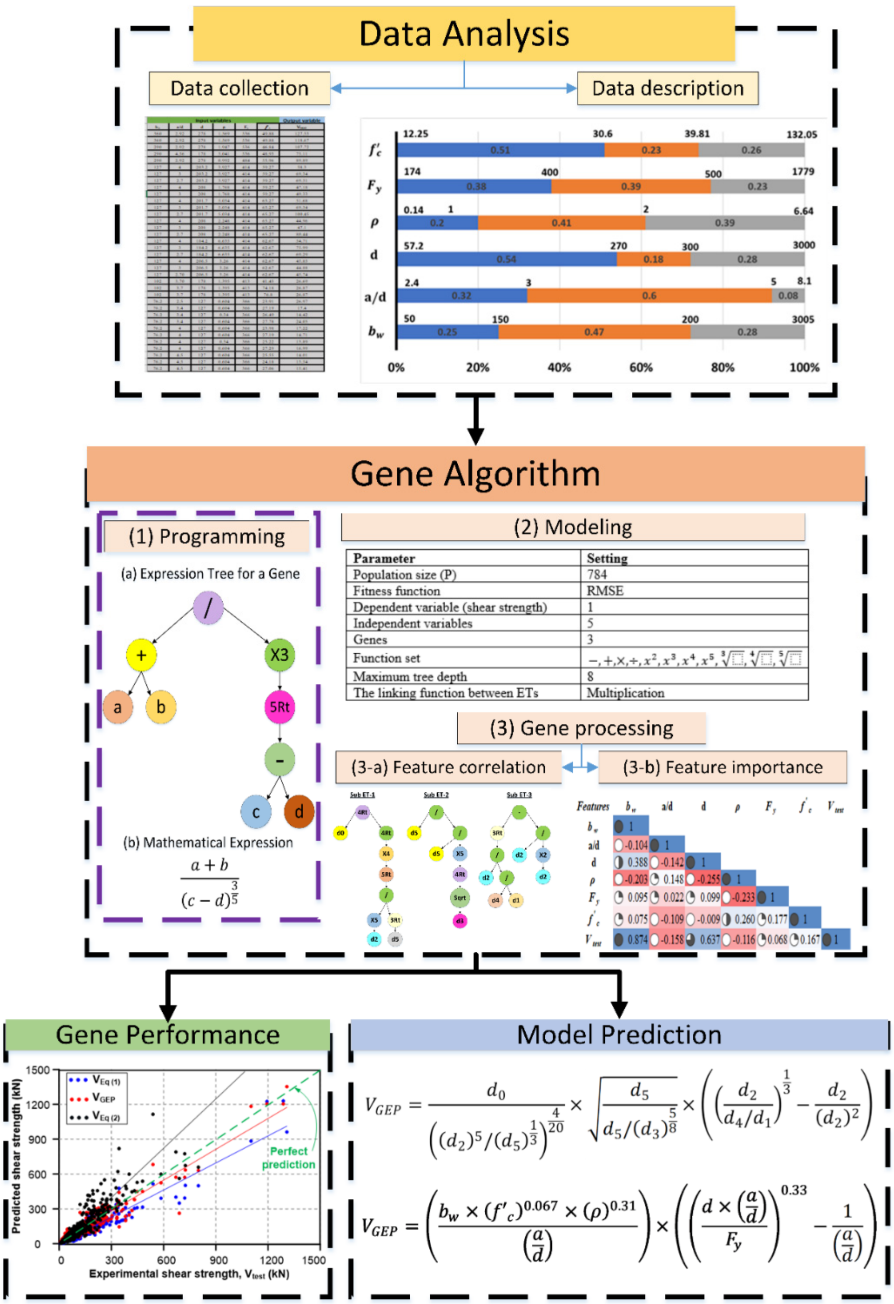

Figure 1. Flowchart of the research methodology.

2. Description of Experimental Database

This study used a collected database of 784 specimens from the literature [43,45,46,51–146]. Table 1 symbolizes the key parameters employed in this work, with their description. The ranges and distributions of the collected database are also shown in Figure 2, which includes b_w, d, f'_c, a/d, ρ_w, and F_y. It can be seen that about 75% of the database involves a concrete compressive strength of 40 MPa, which is classified as representing normal-weight concrete with an effective depth of 300 mm and longitudinal steel reinforcement of less than 2%. The statistical measures of the tested database are shown in Table 2, which includes the variables of mean, median, and standard deviation. The median of b_w, d, f'_c, a/d, ρ_w, and F_y are 153 mm, 268 mm, 30 MPa, 3.2, 1.8%, and 421 MPa, respectively. Moreover, Figure 3 shows a 7×7 matrix where the matrix diagonal illustrates the distribution histogram of each variable, while the upper and lower triangles of the matrix show the scatter distribution between the investigated variables. The figure shows that the database includes a wide range of information that can be effectively used to build, train, and test the machine learning algorithms to predict the shear strength of RC beams without shear reinforcement.

Table 1. The vital parameters utilized in this study.

Number	Symbols	Definition
1	b_w	distribution of beam width
2	d	effective beam depth
3	f'_c	concrete compressive strength
4	a/d	shear span ratio
5	ρ_w	longitudinal steel-structured proportionality
6	F_y	longitudinal steel yield stress
7	V_C	estimated shear strength of ACI318-19
8	λ	the factor that considers the type of concrete
9	λ_s	the impact of the size factor
10	v_u	estimated shear strength from Equation (2)
11	a_g	the maximum size of coarse aggregate
12	V_{GEP}	the proposed shear strength
13	$RMSE$	root mean square error
14	MAE	mean absolute error
15	$MAPE$	mean absolute percentage error
16	R^2	coefficient of determination
17	Y_i	real quantities of the shear strength
18	$\overline{Y}$	average of Y_i
19	m	total number of datasets used

Table 2. Statistical information from the collected database.

Features	Mean	Median	Mode	Standard Deviation	Minimum	Maximum	Q_1	Q_2	Q_3
b_w	218.6	153.1	152.4	207.1	50.0	3005.0	150	153	203.2
a/b	3.5	3.2	3.0	1.0	2.4	8.1	2.9	3.2	4
d	345.5	268.2	252.5	303.3	57.2	3000.0	203.6	286.2	342
ρ	1.9	1.8	2.6	1.1	0.1	6.6	1	2	3
F_y	449.9	421.0	414.0	153.6	174.0	1779.0	370	421	494
f'_c	37.4	30.4	49.4	20.0	12.3	132.1	24.9	30.4	41.3
V_{test}	98.2	61.1	53.4	124.0	7.2	1308.4	41.1	61.1	106.7

Q_1, Q_2, and Q_3 are 25th, 50th, and 75th percentiles, respectively.

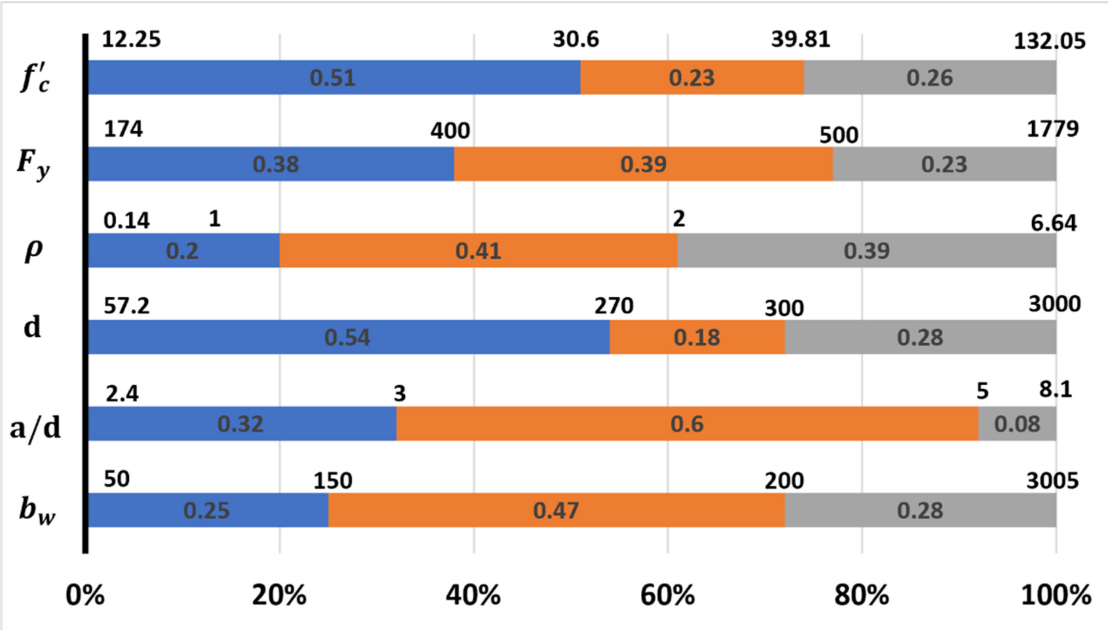

Figure 2. Ranges of the input variables.

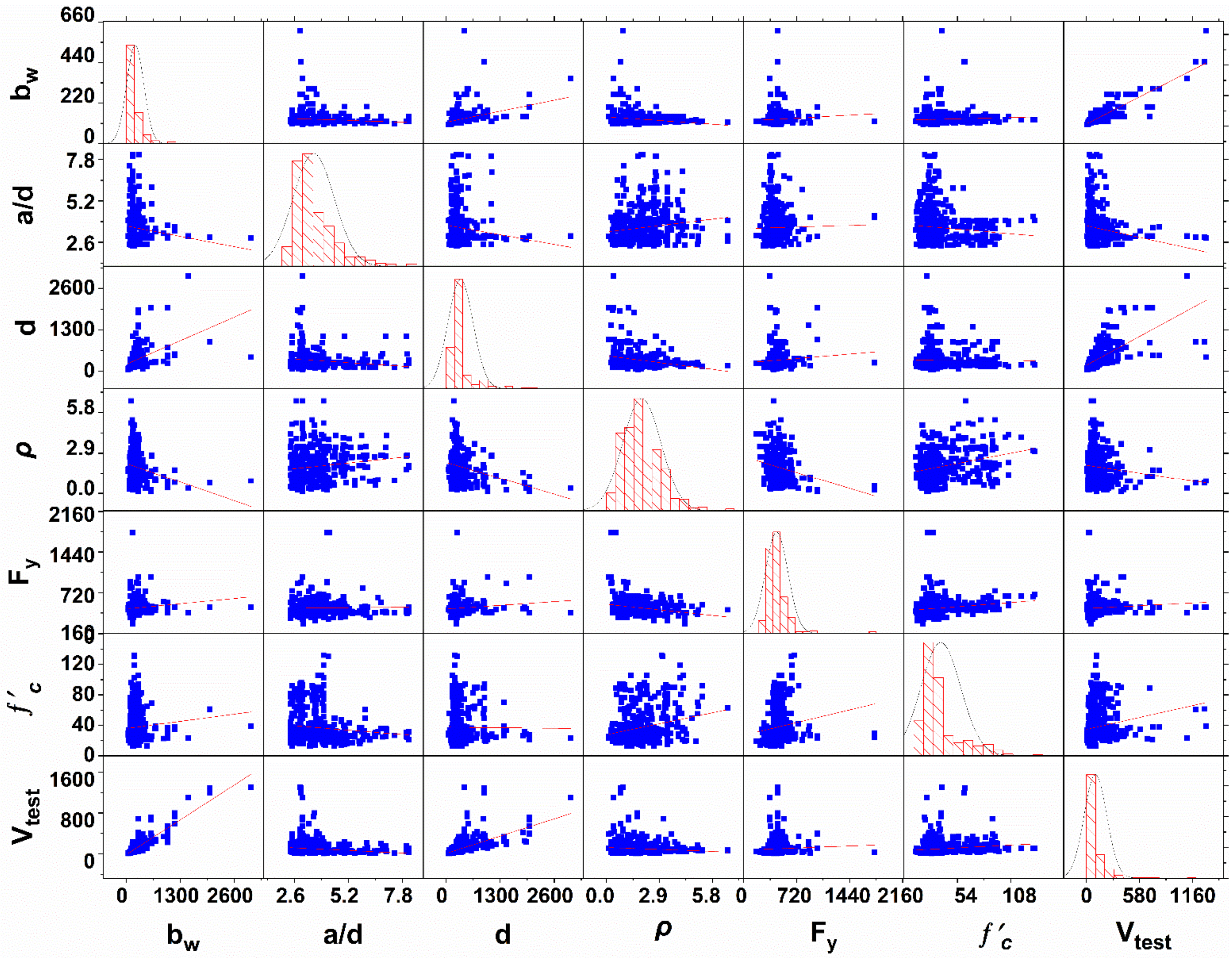

Figure 3. Statistical distribution of the input variables.

3. Gene Expression Programming

In structural engineering, there has lately been a considerable shift toward machine learning and gene expression programming (GEP). GEP can produce reliable data-driven mathematical simulations. As a result, GEP will be utilized to construct a shear strength model for structured concrete beams without shear reinforcement by using machine learning. Ferreira [144] developed the gene expression programming (GEP) process, in which genes are made up of a series of connected chromosomes that resemble trees and include many factors ordered at the first and last points. As demonstrated in Figure 4, such trees form GEP expression trees, which can be translated into a numerical expression.

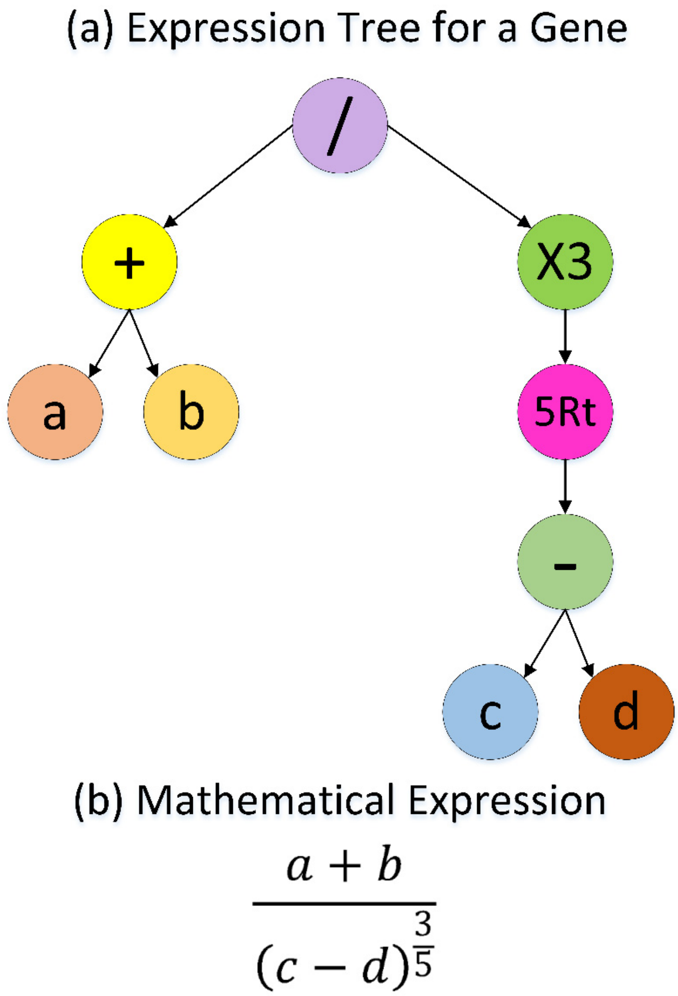

Figure 4. (**a**) Expression tree (ET) form, with (**b**) the equivalent numerical function.

The GEP process entails multiple steps, including constructing and representing chromosomes for the databank, implementing the GEP algorithms, assessing the fitness standards, such as $RMSE$ or R^2, and halting the training procedure if the fitness measures are reached. Therefore, the gene expression must be replicated through variable crossovers or mutation. Figure 4 depicts a GEP algorithm in the form of an expression tree (ET). The process is begun by running the GEP algorithm, which involves creating chromosomes with the required mathematical operations and fitness standards for parameters a, b, c, and d. The chromosomes are next processed and turned into ETs; if the ETs match the fitness criteria, the framework processing ends. However, if the fitness requirements are not met, gene mutation, crossover, or a combination of these operations may be implemented to improve the algorithm accuracy. To make the design applications easier, ETs are eventually transformed into numerical equations.

The empirical databank was processed to construct the GEP framework to forecast the shear strength of SRCB-WS. The database was split into training and testing sets to ensure the constructed model's applicability and validity across various parameters, while avoiding overfitting. The experimental training dataset was utilized solely to build the GEP algorithm, whereas the experimental testing dataset was utilized to confirm that the model satisfies the target accuracy. In this research, 67 percent of the database specimens were randomly selected for training data, whereas only 33 percent were used for the testing set.

To obtain a high accuracy model, the GEP's limitations are outlined in Table 2. The least value of $RMSE$ controls the algorithm analysis; the studying data value was 784. The independent variables had a value of 5, such as b_w, d, f'_c, a/d, ρ_w, and F_y. In addition, the multiplication function linked three genes with an eight-layer-maximum tree depth. The GEP algorithm uses two-thirds of the experimental database to build and validate the shear strength model and one-third of the database to test the model. The genes undergo various operations, such as mutation and crossover, to satisfy the target statistical performance criteria. The algorithm only uses the specified mathematical operations listed in Table 3 to construct the most efficient and simplest GEP model for predicting the shear strength of RC beams without stirrups. The resulting gene sequence is called an expression tree (ETs), representing the raw gene model, which needs a post-processing step to benefit from.

Table 3. GEP settings.

Parameter	Setting
Number of samples	784
Fitness criteria	$RMSE$
Output parameter (shear strength)	1
input parameters	5
Number of genes	3
Mathematical operations	$-, +, \times, \div, x^2, x^3, x^4, x^5, \sqrt[3]{}, \sqrt[4]{}, \sqrt[5]{}$
Depth of tree	8
The mathematical operation to link ETs	Multiplication

Figure 5 demonstrates the established expression form of the GEP model, which contains ET1, 2, and 3, which are multiplied by each other to form the GEP model. The ET1, ET2, and ET3 have tree depths of 7, 6, and 5, respectively. The tree depth is controlled by various factors, such as the accuracy level of the model, the degree of variable complexity, the volume number of the database, the simplicity of mathematical operations, the number of genes, and so on. These ETs are considered to be the raw version of the gene expression model, which needs to be treated and converted into the mathematical model. This process may include simplification and a combination of mathematical operation sets. Table 4 illustrates the physical meaning of the six variables in the established d_0, which represents b_w, while d_1 refers to d, d_2 is a/d, d_3 denotes ρ_w, d_4 is F_y, and d_5 represents f'_c. The predicted shear strength (V_{GEP}) results from multiplying the three ETs. The GEP algorithm, in the form of ETs that forecast the shear force (V_{GEP}), is converted into a numerical expression, as displayed in Equation (3), which is re-arranged to it and is simplified as illustrated in Equation (4).

$$V_{GEP} = \frac{d_0}{\left((d_2)^5/(d_5)^{\frac{1}{3}}\right)^{\frac{4}{20}}} \times \sqrt{\frac{d_5}{d_5/(d_3)^{\frac{5}{8}}}} \times \left(\left(\frac{d_2}{d_4/d_1}\right)^{\frac{1}{3}} - \frac{d_2}{(d_2)^2}\right) \tag{3}$$

$$V_{GEP} = \left(\frac{b_w \times (f'_c)^{0.067} \times (\rho)^{0.31}}{\left(\frac{a}{d}\right)}\right) \times \left(\left(\frac{d \times \left(\frac{a}{d}\right)}{F_y}\right)^{0.33} - \frac{1}{\left(\frac{a}{d}\right)}\right) \tag{4}$$

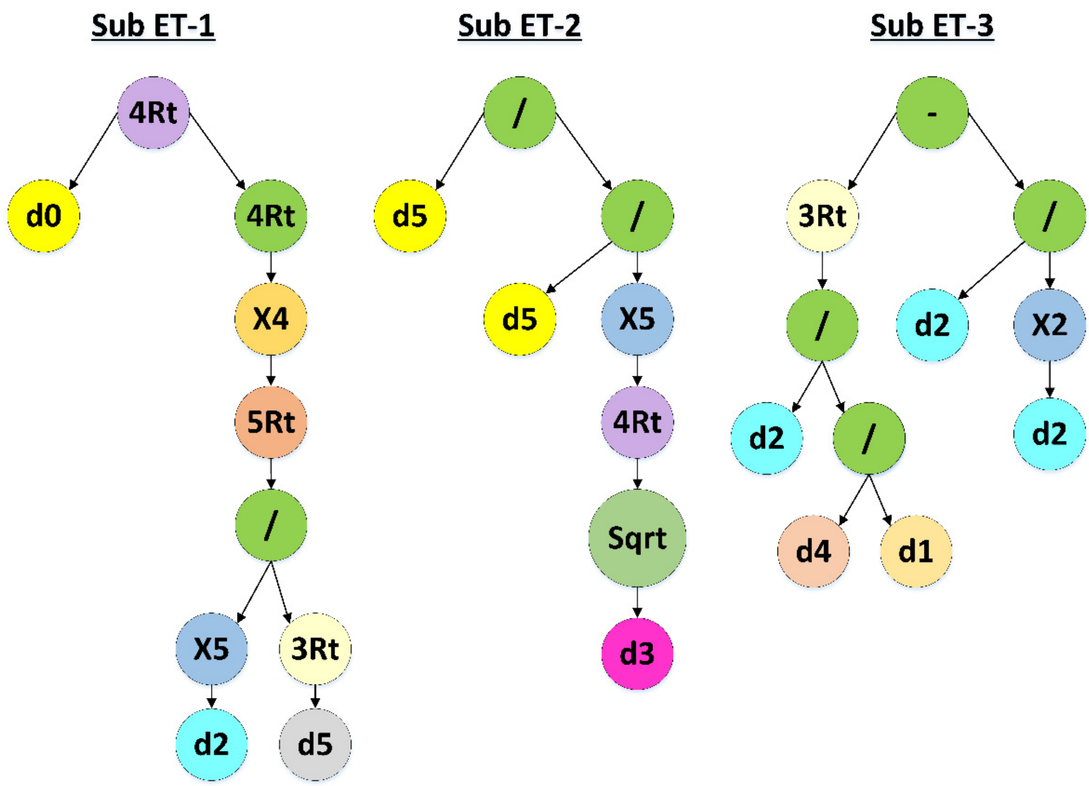

Figure 5. GEP model in ET form.

Table 4. GEP factors.

Parameter to Shear Strength	Symbol	Symbol Explanation
Beam width, mm	d_0	b_w
Effective beam depth, mm	d_1	d
Shear span-to-effective depth ratio	d_2	a/d
Flexural steel ratio, %	d_3	ρ_w
Yield stress of flexural steel, MPa	d_4	F_y
Concrete compressive strength, MPa	d_5	f'_c

Equation (4) shows that variables b_w and d have a positive relation to the predicted shear strength, which follows the mechanics of material principles. However, the variables a/d and ρ_w are nonlinearly related to the predicted shear strength. These relations are also consistent with the results of Lubell et al., 2009 [145], and are in line with Equation (1), where the shear strength is dependent on $(\rho_w)^{1/3}$, and is nonlinearly related to a/d. Moreover, the variables f'_c and F_y are nonlinearly related to the predicted shear strength. These trends are consistent with Equation (1); the Canadian code CSA A23.3 (2004) [146] also reveals high predicted shear strength for beams with a low strain in longitudinal steel rebars.

The GEP models have the advantage of tracking the complex interface of critical variables, which enhances the forecast precision in contrast to other empirical-based models. Though the GEP modeling was effectively utilized in a variety of applications in the field of structural engineering [38,39], it is essential to use GEP modeling in forecasting the SRCB-WS shear strength because of the complexity and heterogeneous components of the shear transfer mechanism. The high amount of the experimental databank helps to train, validate, and test effective GEP algorithms to forecast the shear strength.

On the other hand, more variable features are needed to improve the prediction accuracy of GEP algorithms. Although increasing the number of ETs enhances the modeling performance, model overfitting may occur if an excessive number of ETs is used. Therefore, special caution should be given in processing the GEP algorithm and extra time is needed to efficiently build the GEP model, compared to other machine learning techniques.

To introduce an answer to this difficulty, a closed-form solution is of great interest to practitioners. In this respect, the GEP-based models [38,39] have become more widespread for developing machine learning models that have simple mathematical solutions. Considering the ample number of experimental databases in RC beams, using GEP to forecast the shear strength and other desired performance measures would greatly impact the design of optimized RC beams.

4. Results and Discussion

4.1. Assessment of the Significance of the Features

Pearson's correlation method for determining the relationship between two or more features has been implemented, as shown in Figure 6; the impact of these features on each other and the projected numbers were evaluated, using the shear strength of SRCB-WS given in the database. The correlation of each variable with the predicted shear strength is given a factor ranging between +1 and -1, where a correlation factor close to +1 represents a strong positive linear correlation with the shear strength. In contrast, a factor near to -1 indicates a strong negative linear correlation with the shear strength. On the contrary, a value close to zero indicates a nonlinear relationship with the predicted shear strength. Figure 6 shows that the most influential factors are b_w and d, which have a strong positive linear relation to the experimental shear strength that is compatible with the fundamentals of structural mechanics, whereas the shear force increases if the beams' section area increases. However, a/d and ρ_w had a nonlinear relation to the shear strength in an experiment. These relationships are compatible with the observations of Lubell et al. 2009 [145]. The results are also in line with Equation (1), where the shear strength is dependent on $(\rho_w)^{1/3}$ and the interaction between moment and shear stresses becomes more critical for slender RC beams with an a/d of more than 2.5. This explains why a/d is nonlinearly related to the shear strength of RC beams. In addition, f'_c and F_y have a nonlinear relation to the experimental shear strength. These trends align with the ACI 318-19 equation, which relates to the shear strength multiplied by the concrete compressive strength squared, while the Canadian code CSA A23.3 (2004) [146] shows high shear strength for low strain in longitudinal steel reinforcement. It is worth mentioning that concrete with high compressive strength exhibits brittle behavior, where the strain capacity of concrete declines even if the concrete has high ultimate compressive strength. This is a crucial parameter to set the relationship between concrete compressive strength and the shear strength of RC beams.

Features	b_w	a/d	d	ρ	F_y	f'_c	V_{test}
b_w	1						
a/d	-0.104	1					
d	0.388	-0.142	1				
ρ	-0.203	0.148	-0.255	1			
F_y	0.095	0.022	0.099	-0.233	1		
f'_c	0.075	-0.109	-0.009	0.260	0.177	1	
V_{test}	0.874	-0.158	0.637	-0.116	0.068	0.167	1

Figure 6. Correlation matrix analysis.

A good comprehension of the model's attributes will benefit structural engineers by effectively stimulating and establishing a model to evaluate SRCB-WS. Therefore, an analysis of the important features was performed to determine the significance of each variable involved in anticipating SRCB-WS shear strength. The feature scale plot was used to determine the relative value of every element, as illustrated in Figure 7. In addition, as described in Figure 7, the features were classified in descending order, based on the importance score: d, b_w, ρ_w, F_y, f'_c and a/d. The beam width, depth, longitudinal steel reinforcement ratio, and the concrete compressive strength were considered in the ACI 318-19 equation, shown as Equation (1). However, the feature importance analysis revealed the significant importance of the F_y, and a/d. Therefore, the above two elements were considered in the proposed gene expression model to improve the prediction accuracy of SRCB-WS shear strength.

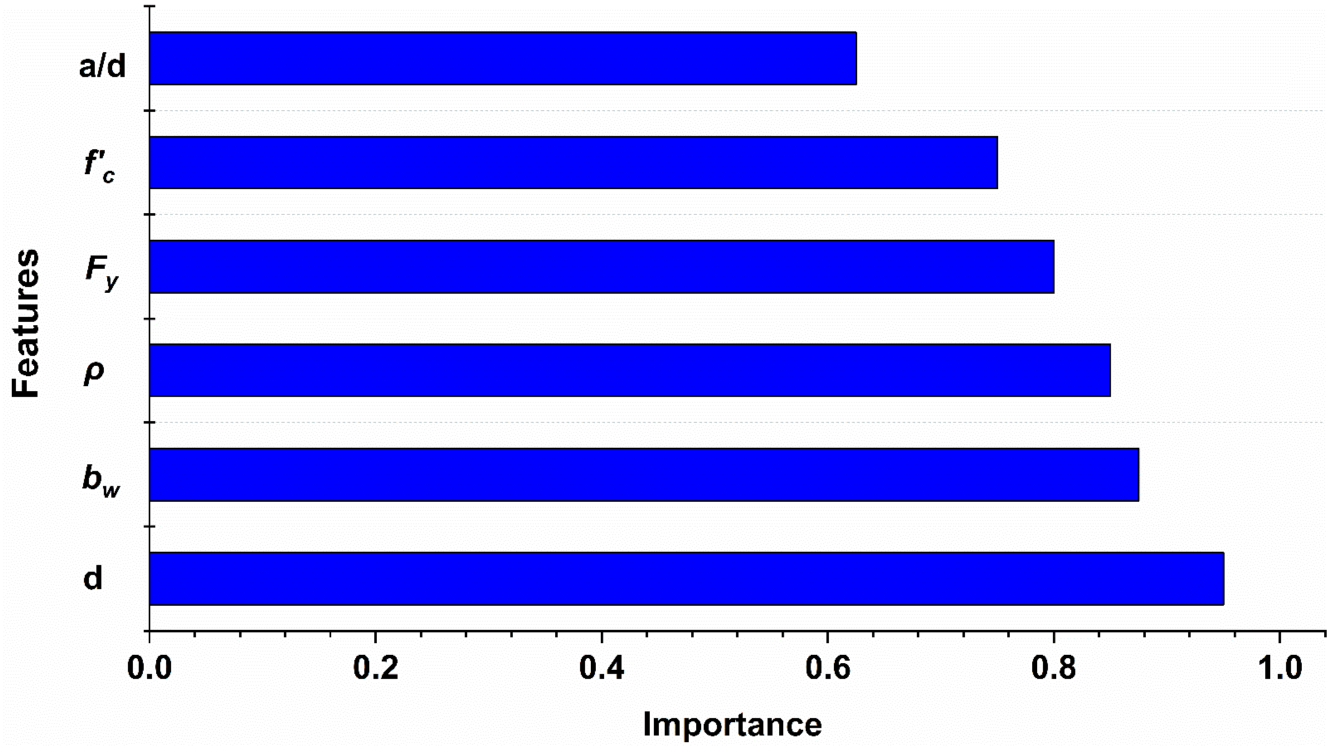

Figure 7. The feature importance of the investigated variables.

4.2. Evaluation of the Prediction Accuracy

After selecting the most important features and establishing the shear strength model, it is critical to assess the effectiveness of the proposed algorithm. Thus, the suggested model's efficiency was assessed using three different metrics, such as $RMSE$, $MAPE$, MAE, and R^2. The mathematical definition of each statistical factor is presented in Equations (5)–(8):

$$MAE = \frac{1}{m}\sum_{i=1}^{m}\left|Y_i - \overline{Y_i}\right| \tag{5}$$

$$RMSE = \sqrt{\frac{1}{m}\sum_{i=1}^{m}\left(Y_i - \overline{Y_i}\right)^2} \tag{6}$$

$$MAPE = \frac{1}{m}\sum_{i=1}^{m}\left|\frac{Y_i - \overline{Y_i}}{Y_i}\right| \times 100 \tag{7}$$

$$R^2 = 1 - \frac{\sum_{i=1}^{m}\left(Y_i - \overline{Y_i}\right)^2}{\sum_{i=1}^{m}\left(Y_i - \overline{Y}\right)^2} \tag{8}$$

where Y_i represents the real (measured) quantities of the shear strength for SRCB-WS, $\overline{Y_i}$ symbolizes the predicted shear strength, $\overline{Y}$ reflects the average of Y_i, and m represents the total number of datasets used. The model accuracy will be increased if the R^2 value approaches 1, as well as if the $RMSE$, MAE, and $MAPE$ measures approach 0 [147]. The comparison of the effectiveness of the gene expression-based model is assessed with Equation (1), while Equation (2) is used to indicate the shear strength of SRCB-WS, as executed and summarized in Table 5.

Table 5. Performance measure comparison of *ML* models.

Performance Metrics	Prediction Models		
	Equation (1)	Gene Expression	Equation (2)
MAE	28.5	21.5	27.98
RMSE	47.5	35.2	82.4
MAPE	30.8	29.4	23.9
R^2	24.92	25.95	88.6

The comparison results show that the gene expression model has a high value of $R^2 = 95\%$, which is 3% more than Equation (1) and 6.4% more than Equation (2). The high accuracy of the suggested gene expression model is possible because the model is more comprehensive in terms of the critical variables, compared to the other models. It is worth mentioning that Equations (1) and (2) do not consider the effect of F_y and a/d, which have significant importance, as shown in Figure 7. Furthermore, Equation (2) considers the effect of the maximum size of the aggregate, which is not commonly reported in the literature. The above equation assumes the maximum size of aggregate to be taken as 19 mm, which may undermine the accuracy of the predicting model; the R^2 for Equation (2) was 88.6, which is lower than the performance of the other two equations. In addition, the proposed gene expression model reveals lower MAE, $RMSE$, and $MAPE$ values than the predictions of Equations (1) and (2). These three statistical dimensions reveal the high accuracy and lower scatteredness of the proposed GEP model. Several factors improved the accuracy of the proposed shear strength model, such as the high amount of dataset, the selection of the most significant variables to be included in the model, and the use of a sophisticated algorithm that traces the complex interactions between the considered variables. Therefore, the gene expression model offers a better fit for the actual value of shear strength.

4.3. Results of Model Prediction

Figure 8 depicts a scatter plot of SRCB-WS experimental shear strength versus the anticipated shear strength. using Equation (1), Equation (2), and the gene expression model. The trend of prediction by the gene expression equation is the nearest to the perfect prediction line (the green dashed line) in Figure 8. Equation (2) tends to overestimate the shear strength of SRCB-WS. This result is to be anticipated since the Equation does not account for critical factors such as the a/d and F_y. On the other hand, Equation (1) underestimates the shear strength of SRCB-WS because this equation also does not account for important factors and uses an empirical variable (a_g) that considers the effect of the maximum size of the aggregate. Most experiments included in the literature review do not report this information. Therefore, Equation (1) assumes the a_g value should be taken as 19 mm. The inclusion of the maximum size of the aggregate parameter reduces the shear strength in the prediction model. The R^2 of Equation (1) equals 88.6, which is the lowest value compared to the other two models. Overall, the prediction results indicate the superior performance of the gene expression model over Equations (1) and (2). In addition, Figures 9 and 10 show the effect of various variables such as a/d, d, ρ_w, f'_c, F_y, and b_w on the prediction of Equations (1) and (2) and the gene expression model. The shear strength predictions of Equations (1) and (2) reveal high scatteredness compared to the proposed Gene Expression model. This shows that the suggested model is more powerful and considers the most important variables influencing SRCB-WS shear strength. The a/d is exponentially related to the predicted shear strength using Equation (1). This relation is also linearly predicted for Equation (2). However, the correlation is close to a constant line for the GEP model. Similarly, the predicted shear strength by Equations (1) and (2) exponentially decays with d and b_w, which indicates that the size effect of deep beams is not accurately predicted by these two equations. Although the longitudinal reinforcement ratio and concrete compressive strength are considered in the three models, Equations (1) and (2) have a high prediction variance compared to the GEP model.

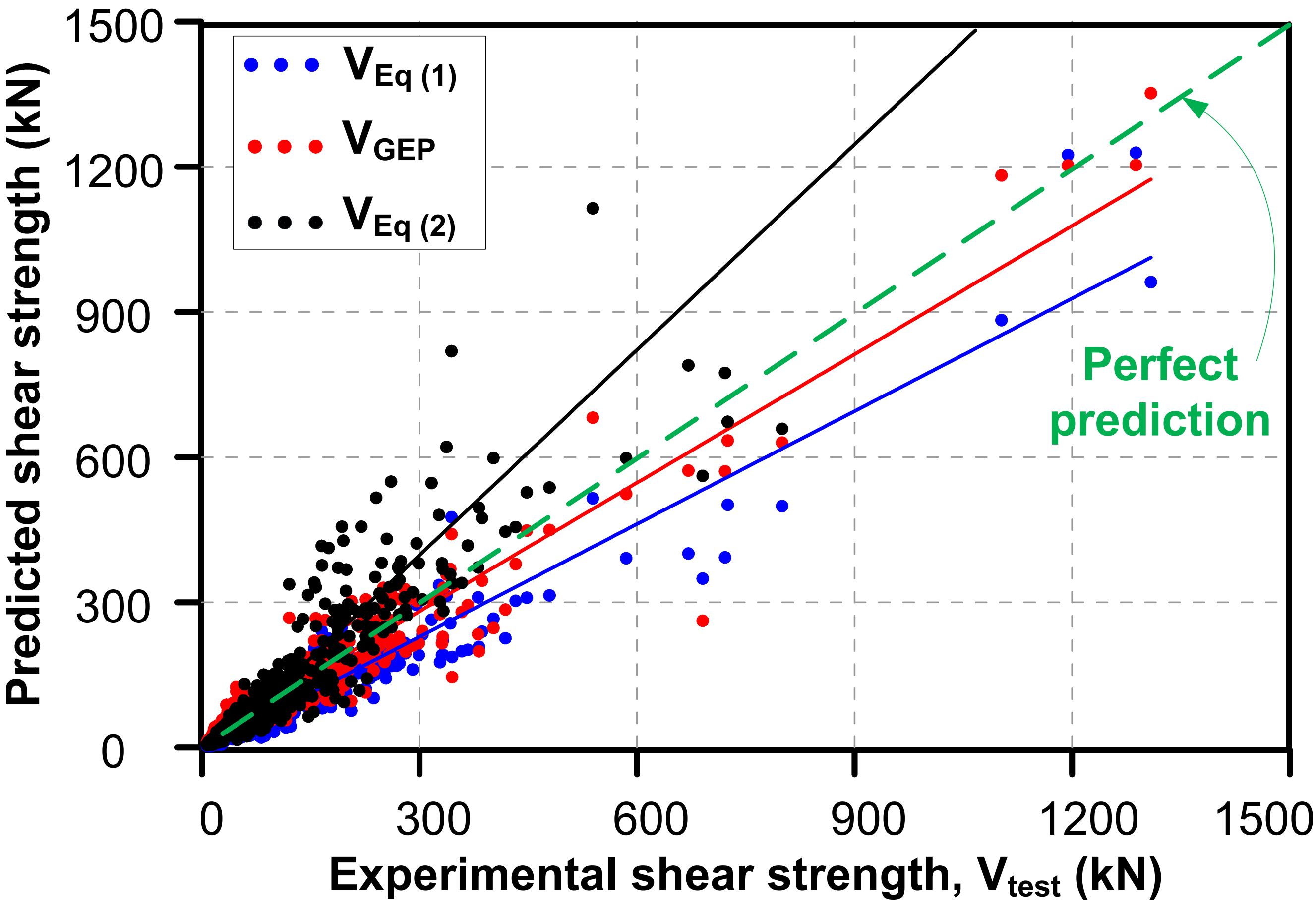

Figure 8. Prediction of the shear strength of the beams in the database using Equations (1) and (2), and the gene expression model.

Based on the analysis in this research, the proposed gene expression model revealed superior performance compared to the up-to-date and widely used ACI 318-19, Equation (1), other available equations in the literature, and Equation (2). The current study encourages researchers to deploy sophisticated machine learning tools to accurately estimate the complex shear strength of SRCB-WS since the interaction of various variables influences the shear strength. However, simple models such as the one in Equation (2) cannot accurately predict the shear strength; Equation (2) is based on linear gene expression, which may not capture the nonlinear interaction of various variables.

It is worth mentioning that the developed model allows the user to set the values for the shear span ratio (a/d) and the yield stress of longitudinal steel rebars (F_y), which are one-of-a-kind features. Additionally, the results show that the model has excellent efficiency in enhancing the proposed model accuracy, compared with the ACI 318-19 code.

As the currently available models within the literature lack comprehensiveness regarding the shear strength evaluation., the current research aims to fill the gap by introducing a comprehensive model that is capable of providing accurate shear value estimations.

Features such as b_w, d, f'_c, a/d, ρ_w, and F_y play a critical role in shear strength evaluation, while the findings of the current study have proven that a/d and F_y are influential attributes. Thus, those two key factors might not be relaxed and may need to be explicitly considered within the shear evaluation model.

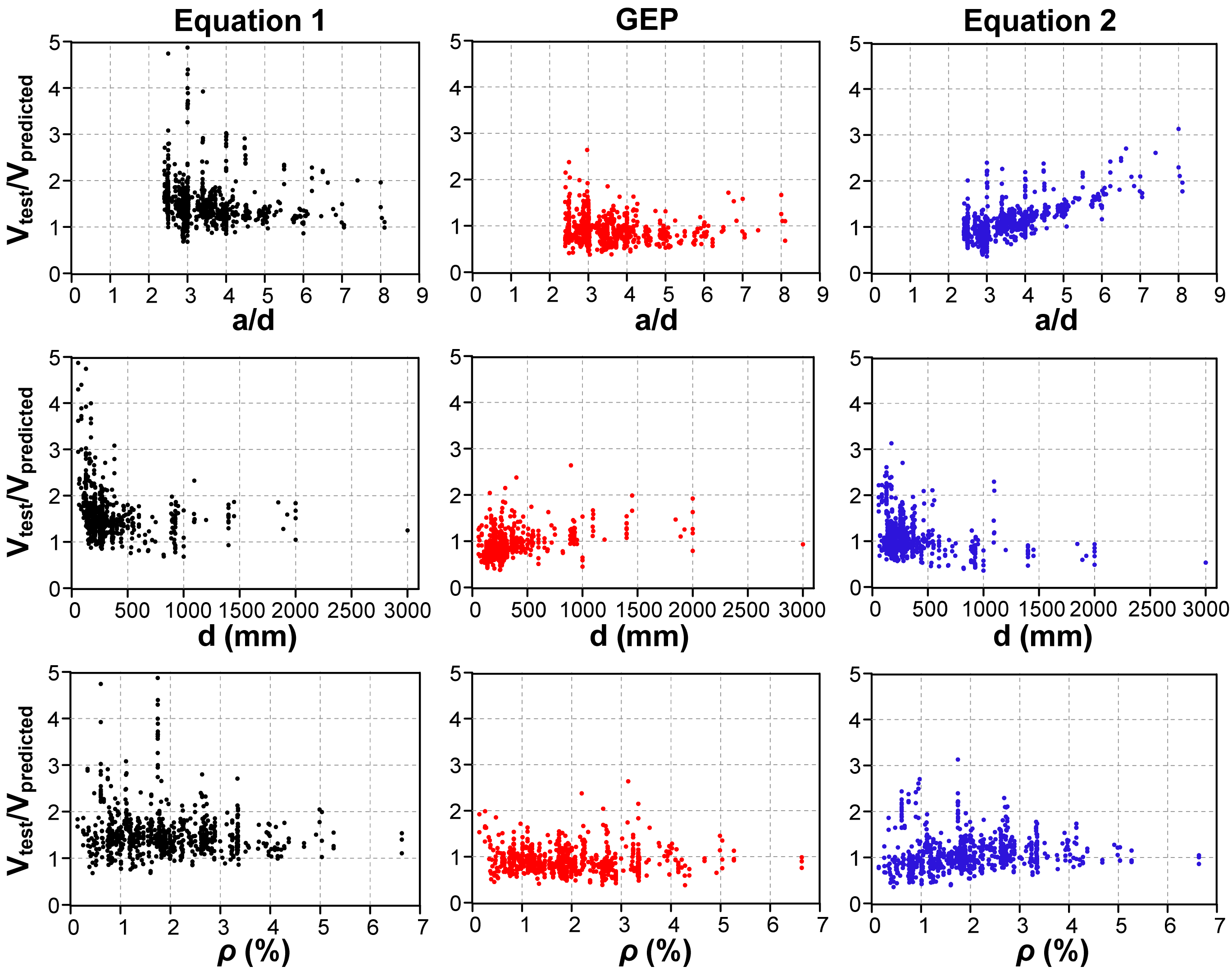

Figure 9. Effect of a/d, d, and ρ_w on the prediction of Equations (1) and (2), and the gene expression model.

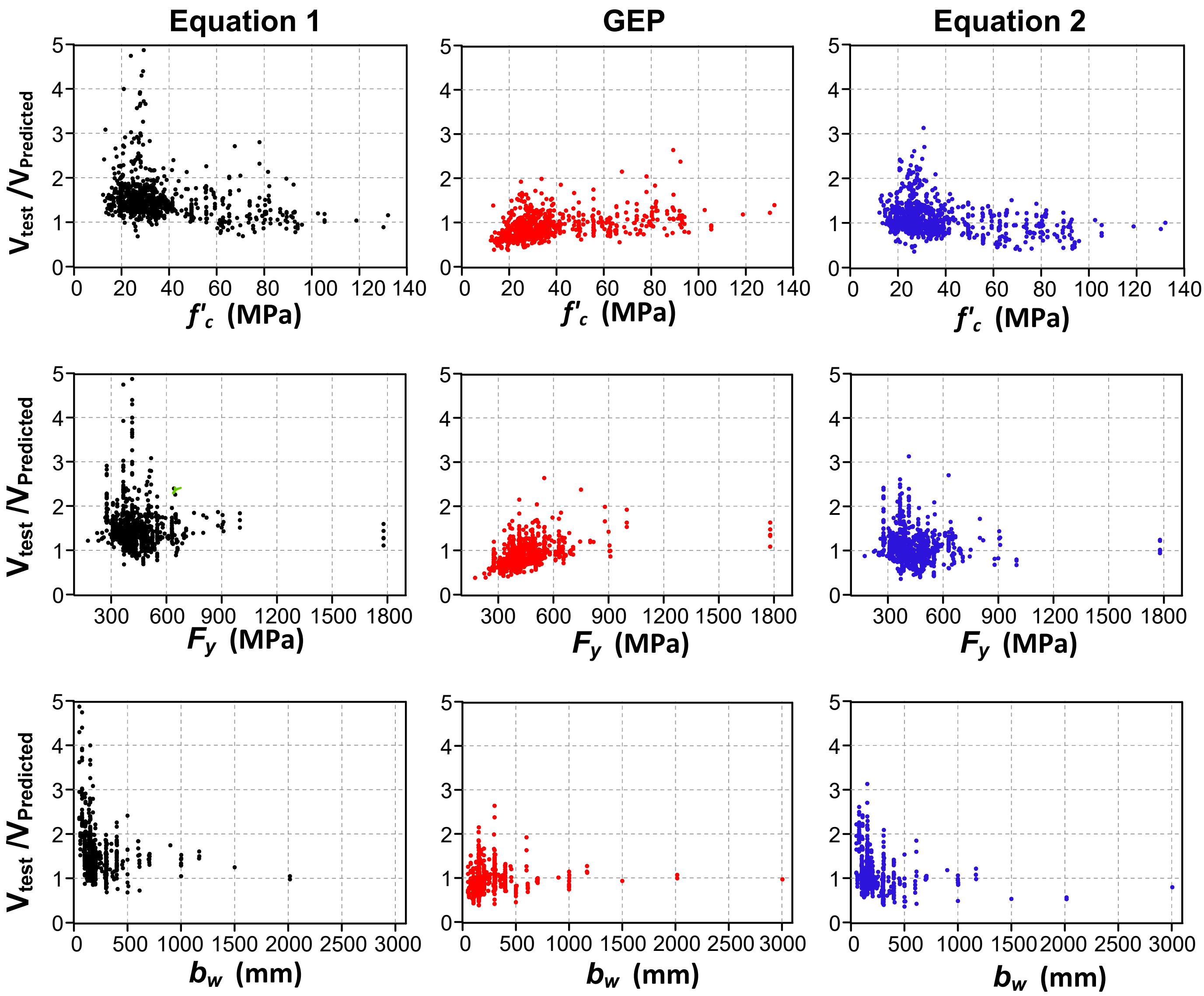

Figure 10. Effect of f'_c, F_y, and b_w on the predictions of Equations (1) and (2), and the gene expression model.

5. Summary and Conclusions

Cutting-edge technological tool utilization plays a vital role in developing robust frameworks that can enhance the decision-making process within the construction industry arena. Such a machine and deep learning-based technological tools are vital for providing a robust, fast, accurate, and flexible forecasting framework for the prediction of the shear strength of slender reinforced concrete beams without stirrups (SRCB-WS). However, machine learning algorithms are not closed-form equations that can be used to predict the desired outputs. The current study investigates the use of gene expression (GEP) algorithms to improve the efficiency of determining the shear strength of SRCB-WS. A closed-form solution gene expression-based model was trained and evaluated using a dataset of 784 specimens.

The proposed model considers various features, such as b_w, d, f'_c, a/d, ρ_w, and F_y. The results revealed that the variables of d, b_w, and ρ_w are the most significant factors in estimating the SRCB-WS shear strength. The statistical performance metrics of the GEP model, such as the MAE, $RMSE$, $MAPE$, and R^2, show that the proposed GEP model has superior accuracy and comprehensiveness regarding various parameters than Equation (1) (ACI 318-19) and Equation (2). The R^2 value of the predicted shear strength using the proposed GEP equals 95%, while the other two models have R^2 values of 92% and 88.6% for

Equations (1) and (2), respectively. The proposed GEP accurately predicts the shear strength of SRCB-WS, while Equation (1) underestimates and Equation (2) overestimates the shear strength, as the GEP model considers the most critical variables and uses a sophisticated algorithm for simulating the contribution of the dependent variables.

The current study's findings represent a solid base for practitioners to evaluate shear strength smoothly and precisely. The utilization of emerging machine learning-based forecast algorithms is matchless in providing research that supports construction automation. The authors expect the developed prediction model to provide its end users with new insights and a comprehensive understanding of how numerous concrete characteristics affect the shear strength value.

As a future research recommendation, data collection and recording procedures might be improved, as comprehensive datasets are vital to forecast shear strength correctly. Although this study explored the experimental database of slender beams ($a/d \geq 2.5$) without stirrups, further studies are needed to investigate the estimation of the shear strength of short beams ($a/d < 2.5$), as well as the effect of adding steel or synthetic fibers, which will be of great interest in future studies to quantify the contribution of bridging fibers to the shear strength. Thus, improved data collection processes and tools are encouraged to allow improved data recording, categorizing, and filtering processes to ensure the development of more accurate findings. Moreover, sophisticated ML-based algorithms are recommended to produce better prediction results, wherein more holistic prediction modeling might be conducted according to further advanced algorithms after undergoing fusion with technological tools (e.g., building information modeling (BIM), digital twins, the Internet of Things (IoT), and blockchain) which might be utilized to automatically forecast the shear strength of various types of reinforced concrete beams.

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