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Shear Strength Prediction of SFRC Beams Using Machine Learning

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Abstract. Concrete is one of the most used structural materials in the world, but it has some limitations such as brittle behavior and low deformation capacity when being tensioned, which makes it susceptible to the appearance of cracks that occur in its interior. The steel fiber reinforced concrete (SFRC) improves the mechanical behavior of concrete structures allowing, for example, the partial or total replacement of the stirrup reinforcement in structural elements. However, due to the complex shear behavior, it is necessary to understand the contribution of each composite parameter to the behavior of the structural member in order to better design new structures with this material. Therefore, the present work uses Machine Learning algorithms to predict the shear strength of SFRC beams from a survey of experimental data found in the literature. Different input parameters are considered for this study, such as the fiber volume fraction, fiber aspect ratio, among others. The results demonstrated a high accuracy of the ML algorithm, reaching a $R^2 = 0.96$. Moreover, a comparison of the shear prediction capacity between ML approach and the analytical models available in literature is performed. This research aims to contribute to a better understanding of the shear phenomenon of SFRC beams, taking into account different aspects that can assist and aid design engineers in the conception and execution of structural projects.

Keywords: SFRC beams, Machine Learning, Shear Strength Prediction, Hooked-end Steel Fibers.

1 Introduction

Among the main characteristics of Steel Fiber Reinforced Concrete (SFRC) is the improvement of the behavior of the concrete in the Ultimate Limit State (ULS) and Serviceability Limit State (SLS). The addition of steel fibers is related to the post-cracking behavior enhancement. According to Bitencourt Jr. [1], the fibers act as a bridge transfer mechanism between the cracks, avoiding stress concentrations at the crack tip, increasing the fracture energy of the composite and preventing the occurrence of an abrupt failure. As stated by Bentur and Mindess [2], the main factors that influence the behavior of SFRC are the cement matrix microstrucure, the distribution and geometry of the steel fibers and the fiber-matrix interface.

The use of steel fibers in concrete structures provides a 3D distributed reinforcement in the matrix and not only in a specific localized region as steel bars, improving the shear strength. This effect turns possible the partial or complete substitution of stirrups in structural members such as beams.

The shear behavior of SFRC has been investigated by many authors in the last decades. From experimental tests, different analytical equations to determine the shear strength of beams have been proposed. This study gathered the experimental results presented in the literature by different authors, aiming to develop a Machine Learning model capable of predicting the shear strength capacity of SFRC structures. This model can provide a better understating of the main factors that have influence on the shear behavior, contributing to improve the prediction of the shear strength capacity. Rahman [3] cited the recently significant step forward in the estimation of intricate networks through machine learning approach, which can provide a better understanding of complex physical phenomena studied in many areas of knowledge.

2 Methodology

To perform this data-driven approach, the study was conducted in three main phases: database creation, Machine Learning (ML) model development and comparison of existing analytical models.

At the first phase, a literature review is carried out to understand the main variables involved in shear behavior of SFRC beam. Then, a database was created with specimens results from different researches. At the second phase, Machine learning algorithms were tested to predict the shear strength. The relative importance of each input parameter of the ML model was obtained. At the third phase, analytical models found in literature were tested with the same data in order to compare the models efficiency.

2.1 Database creation

The first step to create a database was identifying critical variables that are involved in the process by analyzing researches from the last four decades. Even though many results are available, not all of them contains the same set of parameters registered during the laboratory tests. The created database was filtered to analyze just specimen results with the considered set of parameters. All datasets were composed by specimens with hooked-end steel fibers without stirrups. The database was filled with a total of 146 experiments from 13 references.

2.2 Machine Learning model development

Depending on the nature of the studied problem, there are different techniques of Machine Learning that could be applied based on the type and volume of the data, which can be designated as supervised learning, unsupervised learning and reinforcement learning. According to Müller and Guido [4], the supervised learning problems can also be separated into classification and regression problems. This study is focused in a regression problem, which means predicting a continuous number by inferring a relationship between other features.

To predict the shear strength of SFRC beams tested in 3 or 4 point bending tests, 5 machine learning algorithms were tested for this regression problem using Python programming language: extreme gradient boosting (XGB), gradient boosting regressor (GB), decision tree regressor (DT), random forest regressor (RF) and K-Nearest Neighbors regressor (KNN). Table 1 describes the input parameters considered in the models.

Table 1. Set of input parameters

Parameter	Unit	Symbol
Test type	—	3-PBT / 4-PBT*
Fiber volume fraction	%	V_f
Fiber length	mm	L_f
Fiber diameter	mm	D_f
Concrete compressive strength	MPa	f_c
Ratio of shear span to effective depth	—	a/d
Longitudinal reinforcement ratio	%	ρ
Width of the beam cross-section	mm	b_w
Height of the beam cross-section	mm	h
Effective depth of the beam cross-section	mm	d
Maximum aggregate size	mm	a_g

* PBT: Point bending test

2.3 Comparison with analytical models

The results of the shear strength prediction by the Machine Learning model were also compared to those calculated from equations proposed by different researches, aiming to validate the ML model proposed in this study. Table 2 presents the analytical equations. The main parameters considered in these analytical equations are the concrete compressive strength (f_c), effective depth of the beam cross-section (d), shear span (a), longitudinal reinforcement ratio (ρ), fiber length (L_f), fiber diameter (D_f), fiber volume fraction (V_f) and fiber bond-factor (d_f).

Table 2. Analytical equations for shear strength of SFRC beams

Author	Condition	Equation for v_u (MPa)	
Sharma [5]	—	$v_u = kf_{ct}\left(\frac{d}{a}\right)^{0,25}$ $f_{ct} = 0{,}79\sqrt{f_c}$ $k = 4/9$	(1)
Ashour, 1 [6] *	—	$v_u = \left(0{,}7\sqrt{f_c} + 7F\right)\frac{d}{a} + 17{,}2\rho\frac{d}{a}$	(2)
Ashour, 2 [6] *	$a/d \geq 2{,}5$	$v_u = \left(2{,}11\sqrt[3]{f_c} + 7F\right)\left(\rho\frac{d}{a}\right)^{0,333}$	(3)
	$a/d < 2{,}5$	$v_u = \left(2{,}11\sqrt[3]{f_c} + 7F\right)\left(\rho\frac{d}{a}\right)^{0,333}\left(\frac{2{,}5}{a/d}\right) + v_b\left(2{,}5 - \frac{a}{d}\right)$ $v_b = 0{,}41.\tau.F$ $\tau = 4{,}15\ MPa$	(4)
Khuntia [7] *	$a/d \leq 2{,}5$	$v_u = (0{,}167\alpha + 0{,}25F)\sqrt{f_c}$ $\alpha = 2{,}5(d/a)$	(5)
	$a/d > 2{,}5$	$v_u = (0{,}167\alpha + 0{,}25F)\sqrt{f_c}$ $\alpha = 1$	

* F: Fiber factor calculated as $F = \left(\frac{L_f}{D_f}\right)V_f d_f$

3 Results and discussion

The 146 experiments of the database were split into train, test and validation datasets. A random group of 10 experiments representing new unseen data were considered to perform a validation as double check to the best Machine Learning model apart from the usual test datasets, which were also being compared with the analytical equations results. Thus, the remaining 136 experiments were used to train (80%) and to test (20%) the models performance based on the coefficient of determination (R^2) results. Table 3 shows the R^2 values for each ML model on both test and validation datasets. The extreme gradient boosting was the better model with $R^2 = 0{,}9603$ for validation dataset.

Table 3. Machine Learning algorithms performance comparison

ML Algorithm	R^2 test	R^2 validation
XGB	0,9531	0,9603
GB	0,9350	0,9304
RF	0,9502	0,9071
DT	0,9292	0,7776
KNN	0,6969	0,7391

The train/test (136 experiments) and validation (10 experiments) datasets were used to evaluate the proposed ML model (XGB) with analytical equations available in the literature. Table 4 shows these R^2 results for the prediction of shear strength. Figure 1 presents the graphical plots of real and predicted shear forces (Vu) for each model considering the validation dataset.

Table 4. ML and analytical models performance comparison

Model	R^2 train/test	R^2 validation
ML (XGB)	0,9903	0,9603
Ashour, 1 [6]	0,7704	0,7962
Ashour, 2 [6]	0,7190	0,7836
Khuntia [7]	0,7103	0,6477
Sharma [5]	0,6347	0,4440

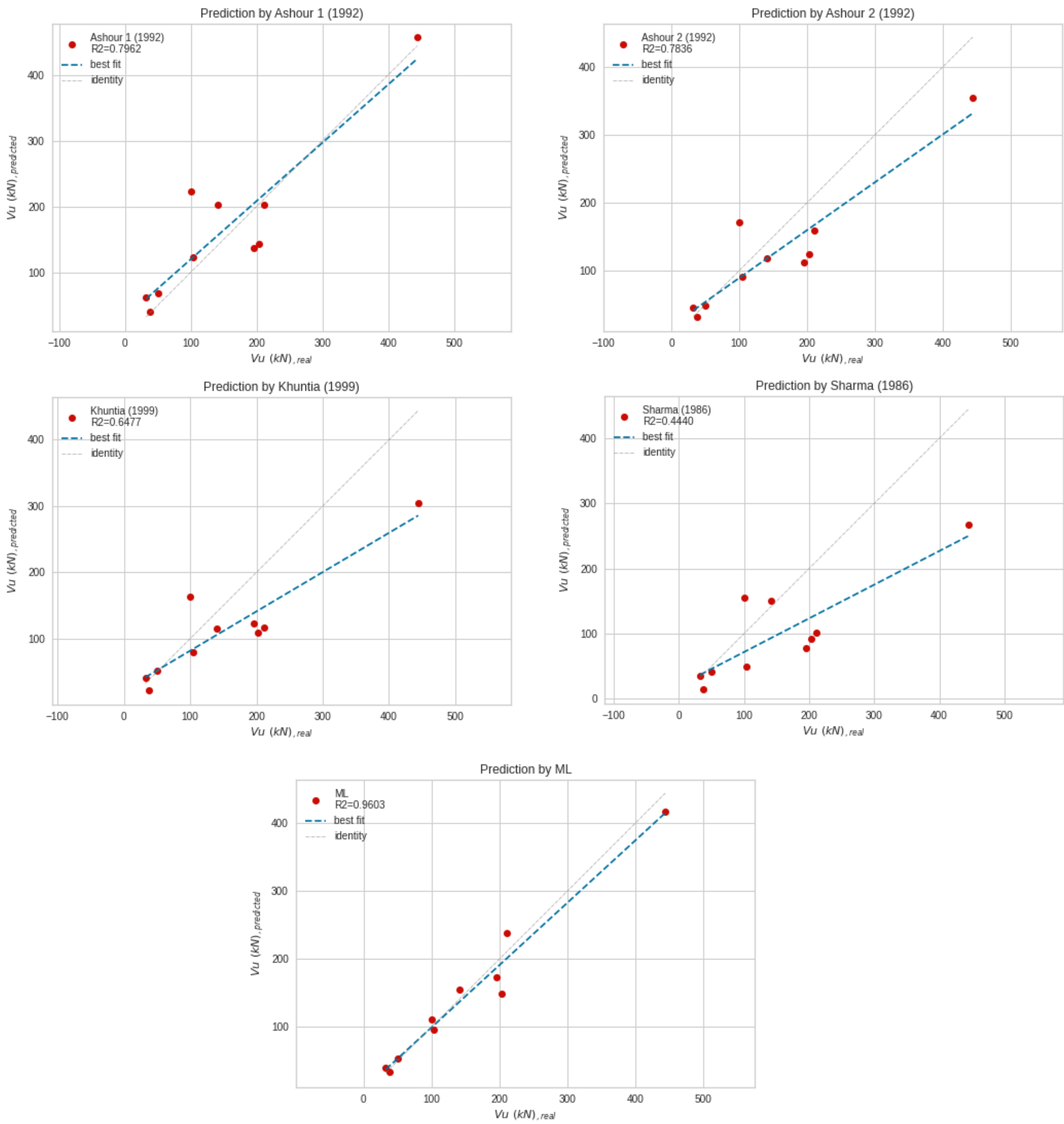

Figure 1. Real and predicted shear forces for analytical and ML models

For this proposed ML model, it was noticed that the most important parameters were the cross-section dimensions of the beams, as expected. Those are relevant parameters and should be used to create a model with an improved prediction capacity. To evaluate just the most important parameters related to fibers properties, a new machine learning model was developed removing some geometrical input parameters, such as the cross-section dimensions and effective depth (bw, h and d) and test type. A total of 7 parameters were used as inputs.

In this model, the R^2 value for test dataset was equal to 0,8903 and for the validation dataset was 0,5926. Figure 2 shows the real and the predicted shear capacity. Figure 3 presents the relative importance of each input parameter considered in the analysis. It is clear that the ratio between shear span and effective depth is the most important feature to predict the shear strength in this case, followed by the concrete compressive strength, maximum aggregate size, longitudinal reinforcement ratio, fiber diameter, fiber length and fiber volume fraction, respectively.

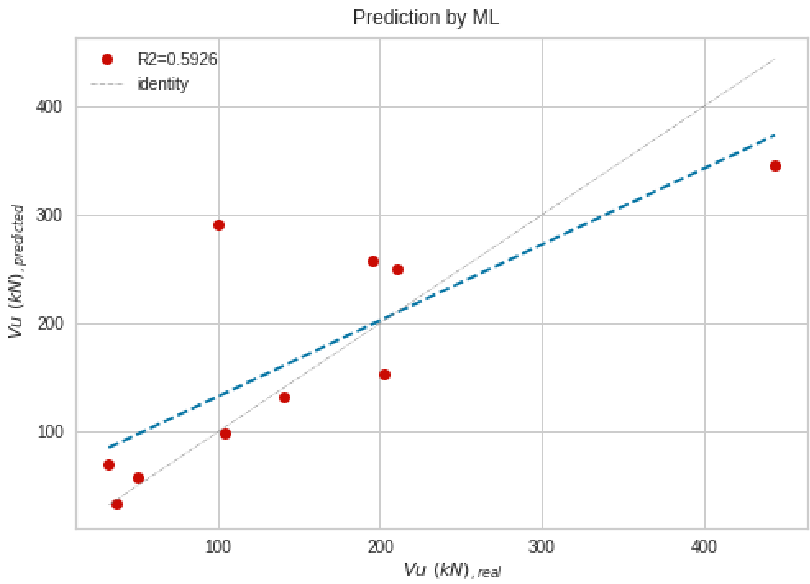

Figure 2. Real and predicted shear forces for the fibers features ML model

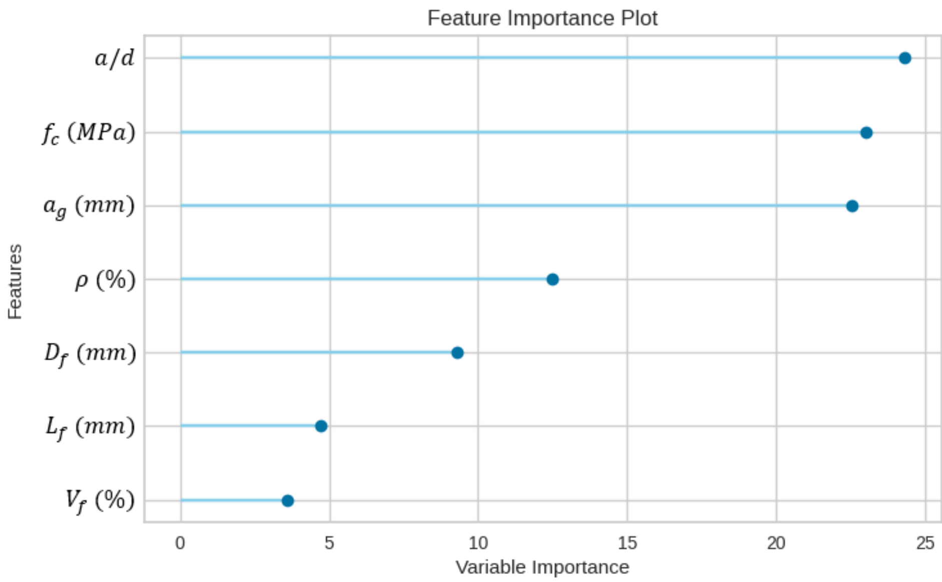

Figure 3. Feature importance for the fibers features ML model

4 Conclusions

From this study, it is possible to conclude that Machine Learning algorithms can provide a reliable and fast method for estimating, with high accuracy, the shear capacity of structural elements, surpassing the analytical equations. Nevertheless, it is still important to evaluate the results from these analytical equations to understand if the predicted values are in a reasonable margin of error.

From the studied algorithms, the extreme gradient boosting (XGB) resulted in the best accuracy to predict the shear strength of SFRC beams considering a database composed by 146 experimental data available in literature. The first equation proposed by Ashour [6] was the best analytical model when compared with the others, being only worse than the ML model.

The ML model performs much better when geometrical features are considered as inputs, followed by concrete properties, existing reinforcement in specimen and fibers properties.

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