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Research Article

A Simplified Approach to Determine Shear Strength for Corroded RC Beams

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ABSTRACT

Corrosion damage, which can be considered a construction or service failure during the life of the structure, is an important parameter for structural elements. Strength loss due to corrosion is observed in reinforced concrete (RC) members and is an important parameter affecting the performance of the structure. Determining the shear strength of beams with corroded reinforcement is important in terms of strength loss, design, and reinforcement criteria in the structural member. In this context, data from 157 experimental tests of corroded RC beams reported in the literature were collected and the ultimate shear strength values of the beams were determined as a function of the test parameters. Strength estimation was performed using the machine learning regression algorithms XGBoost and AdaBoost. The results obtained were evaluated using the R^2, RMSE and MAE performance metrics and high estimation success was achieved. The study shows that with these systems, which can perform learning based on experimental data, it is possible to estimate the shear strength values of corroded beams with known production parameters without the need for experimental measurements.

Keywords: *Corroded beam, Shear strength, Machine learning, XGBoost, AdaBoost.*

Korozyona Uğramış Betonarme Kirişler için Kesme Dayanımını Belirlemeye Yönelik Basitleştirilmiş Bir Yaklaşım

ÖZ

Yapı ömrü boyunca yapım ya da kullanım kusuru sayılabilecek korozyon hasarı yapı elemanları için önemli bir parametredir. Korozyon sebebiyle betonarme elemanlarda dayanım kaybı görülmekte bu da yapı performansını etkileyen önemli bir parametre olmaktadır. Donatısı korozyona uğramış kirişlerin kayma mukavemetinin belirlenmesi, yapı elamanında dayanım kaybı, tasarım ve güçlendirme kriterleri açısından önemli olmaktadır. Bu çalışmada yapay zekâ algoritmaları ile betonarme kiriş deneylerinden elde edilen kesme dayanımı değerlerinin deneysel çalışmaya gerek kalmadan belirlenmesi amaçlanmaktadır. Bu kapsamda literatürde gerçekleştirilmiş korozyona uğramış betonarme kiriş deneyleri verileri toparlanmış, deney parametrelerine bağlı olarak kirişlerin nihai kesme dayanımı değerleri tespit edilmiştir. Dayanım tahmini makine öğrenmesi regresyon algoritmalarından XGBoost ve AdaBoost ile gerçekleştirilmiştir. Elde edilen sonuçlar R^2, RMSE ve MAE performans metrikleri ile değerlendirilmiş ve yüksek tahmin başarısına ulaşılmıştır. Çalışma göstermektedir ki deneysel verilere bağlı öğrenme gerçekleştirebilen bu sistemler ile üretim parametreleri bilinen ve korozyona uğramış kesme dayanımı değerlerini deneysel ölçümlere ihtiyaç duymadan tahmin etmek mümkündür.

Anahtar Kelimeler: *Korozyonlu kiriş, Kesme dayanımı, Makine öğrenmesi, XGBoost, AdaBoost.*

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I. INTRODUCTION

Corrosion can develop in the reinforcing steel due to effects such as the choice of an inappropriate concrete cover in RC structural elements, inappropriate materials and manufacturing practices in the concrete mix (aggregate granulometry, use of sea sand, porosity of the concrete, etc.), exposure of the elements to a humid environment for a long period of time. The cross-sectional area of the corroded reinforcement is reduced and the concrete cover on the reinforcement increases in volume due to the volume of rust on the reinforcement, causing the concrete shell to shed over time. There is also deterioration of the reinforcement and loss of adhesion between the concrete and the reinforcement. With all these effects, rebar corrosion, which occurs as a manufacturing and service failure, is known to cause significant capacity loss in RC elements.

Various experimental studies have been carried out to investigate the effects of corrosion on the structure and performance of structural elements. Corrosion studies on RC columns have shown serious reductions, particularly in the load carrying capacity of the column [1-3]. There are several studies in the existing literature to investigate the structural behaviour of corroded RC beams [4-7]. Rodriguez et al. [8], in their study examined the changes in the load carrying capacity of a corroded RC structure and found that corrosion reduces the ultimate strength and also increases the crack widths on the element. The study found that the failure mode of the beams with corroded sections changed compared to the normal reinforced beams. In addition, the study by Higgins and Farrow's [9] also carried out an experimental investigation of corrosion on RC beams, and as a result of the experiment, low deformation and shear capacity were observed in the corroded sections. Ye et al. [10] observed the effect of corrosion on shear strength by observing the corroded stirrups in the studies and pointed out the low shear strength in beams with highly corroded stirrups. Based on real field data as well as experimental studies, Poupard et al. [11] carried out investigations on beams exposed to corrosion for many years and observed that cracking became widespread in the beam area where high corrosion levels were observed. Corrosion damage in RC beams is shown in Figure 1.

Figure 1. *Images of corroded RC beams*

In recent years, various artificial intelligence methods have been used to solve complex problems in structural and earthquake engineering (Figure 2). The use of machine learning systems in structural engineering is quite common in studies in the literature. Although the evaluation process is difficult due to the large amount of data in the field of structural health monitoring, machine learning systems have been widely used in this field [12, 13]. Prediction of post-earthquake seismic response and evaluation of structural safety have been another area of study using machine learning applications

[14, 15]. In addition, strength estimation and structural damage modes and estimation in RC elements after earthquakes, crack detection in elements have also been among the machine learning applications in the literature [16-24].

In this study, the estimation of shear strength was investigated using machine learning algorithms, depending on the experimental study data in which the corrosion effect was observed in RC beams. The study used machine learning from the field of artificial intelligence, which is one of the innovative technologies in the field of engineering. Machine learning, as a product of evolving technology, shed light on an important problem in the field of structural engineering in this study, and with the statistical approach of artificial intelligence, it was possible to estimate the strength of corroded beams by knowing various parameters without the need for experimental analysis.

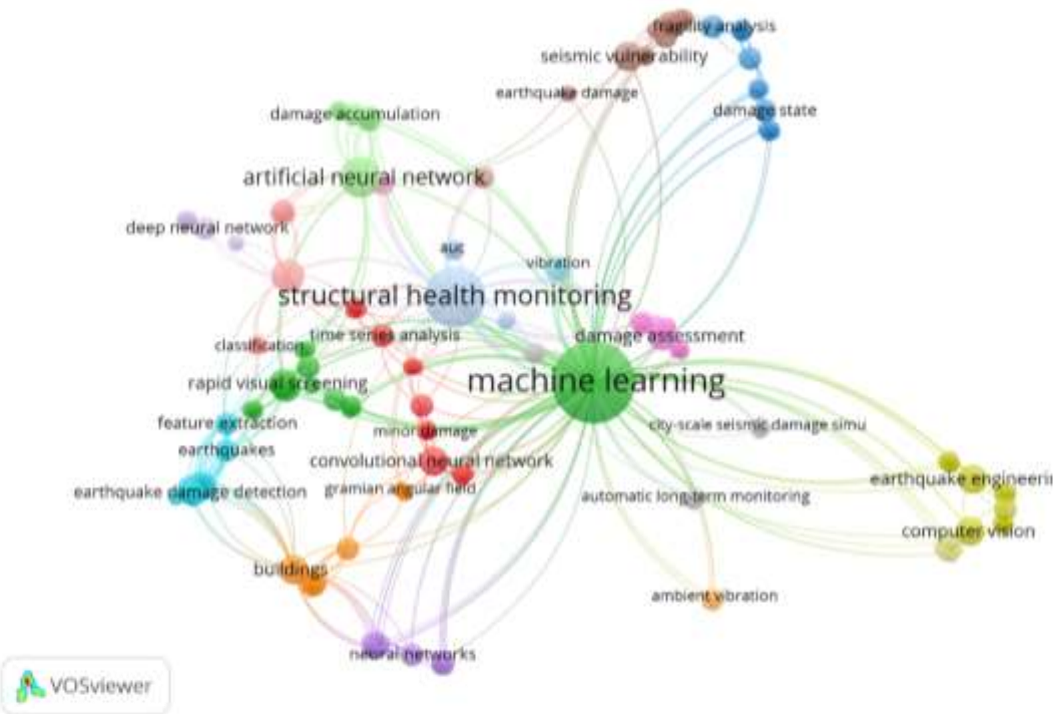


Figure 2. *Machine learning studies in structural and earthquake engineering*

II. MACHINE LEARNING

Machine learning (ML), which is one of the systems of artificial intelligence, is the functioning of machines similar to the information transfer, experience and decision mechanisms in humans. It is based on a mathematical-statistical system. ML is a system that produces results by evaluating multiple parameters and statistical results. With sufficient learning, it can be used as a decision support system to solve important problems. In short, it can be defined as the implementation on machines of training and learning processes that are possible in human physiology, thanks to the algorithms developed.

ML uses coded algorithms to correlate the result with incoming information and the instructions given to complete a task. ML has algorithms that can also produce solutions to complex engineering problems. How the input and output data are introduced into the network structure while the algorithm is being built is important to the success of a network model in coding. ML algorithms allow us to perform tasks such as classification, prediction, and object recognition. For these processes, ML is divided into two as supervised (trained) and unsupervised (untrained) learning according to the training state of the data. Supervised learning is a branch of ML that produces results (output) based on training data. Regression (prediction) and classification are supervised learning methods. Unsupervised learning analyses and cluster datasets. Without human intervention, these algorithms discover connections between similarities and differences between data sets. This algorithm is ideal for data analysis, segmentation, and image recognition. In this study, regression algorithms for ML were used as the estimation problem for the data was investigated.

Regression is a statistical measurement that determines the strength of the relationship between a dependent variable and other independent variables and makes predictions based on that relationship. Regression-based machine learning algorithms are used to estimate unknown values for data. These algorithms are used to make predictions from data using indicators of past behaviour. Particularly in engineering problems, regression algorithm can be used to find a solution based on the relationship between the data. In the case of dependent variable (y) and independent variable (x) from more than one variable, the regression method, which is defined as a function of (y) dependent on (x), is diversified according to the type of function among the variables in the data.
One of the most popular regression algorithms is Decision Tree, and many new and updated models have been developed accordingly. It is a model that brings practicality to problems with complex data. Decision trees are an algorithm that is constructed by dividing the input data into smaller clusters, just like the physiology of a tree from the root to the leaves. The first cells of the decision trees are called root nodes. Root cells have nodes below them. The complexity of the model increases as the number of nodes increases. At the bottom of the decision tree are leaf nodes. Leaves give us the result [25]. A representative decision tree network structure is shown in Figure 3.

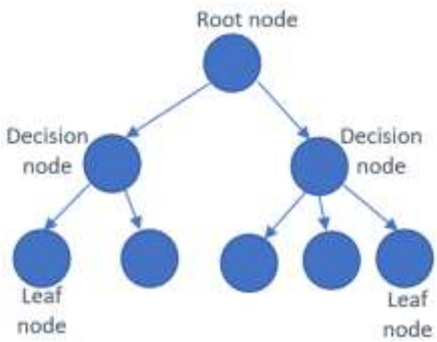


Figure 3. *Decision tree architecture*

Boosting algorithms are tree-based algorithms used to strengthen accurate predictions in machine learning models. This model, which is an ensemble method, can be used to strengthen weak models. This method uses sequential rather than parallel computation (Figure 4). XGBoost, AdaBoost, GradientBoost and CatBoost algorithms are types of Boosting algorithms. XGBoost (eXtreme Gradient Boosting) was developed in 2016 by Chen and Guestrin [26] using a gradient boosting framework designed for speed and performance. The main feature of the algorithm is that it works faster than other regression models. Process of XGBoost is calculated by Eq. 1 [27]. Number of trees are important parameters for XGBoost model. Target loss function shown in Eq. 2. and Eq.3 is found with the help of Eq. 1 and Eq. 2. The final target loss function is then converted to Eq. 4 and the XGBoost model is trained according to this target. Regularization term is calculated in Eq. 5. For all equations; y_i is the actual value, $\ddot{y}_i^{(t)}$is the final tree model; $\ddot{y}_i^{(t-1)}$is the previously generated tree model; $f_t(x_i)$ is the newly generated tree model, and *t* is the total number of tree models; g_i and h_i are the first and second order gradient statistics on the loss function.

$$y_i^{(t)} = \sum_{k=1}^{t} f_k\,(x_i) = \ddot{y}_i^{(t-1)} + f_t(x_i) \tag{1}$$

$$Obj^t = \sum_{k=1}^{t} L\left(y_i, \ddot{y}_i^{(t)}\right) + \sum_{k=1}^{t} \Omega(f_i) \tag{2}$$

$$Obj^t = \sum_{k=1}^{t} L\left(y_i, \ddot{y}_i^{(t-1)}\right) + f_t(x_i) + \Omega(f_t) + constant \tag{3}$$

$$Obj^t = \sum_{k=1}^{t} \left[g_i f_t(x_i) + \frac{1}{2} h_i f_t^2(x_i)\right] + \Omega(f_t) \tag{4}$$

$$\Omega(f)=\gamma T+1/2\lambda||\omega||^2 \tag{5}$$

Adaptive boosting (AdaBoost) is one of the simplest boosting algorithms. Although it is similar to Random Forest in terms of the prediction system, the training set is trained with the first weak learner. The training data that gives incorrect results in the estimation of the training result are retrained by increasing the weights of the training data. This is continued by training the output of the weak learner as the input to the other learner, and finally the results are combined to form the final result. Since there are models that perform slightly better than random prediction, weak learners are trained until they reach at least random prediction performance. In this algorithm model, decision trees are used in the training series. The AdaBoost model is calculated using Eq. 6 and 7. For equations **t**: number of trees, **w:** leaf weights, **s:** single tree structure.

$$y = \sum_{t=1}^{t} f_t\,(x) \tag{6}$$

$$F = \{f_t = w_s(x)\} \tag{7}$$

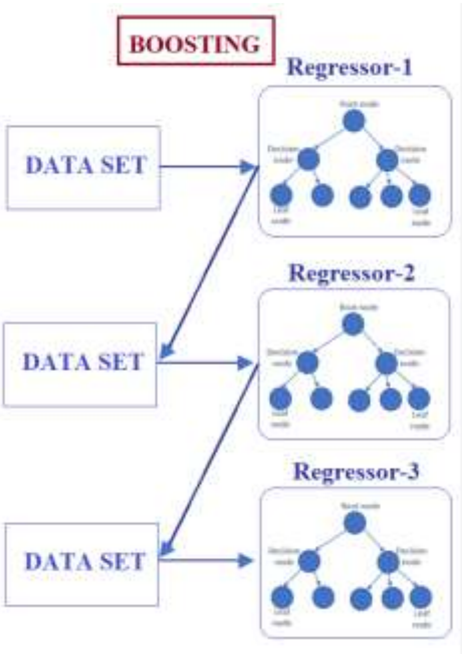


Figure 4. *Boosting algorithms*

III. ANALYTICAL STUDY

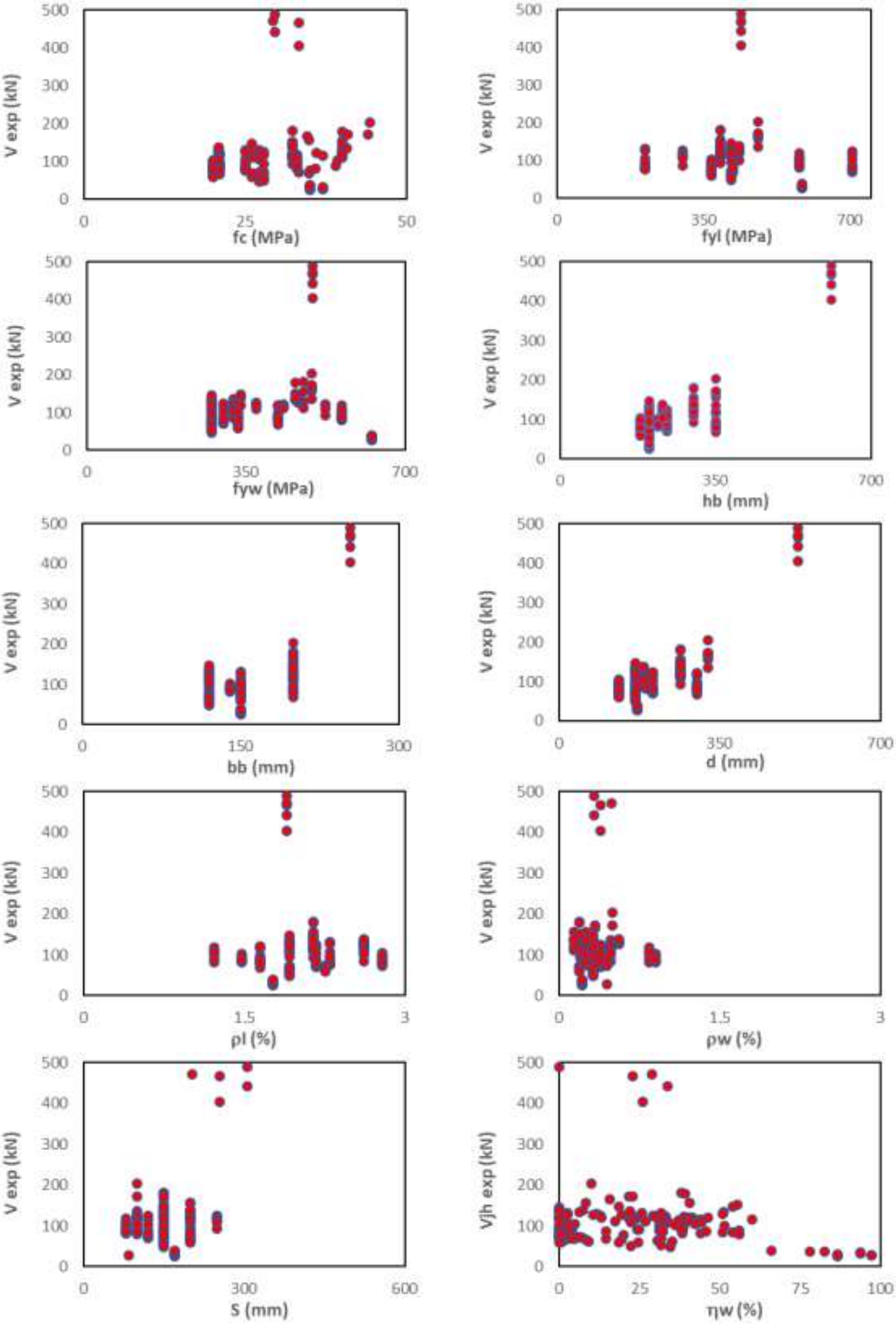
A. PREPARING THE DATA SET

Within the scope of the study, the shear strength values determined as a result of the tests performed on the corroded RC beams are to be determined using machine learning algorithms provided that similar production parameters are known. For this purpose, data from experimental studies in which the shear strength was determined for corrosion-damaged RC beams were collected from in the literature. For the experimental studies, the beam test data in the studies of Fu and Feng [28] studies [8, 9, 28-38] were compiled. Beam dimensions and shear span to depth ratio, concrete compressive strength, yield strength of longitudinal and transverse reinforcement, stirrup spacing, reinforcement ratios, corrosion parameter of longitudinal and transverse reinforcement are used as input parameters for algorithms, and shear strength value is output (target) in experimental studies. Parameters for the algorithm are given for algorithm as input and output parameter definition, values as range of change and units in Table 1.

Table 1. *Statistical values of experimental database*

Parameters		Details	Min	Max	Mean	Units
Material	f_c	Concrete compressive strength	20	44.40	28.12	MPa
	f_{yl}	Yield strength of reinforcement	210	706	430.59	MPa
	f_{yw}	Yield strength of stirrup	275	626	397.49	MPa
Cross sectional	h_b	Cross sectional height	180	610	257.34	mm
	b_b	Cross sectional width	120	254	159.19	mm
	d	Effective depth	130	521	214.32	mm
	a/d	Shear span to depth ratio	1	4.7	2.33	(%)
Reinforcement	ρ_l	Longitudinal tension reinforcement ratio	1.22	3.27	2.17	(%)
	ρ_w	Stirrup ratio	0.14	0.90	0.36	(%)
	S	Space of stirrup	80	305	155.68	mm
	η_l	Section loss ratio of longitudinal reinforcement	0	26	3.02	(%)
	η_w	Section loss ratio of stirrup	0	97.2	23.44	(%)
Output	V_{exp}	The sectional shear strength at beams obtained from the experiment	26.60	594	118.55	kN

In the data, the effect of each input data, namely the parameters effective in beam production, on the shear strength of the beams was examined and the statistical distribution of the parameters depending on the target value is shown in Figure 5. From the interaction relationships between the parameters shown in Figure 5, it can be seen that the beam dimensions change the beam shear strength proportionally. It is clear that the increasing the values of these parameters increase the capacity. It can be seen that the corrosion occurring in the longitudinal reinforcement in the beam has a greater effect on the strength value. In addition, there is no linear change between material strengths and beam shear strength. This situation also shows that linear approaches do not give accurate results when estimating the shear capacity of the beam. This result also shows that this problem cannot be solved with linear models from machine learning prediction algorithms.


V exp (kN)
fc (MPa)
fyl (MPa)
fyw (MPa)
hb (mm)
bb (mm)
d (mm)
ρl (%)
ρw (%)
S (mm)
Vjh exp (kN)
ηw (%)

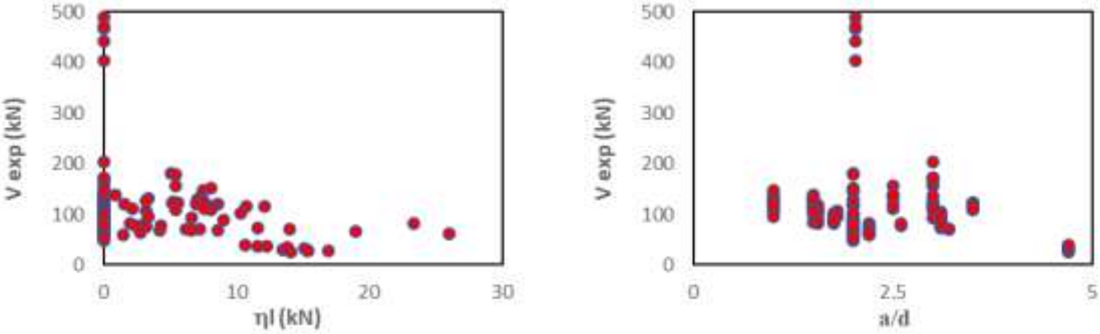


Figure 5. *Correlation between the input parameters and the corroded shear strength (output)*

B. APPLICATION OF ALGORITHM MODELS

Machine learning algorithms, one of the methods artificial intelligences, were used to estimate of shear capacity as a function of parameters in corroded RC beams. In the study, the shear strength was estimated from the test data based on RC beam dimensions, material information and corrosion parameters. For this reason, "XGBoost" and "AdaBoost" algorithms, which are among the machine learning regression (prediction) algorithms and the most recently developed models in the literature, were used in the study. These algorithms are considered to be more successful algorithm architectures, because they use multiple decision tree models to reach the final prediction value, are ensemble models, and have more accurate decision-making capabilities compared to a single algorithm model.

During the development of the algorithm, the coding process was carried out in the open-source software Python [39]. The Numpy and Pandas libraries, which are required libraries on the software, were loaded into the Python environment to process the data and apply algorithms in Regression models. First, the data was pre-processed. The data is introduced to the system as input and output, and then separated into training and test data. Prediction algorithms are trained using the training set and the algorithm is provided to learn in this way. The algorithm then tests the predictive success of the model using the test data. By using the random split method in the data, the size of test data was determined to be 0.15. This means: Approximately 85% of all data was randomly allocated as training set and 15% as test set. Therefore, 133 data out of 157 beam test data were randomly assigned as training set and 24 data were randomly assigned as test set.

The Sci-Kit Learn (sklearn) library was used to train and predict on the data. The data was trained using the “fit()” function of the Sklearn library, and the predictions were made using the “predict()” function. The estimated shear strength values obtained from the regression algorithms are shown in Table 2 in comparison with the actual (experimental) data.

The predicted corroded shear strength values obtained from XGBoost and AdaBoost algorithm models were compared with experimental shear strength values from literature and are shown in Figure 6.

Table 2. *Comparison of experimental and predicted shear strength results for RC beams (ML regression algorithms)*

$V_{Experimental}$ (kN)	$V_{predicted}$ (kN)		$V_{Experimental}$ (kN)	$V_{predicted}$ (kN)	
	$V_{XGBoost}$	$V_{AdaBoost}$		$V_{XGBoost}$	$V_{AdaBoost}$
60	55.7844	75.1097	67	63.7804	86.9622
77.4	84.4685	96.0281	96	81.6249	88.3667
89	80.0155	93.1793	443	452.157	438
91	77.6275	93.1793	136	148.504	145.01
119.4	105.134	107.663	138.2	135.954	119.15
133.9	136.474	119.150	121.6	122.845	109.261

145.4	153.894	141.255	112	122.873	107.663
29.1	32.1221	57.3692	121.7	112.378	115.144
90	85.2479	98.9606	75.9	82.6737	88.3667
124.3	113.230	109.261	131	123.107	105.807
204	169.634	148.924	105	90.8575	115.977
139.2	140.314	140.087	115	119.847	93.1793

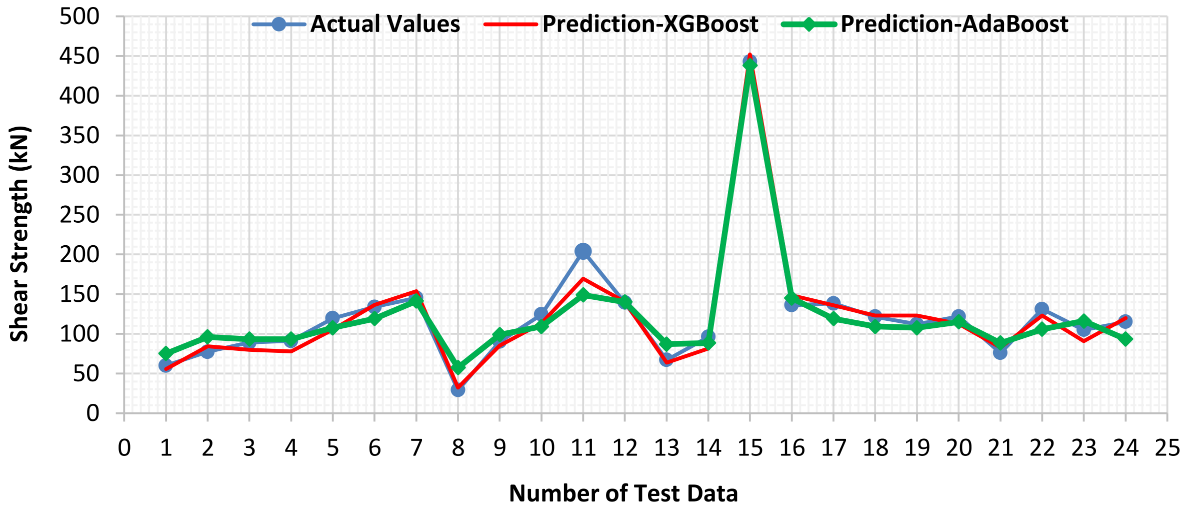


Figure 6. *The predicted (ML) and actual shear strength values of beam for regression model*

C. PERFORMANCE METRICS

In this study, prediction of shear strength for corroded RC beams has been evaluated with various statistical performance parameters using the proposed ML algorithms. R^2 value, Root Mean Square Error (RMSE) and Mean Absolute Error (MAE) success and error metrics have been used depending on the correlation of predicted shear strength values and those obtained from experimental data for performance values. Metric formulae are given in Eqs.8-10.

$$R^2 = 1 - \frac{\sum_{i=1}^{n}(yi - \overline{yi})^2}{(yi - yi')^2} \tag{8}$$

$$RMSE = \sqrt{\sum_{i=1}^{n}\frac{(yi' - yi)^2}{n}} \tag{9}$$

$$MAE = \frac{\sum_{i=1}^{n}|yi - yi'|}{n} \tag{10}$$

In these equations; y is the actual experimental value, yi' is the predicted value, $\overline{yi}$ is the actual mean value and *n* is the number of dataset. The best for success is values where R^2 is close to one, MAE and RMSE is close to zero.

The performance success of the models trained in this study; measured by the metrics "r2_score (R^2)", "mean_absolute_error (MAE)", "root_mean_square_error (RMSE)" metrics. The performance success of the ML models is shown in Table 3 and Figure 7. The real data, which is the Numpy array for measurement, and the prediction data obtained from the model in which the predict () function works were compared and the success metrics of the model were tested with the success of the model. For RC beam shear strength, the convergence between the actual value as a result of the experimental study and the estimated values obtained from the algorithms is best seen in the XGBoost model. A high R^2 accuracy rate of 97.81% was obtained from the XGBoost algorithm. Among the error metrics, 8.74 MAE values and 11.08 RMSE values converged to zero and a high estimation success was achieved. The AdaBoost algorithm, which is an alternative machine learning method for this important problem in the field of structural engineering, also gave very good results.

Table 3. *Corroded shear strength results of ML regression algorithm*

ML Algorithm	***R^2 score (%)***	***MAE***	***RMSE***
XGBoost	97.8180	8.7456	11.0805
AdaBoost	94.3453	13.8876	17.8377

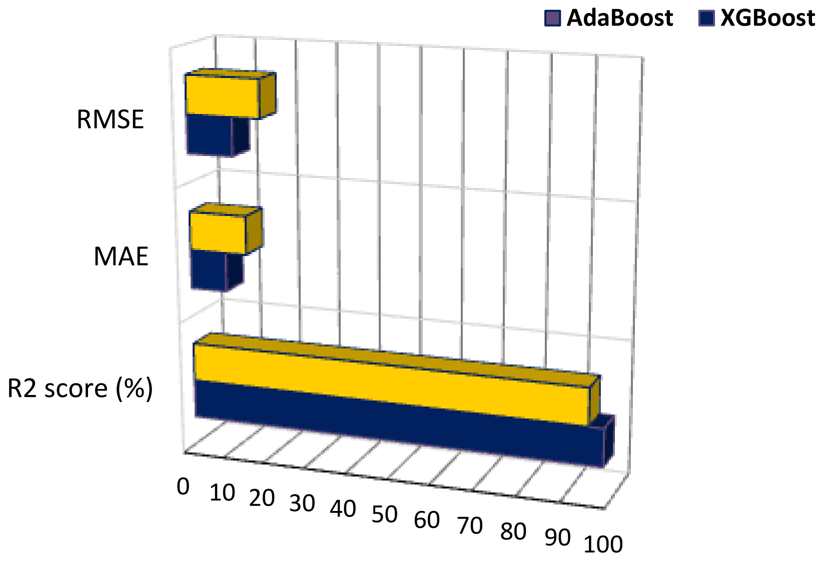


Figure 7. *Performance of ML Models*

<u>IV. CONCLUSION and DISCUSSION</u>

In this study, an artificial intelligence-based machine learning algorithm has been developed that can predict the changes in shear strength due to the effect of damage such as corrosion on beam elements in RC structures. It was found that the developed algorithms can be used with high accuracy, especially in cases where experimental work is costly and difficult, but the effect of corrosion on the shear strength of the beam needs to be known.

A data pool of 157 RC beam experiments was used to develop the algorithm. The XGBoost and AdaBoost machine learning algorithms developed in recent years were used to determine the shear strength of corroded beams and their performance was tested. This is the first time in the literature that the XGBoost and AdaBoost algorithms have been applied to this type of structural problem.

The results of the study show that: A fast and simple application infrastructure has been developed to be used in the determination of shear strength in RC beams after corrosion with the proposed machine learning models. The XGBoost and AdaBoost machine learning algorithms have undergone a good training process and have provided sufficient learning to achieve successful prediction results. The main promise of this system is that, if the beam manufacturing parameters and the corrosion level are known, it can help to determine the shear strength without the need for experimental study. According to the results obtained, the strength values obtained from the analysis performed with the XGBoost algorithm have a 97% estimation success when compared to the values found in the experimental study. Similarly, the AdaBoost algorithm estimated the shear strength in corroded beams with 94% accuracy.

In the results obtained by Fu and Feng [28] from the literature study using the data set, it was observed that the Gradient Boosting Method, one of the boosting models, gave much more successful results. Also, the Gradient Boosting algorithm, one of the machine learning models used to estimate the bending capacity of corroded beams, gave very satisfactory results by Abushanab et al. [40]. Comparing the results of this study, it can be said that the boosting algorithms are quite successful in the strength determination problems of corroded members.

The most important contribution of the study with a high success rate to practice and literature is the success of the practical application. In corrosion testing, a special test setup should be established to bring the structure to the corrosion level it will reach over the years in a short period of time. In addition, it is very important to study the loss of strength value in the corroded structural element in corrosion research, but with this developed model it will be possible to get results in a short time to see the loss of shear strength.

It is very important to test the algorithms developed in the machine learning studies on a larger data set. For this reason, it will be possible to develop algorithms by collecting more data with corrosion-oriented experimental studies and to derive a mathematical model from data set.

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