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Computational Hybrid Machine Learning Based Prediction of Shear Capacity for Steel Fiber Reinforced Concrete Beams

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Abstract: Understanding shear behavior is crucial for the design of reinforced concrete beams and sustainability in construction and civil engineering. Although numerous studies have been proposed, predicting such behavior still needs further improvement. This study proposes a soft-computing tool to predict the ultimate shear capacities (USCs) of concrete beams reinforced with steel fiber, one of the most important factors in structural design. Two hybrid machine learning (ML) algorithms were created that combine neural networks (NNs) with two distinct optimization techniques (i.e., the Real-Coded Genetic Algorithm (RCGA) and the Firefly Algorithm (FFA)): the NN-RCGA and the NN-FFA. A database of 463 experimental data was gathered from reliable literature for the development of the models. After the construction, validation, and selection of the best model based on common statistical criteria, a comparison with the empirical equations available in the literature was carried out. Further, a sensitivity analysis was conducted to evaluate the importance of 16 inputs and reveal the dependency of structural parameters on the USC. The results showed that the NN-RCGA ($R = 0.9771$) was better than the NN-FFA and other analytical models ($R = 0.5274$ – 0.9075). The sensitivity analysis results showed that web width, effective depth, and a clear depth ratio were the most important parameters in modeling the shear capacity of steel fiber-reinforced concrete beams.

Keywords: civil engineering; structural engineering; shear capacity; fiber reinforced concrete beams; machine learning; optimization techniques

1. Introduction

Concrete is the most popular material in the field of construction [1–3]. However, one of the significant disadvantages of concrete is the weakness of tensile strength and shear resistance. Many studies have been performed to overcome this weakness by focusing on additional components to reinforce concrete [4]. Over the decades, fibers have gained tremendous attention from the research community as a potential improvement to the mechanical properties of concrete [5]. A common type of fiber such as carbon, synthetic, vitreous, or steel is mixed into concrete to enhance the concrete's properties [6]. It is worth mentioning that, since 1972, an important number of studies have been conducted that aimed to replace conventional shear reinforcement with steel fibers (SFs) in reinforced and prestressed concrete [7]. Initially, SFs were used to control plastic and drying shrinkage in concrete. Further studies showed that the addition of SFs in concrete strongly increases

flexural toughness and tensile strength, the capacity in absorbing energy, ductile behavior, cracking reduction, and improvement of the shear behavior when reinforced [8–10]. For this reason, the use of steel fiber-reinforced concrete (SFRC) has become extensively popular in different civil engineering applications such as tunnel shells, concrete sewer pipes, higher upper layers, and slabs of large industrial buildings [4]. Despite many advantages, designing SFRC structures still faces challenges, as it is difficult to determine critical shear capacity by conventional methods [11–13].

In the literature, various experimental and numerical studies have been performed on SFRC in order to investigate shear strength capacity [10]. Özcan et al. [8] carried out an experimental and finite element modeling using ANSYS software (Version 15, Ansys Inc., Canonsburg, Pennsylvania, United States, 2014) to analyze the ultimate behavior of SFRC beams. Nino Spinella et al. [14] provided a simple physical design model for predicting the shear strength of concrete beams containing fibers, taking into account the width of cracks and shear crack slips. Additionally, an equation based on the basic principle of mechanics has been proposed to estimate the shear strength of SFRC beams using the slenderness ratio [15]. Last but not least, numerous shear tests on prismatic beams have been performed to provide useful information about SFRC [16]. In general, many empirical formulations have been proposed in the literature to estimate SFRC shear strength over the last four decades. However, there is a significant difference between existing experimental results and prediction formulations due to the accuracy and uniformity of the proposed equations [15]. Moreover, mechanical simulations (e.g., the finite element method [17]) or laboratory experiments can only be applied in limited cases. Since laboratory experiments are usually costly and time-consuming, predicting such behaviors remains challenging and requires a robust numerical model for quicker and better results, such as machine learning (ML) approaches [10,18].

In the last two decades, artificial intelligence-based machine learning approaches have been widely used in civil engineering applications [19–31]. As an example of structural engineering, Kiani et al. [32] applied ML techniques, including support vector machines and neural networks, to derive seismic fragility curves. In a series of papers, Mangalathu et al. proposed various machine learning methods such as neural networks and random forest for tracking the damage of bridge portfolios [33], as well as assessing seismic risks of skewed bridges [34]. In terms of structural failure, typical failure modes of reinforced concrete columns such as flexure, flexure-shear, and shear were investigated by Mangalathu et al. [35,36] using decision trees, support vector machines, and neural networks. In terms of structural uncertainty analysis, various published works by E. Zio should be consulted [37–39]. Dao et al. [1] used artificial intelligence approaches (the Adaptive Network-Based Fuzzy Inference System (ANFIS), Artificial Neural Network (ANN), and Support Vector Machine (SVM)) to predict the compressive strength of geopolymers concrete. Ly et al. [40,41] used hybrid artificial intelligence models (Particle Swarm Optimization (PSO) combined with ANFIS - PSOANFIS and Genetic Algorithm (GA) combined with ANFIS - GAANFIS) to predict the critical buckling load of columns or the buckling damage of steel columns under axial compression. Using hybrid artificial intelligence approaches, Dao et al. [42] successfully predicted the compressive strength of geopolymers concrete with steel slag as both coarse and fine aggregates. ML algorithms have also been used to deal with mechanical engineering problems involving the prediction of structural element properties under various solicitations. For instance, Bimal et al. [43] presented the development of neural network (NN) models to predict the shear strength of SFRC beams using various input parameters. However, NN models usually require many parameters to establish the structure of an NN, such as transfer functions and, in particular, the numbers of neurons and hidden layers. Genetic programming (GP) could be considered as an alternative modeling tool to predict the behavior of structural problems [44]. Additionally, linear genetic programming (LGP), a subset of GP using a linear structure, has been utilized to derive empirical prediction model that can estimate the shear capacity of SFRC beams without stirrups [10]. Finally, Yaseen et al. [45] developed a support vector regression algorithm optimized with particle swarm optimization to predict the shear strength of SFRC using dimensional and material properties as input parameters. Even though ML approaches have been applied in several

studies involving SFRC, more effective and accurate approaches should be developed and investigated for different datasets and experimental results. In addition, the importance of input variables used in the ML models should be carried out to select the suitable factors for prediction.

The main objective of this paper is to develop artificial intelligence-based models for the prediction of the ultimate shear capacity (USC) of SFRC and to discuss the influences of input variables. To this aim, two hybrid ML models were constructed that combined NNs with two distinct optimization techniques (i.e., the Real-Coded Genetic Algorithm (RCGA) and the Firefly Algorithm (FFA)): the NN-RCGA and the NN-FFA. A database of 463 samples, including three groups of input variables (geometry of the beam, concrete mixture, and fiber information) and an output variable (USC), was collected and used to generate the training (70% data) and testing (30% data) datasets. Statistical measures (e.g., Pearson correlation coefficient (R), root mean squared error (RMSE), and mean absolute error (MAE)) were computed to evaluate the performance of the two proposed ML algorithms. In addition, comparisons between the two models and existing empirical equations were performed. Sensitivity analysis using Individual Conditional Expectation (ICE) and Partial Dependence Plot (PDP) investigations was carried out to reveal the importance of different input variables.

2. Significance of the Subject

Many studies have been conducted in the literature regarding the addition of fibers into concrete structures in order to enhance their mechanical properties, especially the ultimate shear capacity. Due to the non-linear behavior between the final response with concrete components, the geometry of concrete beams, and the fiber characteristics, it is difficult to predict the ultimate shear capacity of SFRC beams correctly. Such difficulty might induce costly and time-consuming laboratory or even field experiments. To overcome this problem, ML algorithms such as NNs can contribute as reliable modeling tools to accurately predicting the USCs of SFRC beams. In addition, exploring the importance of input variables using sensitivity analysis can contribute to a better knowledge of the factors affecting the USCs of SFRC beams, which could further recommend promising procedures for experimental researches and facilitate laboratory experiments. Moreover, this numerical prediction model was able to calculate the USC of a single SFRC in less than a second using any personal computer (the function is provided as Supplementary Materials). Therefore, the proposed model could be a potential tool for researchers and structural engineers in estimating the USCs of SFRC accurately (i) within the ranges of values used in this study for the input variables, and (ii) with a reduced time and cost in developing other numerical schemes (e.g., finite element models).

3. Materials and Methods

3.1. Dataset Preparation

In this study, 463 experimental data on SFRC beams—including input variables (represented by geometry of beams, concrete mixtures, and fiber information) and an output variable (ultimate shear strength of the beams)—were gathered from the available database recently constructed by Lantsoght [46] (the database is available in the public domain in xlsx file format). Table 1 summarizes the database, including the number of data collected in each reference and their percentages of proportion. Table 2 indicates the classification and proportion of each cross-section type, fiber type, and failure mode.

Table 1. Database collection.

No	Reference	Number of Data	Proportion of Data (%)	No	Reference	Number of Data	Proportion of Data (%)
1	Abdul-Zaher et al. [46]	3	0.65	32	Li and Ward [47]	22	4.75
2	Adebar et al. [48]	6	1.30	33	Lim and Oh [49]	2	0.43
3	Amin and Foster [50]	2	0.43	34	Lim et al. [51]	7	1.51
4	Aoude and Cohen 2014 [52]	4	0.86	35	Lima-Araujo et al. [53]	2	0.43
5	Aoude et al. [54]	4	0.86	36	Manju et al. [55]	6	1.30
6	Arslan et al. [15]	9	1.94	37	Mansur et al. [56]	9	1.94
7	Ashour et al. [57]	18	3.89	38	Minelli and Plizzari [58]	9	1.94
8	Bae et al. [12]	1	0.22	39	Narayanan and Darwish [59]	37	7.99
9	Batson et al. [60]	43	9.29	40	Noghabai [61]	15	3.24
10	Casanova and Rossi [62]	2	0.43	41	Pansuk et al. [11]	2	0.43
11	Casanova et al. [63]	3	0.65	42	Parra-Montesinos et al. [64]	10	2.16
12	Chalioris and Sfiri 2011 [65]	1	0.22	43	Qissab and Salman [66]	11	2.38
13	Cho and Kim [67]	12	2.59	44	Randl et al. [68]	5	1.08
14	Cohen and Aoude 2012 [69]	1	0.22	45	Roberts and Ho [70]	6	1.30
15	Cucchiara et al. [71]	4	0.86	46	Rosenbusch and Teutsch [72]	19	4.10
16	Danygier and Savir [73]	2	0.43	47	Sahoo and Sharma [74]	7	1.51
17	Dinh et al. [75]	19	4.10	48	Sahoo et al. [76]	3	0.65
18	Dupont and Vandewalle [77]	20	4.32	49	Shoaib [78] (REF prob)	3	0.65
19	Furlan and de Hanai [79]	7	1.51	50	Shoaib and Lubell [80]	2	0.43
20	Gali and Subramaniam [81]	2	0.43	51	Singh and Jain [82]	32	6.91
21	Greenough and Nehdi [83]	9	1.94	52	Spinella et al. [84]	2	0.43
22	Huang et al. 2005 [85]	1	0.22	53	Swamy and Bahia [86]	5	1.08
23	Hwang et al. [87]	7	1.51	54	Swamy et al. [88]	7	1.51
24	Imam et al. [89]	3	0.65	55	Tahenni et al. [90]	9	1.94
25	Jindal [91]	7	1.51	56	Tan et al. [92]	5	1.08
26	Kang et al. [93]	5	1.08	57	Zamanzadeh et al. [94]	3	0.65
27	Kang et al. [95]	2	0.43	58	Zarrinpour and Chao [96]	5	1.08
28	Kim et al. [97]	2	0.43	59	Sharma [98]	1	0.22
29	Krassowska et al. [99]	2	0.43	60	Shin et al. [100]	6	1.30
30	Kwak et al. [101]	4	0.86	61	Zhao et al. [102]	4	0.86
31	Kwak and Suh [103]	4	0.86		Total	463	100.00

Table 2. Information on the database concerning cross-section type, fiber type, and failure mode.

Cross-Section	Number of Data	Proportion (%)	Fiber Type	Number of Data	Proportion (%)	Failure Mode	Number of Data	Proportion (%)
Rectangular	427	92.22	Hooked	282	60.91	Diagonal tension	16	4.06
T-type	18	3.89	Crimped	109	23.54	Diagonal tension + shear tension	9	2.28
I-type	7	1.51	Straight smooth	19	4.10	Diagonal tension + shear tension + shear compression	23	5.84
Non-prismatic	11	2.38	Hooked + straight	7	1.51	Shear	258	65.48
			Brass-coated high strength steel	12	2.59	Shear compression + shear tension	2	0.51
			Chopped with butt ends	1	0.22	Shear compression + shear tension + yielding of steel	3	0.76
			Corrugated	3	0.65	Shear tension + diagonal tension	4	1.02
			Flat	3	0.65	Shear tension + diagonal tension + bond degradation near support	3	0.76
			Flat end	6	1.30	Shear tension + diagonal tension + tension steel yielding	6	1.52
			Mill-cut	4	0.86	Shear, shear-compression	15	3.81
			Recycled	3	0.65	Shear-compression, flexure	1	0.25
			Round	13	2.81	Shear-flexure	48	12.18
			Straight mild steel	1	0.22	Shear-tension	6	1.52

The fiber types in the present dataset contained: hooked (60.9%), crimped (23.5%), straight smooth (4.10%), hooked + straight (1.51%), brass-coated high strength steel (2.59%), chopped with butt ends (0.22%), flat end (1.30%), flat (0.65%), corrugated (0.65%), mill-cut (0.86%), recycled (0.65%), round (2.81%), and straight mild steel (0.22%).

As highlighted in Table 3, the database included four categories of variables: geometry of beams, concrete mixture, fiber information, and ultimate shear capacity. In the geometry of beams category, the considered inputs were web width, height of cross-section, effective depth, span length, shear span, clear shear span, reinforcement ratio, yield strength of reinforcement steel, depth ratio, and clear depth ratio. In the concrete mixture category, the considered inputs were maximum aggregate size and concrete cylinder compressive strength. In the fiber information category, the considered inputs were fiber volume fraction, length/diameter ratio of fibers, tensile strength of fibers, and fiber factor. In the final category, the considered output consisted of the ultimate shear capacity of the beams. These parameters are detailed according to notation, unit, role, and statistical analysis (min, max, average, standard deviation, and coefficient of variation) in Table 3. It can be seen that all the variables exhibited a significant coefficient of variation, ranging from 30% (yield strength of reinforcement ratio) to 76.43% (ultimate shear capacity). Such statistical behavior allows, in a positive way, the development of ML algorithms by covering a broad zone of data values. In addition, the data used in this work are randomly divided into two sub-datasets using a uniform distribution, where 70% of the data is used for training the ML models, and the remaining 30% data serves as validation. The training dataset is scaled to the range of [0, 1] in order to minimize the bias between variables. The scaling parameters of the training dataset are also employed for scaling the corresponding testing dataset so as to prevent pre-correlation. For illustration purposes, Figure 1 displays the correlation graphs and histograms of all input variables versus the ultimate shear strengths of SFRC beams in the present database. However, it should be noticed that this present study did not consider fiber type or failure mode as inputs. Further investigation is needed for evaluating those two parameters.

3.2. Neural Network (NN)

In recent decades, the use of NNs has become popular in civil engineering applications [104]. Neural networks belong to a class of machine learning algorithms, and are patterned after the biological process of the human brain [22,105–108]. Input data conditions do not need to be defined while using an NN algorithm. Techniques based on NNs are especially powerful for finding solutions to complex problems that traditional mathematical models have difficulty solving [109]. NNs consist of many node functions that receive, process, and transfer information from one node to another. The processing units in NNs are mainly grouped into input, hidden, and output layers. The main objective of the input layer is to receive, initialize, and transfer input data to the next layer. The hidden layers contain node functions that process and train the model using the given input data. [110].

The NN model exhibits crucial profits not found in traditional computational methods. Hypotheses or constraints are not necessary when optimizing NNs [111–113], and they are also able to analyze and explore complex (even nonlinear) relationships in data [114–116]. From a computational point of view, NNs are powerful at solving high dimensional problems because of their processing capabilities in parallel [19,117,118]. Based on the various advantages mentioned previously, the NN model has been employed in the past for predicting the failures of structural elements [32–36,119–122].

Table 3. Initial statistical analysis of the database.

Data Type	Variable	Notation	Unit	Role	Min	Q ₂₅	Average	Q ₇₅	Max	StD	CV (%)
Geometry	Web width	b_w	mm	Input	50.00	100.00	140.58	152.40	310.00	50.75	36.10
	Height of cross-section	H	mm	Input	100.00	180.00	284.75	303.60	1000.00	140.19	49.23
	Effective depth	d	mm	Input	85.25	140.00	245.37	266.00	910.00	126.79	51.67
	Span length	l_{span}	mm	Input	204.00	1160.00	1816.70	2220.00	5600.00	888.97	48.93
	Shear span	a	mm	Input	102.00	392.50	713.64	875.00	2800.00	438.39	61.43
	Clear shear span	a_v	mm	Input	52.40	337.50	639.20	775.00	2700.00	418.44	65.46
	Reinforcement ratio	ρ	%	Input	0.37	1.72	2.43	3.09	5.72	0.01	41.39
	Yield strength of reinforcement steel	f_y	MPa	Input	275.86	420.00	469.96	530.00	900.00	98.59	20.98
	Depth ratio	a/d	-	Input	0.70	2.31	2.93	3.50	6.00	0.98	33.66
Concrete mix	Clear depth ratio	a_v/d	-	Input	0.41	2.00	2.60	3.17	5.95	0.95	36.56
	Maximum aggregate size	d_{aggmax}	mm	Input	0.40	9.55	10.66	13.00	22.00	5.11	47.93
	Average measured concrete cylinder compressive strength	f_c'	MPa	Input	9.77	33.22	47.98	54.10	215.00	24.17	50.37
Fiber	Fiber volume fraction	V_f	%	Input	0.20	0.50	0.88	1.00	4.50	0.56	63.30
	Length/diameter ratio of fibers	l_f/d_f	-	Input	25.00	60.00	71.87	80.00	190.50	24.72	34.40
	Tensile strength of fibers	$f_{tenfiber}$	MPa	Input	260.00	1100.00	1241.73	1200.00	4913.00	457.82	36.87
Capacity	Fiber factor	F	-	Input	0.075	0.300	0.536	0.698	2.858	0.365	68.10
	Ultimate shear capacity	V_u	N	Output	12,824.46	45,000.00	124,010.51	170,277.39	396,000.00	94,784.90	76.43

3.3. Selection of Global Optimization Techniques

Aside from traditional gradient-based optimization techniques [123], various metaheuristic methods have been proposed in the literature in order to optimize the weight parameters of the NN model, for instance: Artificial Bee Colony [124], Genetic Algorithm [125], Simulated Annealing [126], Hierarchical k-Means Clustering [127], and Particle Swarm Optimization [5]. Training of a NN model based on gradient of error can be very unstable when searching for a global minimum [128]. Indeed, gradient-based techniques might not escape a local minimum to find a global one [129]. The performance is also dependent on the values of an initial guess, which is generally difficult to choose [128,130]. Moreover, in most structural experiments, the variables are generally obtained as discrete. Consequently, constraints (e.g., stress, displacement) are not explicit (the implicit form of constraints can be achieved only from analytical or finite element models) [131–134]. Therefore, for structural optimization problems, various nature-inspired global optimization techniques have been introduced to overcome these inconveniences, as demonstrated in the literature [5,124,126,135,136]. In this paper, two global optimization techniques were employed, the Real-Coded Genetic Algorithm and the Firefly Algorithm, for calibrating the weight parameters of the NN model.

Figure 1. Cont.

Figure 1. Cont.

Figure 1. Histograms of the parameters: (a) web width; (b) height of cross-section; (c) effective depth; (d) span length; (e) shear span; (f) clear shear span; (g) reinforcement ratio; (h) yield strength of reinforcement steel; (i) depth ratio; (j) clear depth ratio; (k) maximum aggregate size; (l) concrete compressive strength; (m) fiber volume fraction; (n) length/diameter ratio of fibers; (o) tensile strength of fibers; and (p) fiber factor.

3.4. Real-Coded Genetic Algorithm (RCGA)

Derived from the principles of biological evolution, the RCGA is an optimization technique that has been used immensely since its first introduction and investigation by John Holland [137]. It is known as a searching method containing three evolutionary operations—reproduction, crossover, and mutation—by which to solve complex problem [138]. In the RCGA, the search space parameters are represented as strings, called “chromosomes”, and a population is defined as a collection of such strings. A random population, which represents various points in the search space, is initially created. Each string is then correlated with an objective and fitness function that defines the degree of goodness of the string. Based on the survival of the fittest principle, a few strings are selected, and several copies are assigned to each one going into the mating pool. Such strings are used by biologically motivated operators (e.g., cross-over and mutation) to produce a new set of strings. The selection, crossover, and mutation process will continue for a fixed number of generations until certain conditions are matched [139,140]. The process of the RCGA experimental search diagram is presented in Figure 2.

Figure 2. (a) The Real-Coded Genetic Algorithm (RCGA) crossover operator and mutation operator for offspring chromosomes; (b) the structure of the RCGA.

The RCGA technique has been successfully applied in various optimization problems of different scientific fields. Blanco et al. [128] combined the RCGA and recurrent neural networks to perform fuzzy grammatical inference. In another study, Sedki et al. [141] forecast daily rainfall runoff when calibrating the weight parameters of an NN according to the RCGA technique. The main advantages of using the RCGA for training artificial intelligence-based models have been reported in various works, showing that the RCGA is robust in finding the global minimum, including cases of noisy or stochastic objective functions [129,141,142].

3.5. Firefly Algorithm (FFA)

The FFA, which is based on the flashing behavior of fireflies, is a metaheuristic algorithm. Fireflies use bioluminescence and varied flashing patterns (referred to as “bioluminescent communication”) to communicate, search for prey, and find mates. This phenomenon is often used to optimize parameters of machine learning algorithms, such as NNs or the Adaptive Network-based Fuzzy Inference System (ANFIS) [143]. The basic principles of FFA can be summarized as: (i) the fireflies are unisexual and any firefly can be attracted to any other firefly; (ii) a firefly’s attractiveness is directly proportional to the firefly’s brightness, and the brightness reduces when the distance traveled rises; (iii) fireflies shift randomly if they cannot find an attractive firefly in neighboring regions [144]. The FFA measures each firefly’s brightness and relative attractiveness, as a firefly’s location changes based on these two values. All fireflies converge at the best possible position in a search space after a sufficient number of iterations [144]. The FFA could be considered a swarm intelligence based-algorithm like Particle Swarm Optimization (PSO) or Artificial Bee Colony (ABC), which are based on a population finding

the global optima of an objective function [145]. However, FFA is observed to be superior in many scenarios [146]. A diagram of the FFA's experimental search process is depicted in Figure 3.

Figure 3. (a) Fireflies with updated position; (b) the structure of the Firefly Algorithm (FFA).

3.6. Machine Learning Evaluation Criteria

In the present study, Pearson correlation coefficient (R), mean absolute error (MAE), and root mean squared error (RMSE) were used as evaluation criteria to validate the developed ML algorithms. Precisely, the R values allow the statistical relationship between experimental results to be identified, and ML to predict the USC [147,148] by yielding a value between 0 and 1, where 0 is no correlation and 1 is a total correlation. In the cases of RMSE and MAE, which have the same units as the quantity being estimated [24,42], lower values of RMSE and MAE indicate a basically good accuracy of the prediction output using the ML models [149–154]. The values of R, RMSE, and MAE are estimated using the following equations [107,108,115,147]:

$$\text{MAE} = \frac{\sum_{i=1}^n |p_i - v_i|}{n} \quad (1)$$

$$\text{RMSE} = \sqrt{\frac{\sum_{i=1}^n (p_i - v_i)^2}{n}} \quad (2)$$

$$R = \frac{\sum_{i=1}^n (p_i - \bar{p})(v_i - \bar{v})}{\sqrt{\sum_{i=1}^n (p_i - \bar{p})^2 \sum_{i=1}^n (v_i - \bar{v})^2}} \quad (3)$$

where n is the number of samples; p_i and v_i are the actual and predicted outputs, respectively; and $\bar{p}$ and $\bar{v}$ are the mean of the actual and predicted outputs, respectively.

4. Results and Analysis

4.1. Construction of the Hybrid Models (NN-RCGA and NN-FFA)

As demonstrated in the literature, the capability of an NN model depends highly on the selected architecture [124,155–158]. Therefore, the determination of an appropriate architecture is required to study an NN model. More precisely, such architecture is determined through the number of hidden layer(s) and the number of neuron(s) in each hidden layer. As revealed by various works in the literature, NN's architecture using one hidden layer can handle complex problems while also saving computation time and cost [142,153,159]. In this study, NN's architecture using one hidden layer was finally chosen, and there were ten neurons in that hidden layer, exhibiting a total number of weight parameters of 181.

Table 4 shows the characteristics of the NN, while Tables 5 and 6 show the final parameters selected for the RCGA and FFA optimization techniques, respectively, obtained after parametric studies [160]. It is worth noticing that certain ranges of values of parameters are commonly employed for training NN models; for instance, Blanco et al. [128], Irani et al. [129], and Sedki et al. [141] for the RCGA algorithm, while Bui et al. [161] and Sulaiman et al. [162] for the FFA algorithm. Optimization costs of the two hybrid models developed are plotted in Figure 4 involving RMSE, MAE, and R. The RMSE, MAE, and R values are used to assess the prediction performance regarding number of iterations. It was observed that the number of iteration increases could decrease the RMSE and MAE values, whereas the R values tended to increase. As a result, the maximum number of iterations for the NN-FFA was 200, while for the NN-RCGA it was 500. These values were selected when the relative error between two iterations was inferior to 1%. It can be seen that the cost function of testing was highly correlated with training, exhibiting that a no-overfitting zone was established. As such it can be reported that both the FFA and RCGA optimization techniques were efficient in finding the global optimum for the problem.

Table 4. NN characteristics.

Parameter	Value and Description
Neurons in the input layer	16
Hidden layers	1
Neurons in hidden layer	10
Neurons in the output layer	1
Hidden layer activation function	Sigmoid
Output layer activation function	Linear
Cost function	Mean square error
Size of weight of matrix of hidden layer	10×16
Size of bias vector of hidden layer	1×10
Size of weight of matrix of the output layer	1×10
Size of bias vector of output layer	1×1
Total number of parameters	181

Table 5. Parameters of the FFA used in this study.

Parameter	Value and Description
Number of fireflies	30
Maximum iteration number	200
Coefficient of light absorption	1
Coefficient of attraction	2
Mutation coefficient	0.2
Mutation coefficient damping ratio	0.98
Range of uniform mutation	5%
Initial damp mutation coefficient	0.196

Table 6. Parameters of the RCGA used in this study.

Parameter	Value and Description
Population size	70
Maximum number of iterations	500
Length of chromosome	220
Fitness function	linear ranking
Cross-over type	random pair
Cross-over probability	0.4
Number of off-springs	10
Mutation type	random
Mutation probability	0.7
Number of mutants	18
Selection function	roulette wheel selection

4.2. Validation and Comparison of the Hybrid Models

Figure 5a,c shows the prediction performance between the scaled predicted and actual values of the USCs of concrete beams on the training dataset for the NN-FFA and NN-RCGA. Figure 5b,d shows the same information corresponding to the testing dataset. These results suggest that the performances of the two developed hybrid models were similar. However, the NN-RCGA was slightly superior to the NN-FFA when comparing results obtained from the testing datasets (i.e., $R = 0.965$ for NN-FFA and $R = 0.979$ for NN-RCGA). In addition to MAE, RMSE, and R (Table 7), a straight line was fit to the predicted versus actual plots. The slope of the linear fit was used to measure the angle between the x-axis and the linear fit, with angles closer to 45° indicating better performance. As observed, for the training part, the NN-FFA and NN-RCGA yielded slope angles of 42.65° and 43.53° , respectively. For the testing dataset, the NN-FFA and NN-RCGA produced slope angles of 42.52° and 43.86° , respectively. Figure 6 shows a histogram of the distribution of errors of the NN-FFA and NN-RCGA in predicting the USCs of concrete beams using the training and testing datasets. It is observed that the NN-RCGA had a higher peak of error concentration around 0 than the NN-FFA in both cases. In general, although both models performed well and were statistically significant, the NN-RCGA proved slightly superior to the NN-FFA in modeling the ultimate shear capacity of concrete beams.

4.3. Sensitivity Analysis Using ICE and PDP Concepts

The ICE plots of each simulation show how the output response changed according to the change of the selected input variable. The values of each line were obtained by computing by varying the selected feature using values from a grid while keeping all other features unchanged. The next step consisted of applying the ML model for the recently created values. The obtained results appeared in point form for each instance, with analyses of values of each feature from the grid and corresponding predictions. On the other hand, a PDP is an alternative approach to analyzing the dependence of the predicted output versus input variables [163]. The average of all ICE plots gives the PDP, which represents the influence of the corresponding input to the output for the whole dataset. Table 8 summarizes the obtained results of the PDPs for 16 input variables considered in this work. The importance of the inputs can be grouped into several classes, such as very important factors, important factors, slightly important factors, and not important factors. Results of these classes are given in the following sections.

Figure 4. Optimization of the NN using the FFA: (a) RMSE, (b) MAE, (c) R; using RCGA: (d) RMSE, (e) MAE, (f) R.

Figure 5. Prediction regression graphs for the training data using (a) the NN-FFA and (c) the NN-RCGA; and for testing data using (b) the NN-FFA and (d) the NN-RCGA.

Table 7. Prediction capability of the hybrid models.

Method	Dataset	R	RMSE	MAE	Slope	Err.Mean	Err.Std
NN-FFA	Training	0.960	0.066	0.047	0.921	0.001	0.066
	Testing	0.965	0.071	0.053	0.917	−0.004	0.071
NN-RCGA	Training	0.976	0.051	0.036	0.950	0.000	0.051
	Testing	0.979	0.056	0.041	0.961	0.003	0.056

Figure 6. Distribution of error between predicted and actual data.

4.3.1. Not Important Factors

As indicated in Table 8 and Figure 7, clear shear span, maximum aggregate size, fiber volume fraction, and tensile strength of fibers are variables that can be considered not important in the prediction of the USC_s of SFRC beams. The maximum variation values of the ultimate shear capacity while varying these factors were 0.0551, 0.0678, 0.0611, and 0.0118, respectively. A perfect linear relationship was observed between maximum aggregate size and the ultimate shear capacity. With respect to clear shear span, fiber volume fraction, and tensile strength of fibers, nonlinear relationships were found in which maximum values were obtained in the 0.4–0.6 ranges of the corresponding variables. This means that in order to obtain higher values of ultimate shear capacity, the variables should be selected around their average values. Furthermore, increasing the maximum aggregate size could slightly increase the ultimate shear capacity. Overall, the influences of varying these factors on the ultimate shear capacity were rather small (Table 8). As a result, with the presence of the clear shear span, maximum aggregate size, fiber volume fraction, and tensile strength of fibers, the predicted target was reasonably unchanged.

4.3.2. Slightly Important Factors

As shown in Table 8 and Figure 8, the length/diameter ratios of fibers, yield strengths of reinforcement steel, and depth ratios could be considered slightly important variables in predicting the USC_s of SFRC beams. The maximum variation values of the ultimate shear capacity while varying these factors were 0.1013, 0.1175, and 0.1225, respectively. Perfect linear relationships between the yield strength of reinforcement steel, length to diameter ratio of fibers, and ultimate shear capacity were found. The depth ratio seemed to have an exponential relationship with the ultimate shear capacity. However, the latter remained at a constant value when the depth ratio was higher than 0.6. These results could indicate that in order to obtain higher values of ultimate shear capacity, the yield strength of steel should be maximized, whereas a depth ratio larger than 0.6 cannot further enhance the mechanical behavior of SFRC beams. Furthermore, the fiber aspect ratio, or length to diameter ratio of fiber, is not an important influencing factor, as confirmed in a previous work [164]. Overall, the influences of varying these factors on the ultimate shear capacity were rather small (Table 8). As a result, with the presence of the length/diameter ratio of fibers, yield strength of reinforcement steel, and depth ratio, the predicted ultimate shear capacity was slightly changed.

Table 8. Summary of the Individual Conditional Expectation (ICE) variation and classification of the importance of variables.

Group	Variable	Min	Max	End	Class
Geometry	Web width	0	0.5243	0.5243	2
	Height of cross-section	0	0.2911	0.2285	5
	Effective depth	0	0.4238	0.4238	3
	Span length	−0.2028	0	−0.2028	8
	Shear span	0	0.2520	0.2520	4
	Clear shear span	−0.0551	0	−0.0022	16
	Reinforcement ratio	0	0.1906	0.1906	9
	Yield strength of reinforcement steel	0	0.1175	0.1175	11
	Depth ratio	0	0.1225	0.1093	10
	Clear depth ratio	−0.7246	0	−0.7246	1
Concrete mix	Maximum aggregate size	−0.0678	0	−0.0678	15
	Average measured concrete cylinder compressive strength	0	0.2217	0.1523	7
Fiber	Fiber volume fraction	0	0.0611	0.0303	14
	Length/diameter ratio of fibers	−0.1013	0	−0.1013	12
	Tensile strength of fibers	−0.0061	0.0118	−0.0061	13
	Fiber factor	0	0.2342	0.2342	6

Figure 7. ICE (black lines) and Partial Dependence Plot (PDP) (red lines) of clear shear span, maximum aggregate size, fiber volume fraction, and tensile strength of fibers obtained from the NN-RCGA model.

Figure 8. ICE (black lines) and PDPs (red lines) of yield strength, depth ratio, and length-diameter ratio of fiber obtained from the NN-RCGA model.

4.3.3. Important Factors

As shown in Table 8 and Figure 9, shear span, height of cross-section, fiber factor, average measured concrete cylinder compressive strength, span length, and reinforcement ratio are important variables in predicting the USCs of SFRC beams. The maximum variation values of the ultimate shear capacity while varying these factors were 0.2520, 0.2911, 0.2342, 0.2217, 0.2028, and 0.1906, respectively. The span length and fiber factor correlated with the ultimate shear capacity in a perfectly linear manner, whereas nonlinear relationships were found between height of cross-section, shear span, concrete compressive strength, and reinforcement ratio with the ultimate shear capacity. The latter reached its maximum value when the height of the cross-section was about 0.8 and the shear span about 0.9. A reinforcement ratio ranging from 0.6 to 1, or a concrete compressive strength ranging from 0.4 to 1, would not significantly change the value of the ultimate shear capacity. On the other hand, increasing the span length could decrease the ultimate shear capacity, whereas the latter could increase with an additional fiber factor. As a result, the presence of these input variables was determined to be important in predicting the USCs of SFRC beams.

Figure 9. ICE (black lines) and PDPs (red lines) of height of cross-section, span length, shear span, reinforcement ratio, concrete compressive strength, and fiber factor obtained from the NN-RCGA model.

4.3.4. Very Important Factors

As shown in Table 8 and Figure 10, clear depth ratio, web width, and effective depth are the three most important variables for predicting the USCs of SFRC beams. The maximum variation values of the latter while varying these factors were 0.7246, 0.5243, and 0.4238, respectively. The effective depth had a linear relationship with ultimate shear capacity within the 0–0.8 range, whereas from 0.8 to 1 the ultimate shear capacity remained almost constant, reaching a maximum value of 0.4238. Furthermore, the web width correlated with ultimate shear capacity in a perfect, linear, and positive manner, whereas the clear depth ratio correlated with ultimate shear capacity in a linear but negative way. As a result, the presence of these input variables was determined to be crucial in predicting the USCs of SFRC beams.

Figure 10. ICE (black lines) and PDPs (red lines) of effective depth, web width, and clear depth ratio obtained from the NN-RCGA model.

5. Discussions

5.1. Dataset Used for ML Modeling

The trustworthiness of any machine learning algorithm is dependent entirely on the reliability of the utilized database. The experimental results in this study were collected from academic journals published in Scopus or International Scientific Indexing (ISI)'s Web of Knowledge databases. In such a database, the incorporated samples should cover a wide range of values for the input variables concerned, and it is worth noting that an important number of samples in the dataset did not lead to the construction of a more accurate ML model. Indeed, similar values for input and output parameters cannot describe and reveal the behaviors of their material structures, as they do not cover a wide enough range of every possible value. A database is valuable only if it can describe the influence of all parameters on the output variable. Moreover, the precision of the data in the dataset is critical. If

inexact values are used in the learning phase while constructing the ML algorithm, the dataset it will provide imprecise prediction values. This could lead researchers and engineers to a completely different understanding, and the study might go in the wrong direction. Therefore, in this work, an adequate amount of rigorously selected experimental data were gathered from the available literature, including 463 samples, which is to the best of our knowledge a higher number of data used for predicting the USCs of SFRC beams than any previously published work, thus enhancing the development and application of the ML models.

More importantly, most of the input variables in the present database possessed a wider range compared to those reported in the literature. As an illustration, the range of the concrete compressive strength was 9.77–215 (MPa) compared with 20.6–111.5 (MPa) in [13,164,165] or 20.6–99.9 (MPa) in [43]. The reinforcement ratio in the present database ranged from 0.37–5.72 (%) compared with 0.9–5.72 (%) in [164], 1.1–5.72 (%) in [43] or 1.03–2.75 (%) in [13]. The depth ratio was in the 0.70–6.00 range, whereas that in the work of Ahmadi et al. [13] was 1.0–6.0, and in the study of Kara et al. [165] was 2.5–5. The length to diameter ratio of fibers varied from 25.0 to 190.5 compared with 29.1–133 in [164] and 50–133 in [165]. The fiber volume fraction in this work possessed a 0.20–4.50 (%) range, compared with 0.25–3.00 (%) in [164] and 0.25–2.00 (%) in [43]. Once the database contained the relevant information on the constituent materials, the prediction ML tool had the ability to estimate other experiments using the values from the training database used to construct the ML model [166]. Again, a reliable dataset that covers a wide range of input values is crucial for the development of ML models.

5.2. Validation and Comparison of the Hybrid Models

Validation of the hybrid models showed that both the hybrid ML models used in this study were good for predicting the USCs of SFRC beams, but that the NN-RCGA was slightly better than the NN-FFA. This is reasonable, as the NN-RCGA used the RCGA, which is robust and effective at reducing the bias and variation of the models [167]. Other published studies also confirmed the good capability of the RCGA in optimizing the parameters of the ML models [168,169]. A comparison of the results with previously published works (recently compiled by Lantsoght [46]) was also conducted, and is shown in Figure 11 and Table 9 (including the applications of all data). These equations are summarized in Table 10. The values gained between results obtained from the hybrid ML models and those from published works were calculated using Equation (4):

$$\% \text{Gain} = \begin{cases} ((\lambda^{NN-RCGA} - 1) - (\lambda^{literature} - 1)) \times 100 & \text{in case of : R} \\ ((\lambda^{literature} - \lambda^{NN-RCGA}) / \lambda^{literature}) \times 100 & \text{in case of : RMSE and MAE} \end{cases} \quad (4)$$

As shown in Table 9, the proposed ML algorithm possessed a significant improvement in performance compared with the results reported in the literature. The gain in R values varied from 7% to 45%, whereas the gain of RMSE and MAE varied from 57.5% to 83.6% and 55.7% to 84.6%, respectively. It was also found that the NN-RCGA model ($R = 0.9771$) could achieve the best predictive capability for predicting the USCs of SFRC beams compared with the models in previous published works ($R = 0.5274$ – 0.9075). This study reconfirmed that the use of hybrid ML models is more effective than traditional models.

Figure 11. Regression plots using empirical equations to compare the prediction results for all data of (a) the present study using NN-RCGA with the literature; (b) Khuntia et al. [170]; (c) Sharma [98]; (d) Greenough and Nehdi [83]; (e) Ashour et al. [57] with $a/d > 2.5$; (f) Ashour et al. [57] with $a/d < 2.5$; (g) Sarveghadi et al. [171]; (h) Imam et al. [89]; (i) Ahmadi et al. [13] using Formulation 2; (j) Ahmadi et al. [13] using Formulation 3; and (k) Ahmadi et al. [13] using Formulation 4.

Table 9. Statistical measures of the predicted values against experimental ultimate shear strength.

Method	R	RMSE	MAE	% Gain: R	% Gain: RMSE	% Gain: MAE
NN-RCGA model	0.9771	0.0526	0.0374	-	-	-
Khuntia et al. [170]	0.8025	0.1911	0.1252	+17.5	+72.5	+70.1
Sharma [98]	0.8237	0.1936	0.1299	+15.3	+72.8	+71.2
Greenough and Nehdi [83]	0.7205	0.1897	0.1228	+25.7	+72.3	+69.5
Ashour et al. [57] with $a/d > 2.5$	0.8672	0.1642	0.1134	+11.0	+68.0	+67.0
Ashour et al. [57] with $a/d < 2.5$	0.8234	0.2263	0.1653	+15.4	+76.8	+77.4
Sarveghadi et al. [171]	0.9075	0.1238	0.0844	+7.0	+57.5	+55.7
Imam et al. [89]	0.5274	0.3209	0.2423	+45.0	+83.6	+84.6
Ahmadi et al. [13] using Formulation 2	0.8015	0.1809	0.1208	+17.6	+70.9	+69.0
Ahmadi et al. [13] using Formulation 3	0.8517	0.1994	0.1461	+12.5	+73.6	+74.4
Ahmadi et al. [13] using Formulation 4	0.8617	0.2049	0.1509	+11.5	+74.3	+75.2

Table 10. Table 10. Empirical equations gathered from the available literature (mostly from compilation of Lantsoght [46]).

Sarveghadi et al. [171]	$V_u = \left[\rho + \frac{\rho}{v_b} + \frac{1}{a} \left(\frac{\rho f'_t (\rho + 2) \left(f'_t \frac{a}{d} - \frac{3}{v_b} \right)}{\frac{a}{d}} + f'_t \right) + v_b \right] b_\omega d$ $f'_t = 0.79 \sqrt{f'_c}$ $v_b = 0.41 \tau F; \text{ with } \tau = 4.15 \text{ (MPa)}$
Kwak et al. [101]	$V_u = \left[3.7 e f_{spfc}^{2/3} \left(\rho \frac{d}{a} \right)^{1/3} + 0.8 v_b \right] b_\omega d$ $f_{spfc} = \frac{f_{cu}}{20 - \sqrt{F}} + 0.7 + \sqrt{F} \text{ (MPa)}$ $e = \begin{cases} 1 & \text{for } \frac{a}{d} > 3.4 \\ 3.4 \frac{d}{a} & \text{for } \frac{a}{d} \leq 3.4 \end{cases}$
Greenough and Nehdi [83]	$V_u = \left[0.35 \left(1 + \sqrt{\frac{400}{d}} \right) (f'_c)^{0.18} \left((1 + F) \rho \frac{d}{a} \right)^{0.4} + 0.9 \eta_o \tau F \right] b_\omega d$ $\tau = 4.15 \text{ (MPa)}$
Khuntia et al. [170]	$V_u = \left[(0.167 + 0.25F) \sqrt{f'_c} \right] b_\omega d$
Sharma [98]	$V_u = \left(\frac{2}{3} \times 0.8 \sqrt{f'_c} \left(\frac{d}{a} \right)^{0.25} \right) b_\omega d$
Mansur et al. [56]	$V_u = V_c + \sigma_{tu} b_\omega d$ $V_c = \left(0.16 \sqrt{f'_c} + 17.2 \frac{\rho V_d}{M} \right) b_\omega d \leq 0.29 \sqrt{f'_c} b_\omega d$ $\sigma_{tu} = 3.2 \eta_o \eta_1 F \tau; \text{ with } \tau = 2.58 \text{ MPa}$ $\eta_1 = 1 - \frac{\tanh\left(\beta \frac{l_f}{2}\right)}{\beta \frac{l_f}{2}}$ $\beta = \sqrt{\frac{2\pi G_m}{E_f A_f \ln\left(\frac{s}{t_f}\right)}}$ $S = 25 \sqrt{\frac{d_f}{V_{lf}}}$
Ashour et al. [57]	$V_u = \left[(0.7 \sqrt{f'_c} + 7F) \frac{d}{a} + 17.2 \rho \frac{d}{a} \right] b_\omega d$ $V_u = \left[(2.11 \sqrt[3]{f'_c} + 7F) \left(\rho \frac{d}{a} \right)^{0.333} \right] b_\omega d \text{ for } \frac{a}{d} \geq 2.5$ $V_u = \left[\left((2.11 \sqrt[3]{f'_c} + 7F) \left(\rho \frac{d}{a} \right)^{0.333} \right)^{\frac{2.5}{a}} + v_b \left(2.5 - \frac{a}{d} \right) \right] b_\omega d \text{ for } \frac{a}{d} < 2.5$
Arslan et al. [15]	$V_u = \left[(0.2 (f'_c)^{2/3} \frac{c}{d} + \sqrt{\rho(1 + 4F)} f'_c) \sqrt[3]{\frac{3}{d}} \right] b_\omega d$ $\left(\frac{c}{d} \right)^2 + \left(\frac{600\rho}{f'_c} \right) \left(\frac{c}{d} \right) - \frac{600\rho}{f'_c} = 0$
Imam et al. [89]	$V_u = \left[0.6 \psi \sqrt[3]{\omega} \left((f'_c)^{0.44} + 275 \sqrt{\frac{\omega}{\left(\frac{a}{d}\right)^5}} \right) \right] b_\omega d$ $\psi = \frac{1 + \sqrt{\frac{5.08}{d_a}}}{\sqrt{1 + \frac{d}{25d_a}}}$ $\omega = \rho(1 + 4F)$
Yakoub [172]	$V_u = \left[0.83 \xi \sqrt[3]{\rho} \left\{ \sqrt{f'_c} + 249.28 \sqrt{\frac{\rho}{\left(\frac{a}{d}\right)^5}} + 0.405 \frac{l_f}{d_f} V_f R_g \frac{d}{a} \sqrt{f'_c} \right\} \right] b_\omega d \text{ for } \frac{a}{d} \leq 2.5$ $V_u = \left[0.83 \xi \sqrt[3]{\rho} \left\{ \sqrt{f'_c} + 249.28 \sqrt{\frac{\rho}{\left(\frac{a}{d}\right)^5}} + 0.162 \frac{l_f}{d_f} V_f R_g \frac{d}{a} \sqrt{f'_c} \right\} \right] b_\omega d \text{ for } \frac{a}{d} \geq 2.5$ $\xi = \frac{1}{\sqrt{1 + \frac{d}{25d_a}}}$
Ahmadi et al. [13]	$V_u = \frac{d}{a} \left(\frac{F}{d} + 0.555 \sqrt{\rho f'_c} + 1 \right) + 1$ $V_u = \rho - \frac{37.957 \frac{a}{d} \rho}{d + F - 10.57} + \frac{d + (f'_c)^2}{9.44 \frac{a}{d} f'_c}$ $V_u = 0.095 \frac{f'_c}{a} + \frac{\rho - 0.137}{\frac{a}{d} - 0.395} + \frac{0.108d + F}{f'_c - \frac{a}{d} + 85.256}$

5.3. Importance of Selection of the Input Factors

Many studies have showed that the post-cracking tensile strength of fiber-reinforced concrete is an important factor, which is represented by a significant reserve strength in the case of fiber-reinforced concrete beams failing in shear after the first diagonal cracking appears [165]. In the work of Khuntia et al. [170], the authors suggested that the dependence of such post-cracking tensile stress on many factors, including volume fraction, shape, aspect ratio, and the surface characteristics of the fibers, as well as the mechanical properties of concrete. In addition, the type of concrete (i.e., normal or lightweight) and steel fibers was taken into account when using empirical equations. However, in the current work, the type of fibers and concrete have not been taken as input parameters. With the satisfactory precision of the predictive NN-RCGA model, it can be concluded that these input variables would have no significant effect in predicting the USCs of SFRC beams. In the present work, the dataset containing 16 input variables could exhaustively represent all the factors affecting the ultimate shear capacity of steel fiber-reinforced concrete beams. For the sake of comparison, Kara et al. [165] only considered five factors as input variables, and Adhikary and Mutsuyoshi [43] compared the accuracy of the proposed NN algorithms for cases using four and five factors as input variables.

Predicting the USC of SFRC is a difficult task, as the relationship between the constituents and the target is highly nonlinear. Several current codes, guidelines, and studies have proposed some empirical prediction equations. The appearance of any factor in such empirical equations could demonstrate the importance of that factor in predicting the USC. In a series of works by Sarveghadi et al. [171], Kwak et al. [101], Ashour et al. [57], and Ahmadi et al. [13], factors such as the reinforcement ratio, fiber factor, shear span, effective depth, concrete compressive strength, and web width are considered. Several additions apart from the above factors have also been observed in the works of Arslan et al. [15], Imam et al. [89], and Greenough and Nehdi [83]. The height of the compression zone, the maximum aggregate size, and the fiber orientation factor (a value of 0.41 is assumed) have been considered. Furthermore, Khuntia et al. [170] removed shear span in the proposed empirical formulation, and Sharma [98] removed the fiber factor (which includes the diameter, length, and volume percentage of steel fibers), to predict the ultimate shear capacity of the concrete beams. On the other hand, Mansur et al. [56] added the fiber orientation factor, length factor, sectional shear force, and sectional moment to predict the ultimate shear capacity. Last but not least, Yakoub [172] added the fiber volume fraction and, in particular, the fiber geometry factor, to estimate the ultimate shear capacity.

Overall, it is interesting to observe that the sensitivity analysis using ICE and PDPs in the present study could also demonstrate the importance of these factors. The effective depth and web width were found to be the most affecting factors to the prediction tool, as can be determined from the empirical equations (Table 10). The clear shear span to effective depth ratio was also found more influential than the shear span to effective depth ratio [173]. The finding of this work that shear span, height of cross-section, fiber factor, concrete cylinder compressive strength, span length, and reinforcement ratio are all important variables is in good agreement with the literature mentioned above.

6. Conclusions

In this study, two hybrid ML model—namely, NN-RCGA and NN-FFA—were developed and applied for predicting the USCs of SFRC beams. The NN-RCGA and NN-FFA are a combination of a NN and two nature-inspired optimization techniques, namely the RCGA and the FFA, respectively. A database of 463 experimental data, including input variables (geometry of the beam, concrete mixture, and fiber information) and an output variable (USCs of SFRC beams) was constructed from the data collected in published works. Using several statistical criteria such as R, RMSE, and MAE, the predictive capabilities of the proposed hybrid algorithms were validated and compared for both a training (70% data) and a testing (30% remaining data) dataset. Furthermore, sensitivity analysis was also carried out using ICE and PDP to evaluate the importance of input variables.

The results showed that the NN-RCGA ($R = 0.9771$) was better than the NN-FFA and other previously published models ($R = 0.5274$ – 0.9075) in predicting the USC of SFRC beams. Thus, it can be reasonably concluded that the NN-RCGA is a promising tool and method for more accurately predicting the USC of SFRC beams. The sensitivity analysis showed that web width and effective depth were the most important factors positively influencing beam shear capacity. They were considered to be the most critical parameters in modeling the shear capacities of SFRC beams. Removal of unimportant factors found in this study should be investigated and carried out in further study to improve the capabilities of the ML models to predict the USC of SFRC beams. Several prospective works following this study will pave the way for a more comprehensive knowledge concerning reinforced concrete beams, including (i) the gathering of more reliable data of general reinforced concrete beams to verify the possibility of using ML algorithms to predict the USC of reinforced concrete beams; (ii) considering more behaviors of SFRC beams, such as structural behaviors during failure.

The results of this study might help to permit quick and accurate assessments of the shear capacities of SFRC beams for practical engineering purposes. As a consequence, a Matlab function (.m file) using a pre-trained NN-RCGA algorithm (containing the NN-RCGA network used in this study, named as “net”) and the testing dataset (.xlsx file) are given in Supplementary Materials. This function predicts the USC of SFRC beams using 16 input variables.

Supplementary Materials: The following are available online at <http://www.mdpi.com/2071-1050/12/7/2709/s1>. All Supplementary Materials are appended to this paper.

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