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Compressive Strength Prediction of Recycled Aggregate Concrete Based on Different Machine Learning Algorithms

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Abstract

The use of recycled concrete aggregate (RAC) in creating new concrete has gained significant attention for environmental and financial reasons. However, the compressive strength of the product concrete is hard to predict due to many variables. In this study, the compressive strength of recycled aggregate concrete was predicted using eight well-known machine learning algorithms, including support vector machine (SVM), artificial neural network (ANN), XGboost, Tree, Random Forest, Gradient Boosting, CatBoost, and AdaBoost. Every machine learning algorithm's general methodology entails gathering and analyzing input data, training the algorithm, testing the algorithm, and producing an output. A total of 419 data samples (experimental tests) were used in training and testing all the machine learning models. The results show that the best models for estimating RAC compressive strength are Neural Network, AdaBoost, and XGBoost. The other algorithms, random forest, gradient boosting, and Catboost, performed well in predicting the compressive strength of RAC, however, tree decision and SVM performed badly. The primary evaluation metrics used in this study were Mean Squared Error (MSE) and R-squared (R^2), which helped determine the accuracy and reliability of the predictive models.

Keywords- Compressive Strength, Machine learning, Neural Network, Recycled Aggregate Concrete.

I. INTRODUCTION

Concrete is the major construction material around the world. However, it has an increased environmental impact due to the consumption of huge quantities of natural resources and the increased demands of landfills for deuteriation and demolished concrete buildings and other infrastructures. This is true because of the nature of concrete, which is a material in which it is difficult to dissolve. Therefore, the use of Recycled concrete aggregate (RAC) in producing new concrete has become of increased importance for both environmental and economic reasons. Many countries have presented policies that promote the use of recycled aggregates in the construction of new concrete, roads, etc., to encourage the use of recycled aggregates in the construction of new concrete. The use of recycled aggregates has been regulated by codes that either limit the applications of recycled aggregates or limit the use of recycled concrete aggregates according to the properties of recycled aggregates.

The application of RAC in the field of engineering practice is still relatively low, and it is primarily found in concrete used for non-structural purposes,ecause of the negative effects that could occur when using recycled aggregates[1]. Researchers around the world have studied the use of recycled aggregates in producing new concrete for more than two decades and its effects on properties. Compared to natural aggregates, recycled concrete aggregates generally has It is clearly evident that recycled aggregates have a higher water absorption rate, a lower apparent density, lower bulk density, and lower abrasion resistance than the natural aggregate and increased quantities of dust and impurities[1][2][3][4], [5][6].

The deuterating properties of recycled aggregates have been shown to have negative effects on the overall mechanical properties and durability of the newly made concrete. Studies have shown that using RAC could lead to lower compressive, tensile, and modulus of elasticity[6][7][8][9][10]. According to numerous studies, employing recycled aggregate in the new concrete at replacement ratios lower than 25% has little to no impact on the compressive strength of the material[11][12]. Contrarily, very few researchers have discovered that employing recycled aggregates improved the quality of concrete. According to Lofty and Al-Fayez[13], substituting the RCA by 10% to 30% and the recycled fine aggregate by 10% to 20% improved the mechanical properties and durability of concrete. Zhou and Chen[1] have studied different types of recycled coarse aggregates and have found that the compressive strength and flexural strength of RAC are comparable and even exceeded the conventional concrete due to the much higher absorption of RCA which is improving bonding strength between aggregate and cement. One important factor that determines the overall properties of concrete made from recycled aggregates is the properties of the source or parent concrete that the aggregates are produced from. For example, Tabash and Abdelfatah [14] have studied the effects of RCA from different sources and found that when using recycled aggregates from a concrete with a compressive concrete of 50 MPa had better results compared to using recycled aggregates with lower compressive strength. According to the literature, recycled aggregate generated from greater compressive strength concrete has superior qualities than that generated from lower compressive strength concrete. It has improved overall absorption, porosity, density, dust particle reduction, and compressive strength of the new concrete compared to a concrete made from weaker recycled aggregate. As a result, many countries and building regulations have approved the use of recycled aggregates, although with restrictions on the quality of the recycled aggregates.

Many standards and specifications from throughout the world, particularly in Europe, have allowed the use of recycled aggregates as a substitute for natural aggregates, although with some restrictions. Each code has its own set of restrictions and applications for recycled aggregates. The technique for establishing whether recycled aggregates are suitable for use varies depending on the building code, but most of them include a criterion for minimum recycled aggregate density and maximum absorption ratio. For example, The RILEM Standard classifies recycled aggregates into three categories: masonry waste mix of concrete rubble and natural aggregates and for each category there is a limit for the density and maximum absorption ratio for the aggregates to be used. The Japanese standards classify the usage of recycled aggregates into three categories, each with a density and absorption criterion. According to German standards, recycled aggregates are classified into four types: concrete aggregates, brick aggregates, aggregates from other construction materials, and mixed aggregates, with requirements for density, absorption, and other properties such as impurities, plaster, and bitumen content for each type[15].

The benefits of steel fiber reinforcement in concrete were reviewed in the paper, with improvements in compressive strength, tensile strength, and durability highlighted. Steel fibers' role in enhancing resistance to environmental factors and mechanical stresses was emphasized, making concrete more resilient for construction applications, especially in seismic zones

The benefits of steel fiber reinforcement in concrete were reviewed in the paper, with improvements in compressive strength, tensile strength, and durability highlighted. Steel fibers' role in enhancing resistance to environmental factors and mechanical stresses was emphasized, making concrete more resilient for construction applications, especially in seismic zones[16].

Various international standards and specifications have approved the use of recycled aggregates, albeit with restrictions based on density, absorption ratio, and other properties. However, a significant gap remains in the development of standardized methods for predicting the compressive strength of RAC at 28 days using recycled aggregates. While previous studies have explored the properties of RAC and its effects on concrete strength, there is a need for a more systematic approach that leverages machine learning algorithms to accurately predict RAC compressive strength. This study aims to address this gap, contributing to the broader adoption of recycled aggregates in structural concrete applications.

II. MACHINE LEARNING APPLICATION IN CONCRETE

Machine learning (ML) is a type of artificial intelligence (AI) that teaches computers how to make predictions using existing datasets and algorithms. Most notably, it allows computer systems to develop and learn themselves instead of being explicitly programmed. The use of machine learning has been studied now for a while. It can be used for regression, classification by using datasets and that is called supervised Machine learning[17]. In this study, different supervised machine learning algorithms will be used to learn how to predict the compressive strength of recycled aggregate concrete based on the data collected from the literature. A large number of ML algorithms, such as neural networks, decision trees, regression analysis, support vector machines, random forests, and boosting algorithms, have been used in different engineering applications. When it comes to predict the mechanical properties of concrete, the use of ML algorithms is not a new phenomenon, but it increased recently due to the increased interest in artificial intelligence in general and the improved computation power. One of the earliest papers that have predicted the compressive strength of concrete is the work of (Yeh,1998)[18], who have studied the application of artificial neural networks for high performance concrete with good results. Many researchers have applied neural network algorithms to predict the compressive strength of different types of concrete and they all had good prediction models with relatively small errors[19][20][21][22][23][24]. They studied different features to predict compressive strength. Most of the researchers have only studied the materials proportion without taking into consideration the properties of the concrete components. For example, most of the mentioned studies did not include the fines, specific gravity, absorption. Etc. for natural nor recycled aggregates except for [19] with no noticeable improvement in the model. For Yaprak et al. [21], they even did not include the proportions of sand and gravel and studied curing type and obtained good results. Using linear regression, multiple linear regression does not yield great results due to the nonlinearity of the relationship between all the features[25]. One more popular algorithm is the SVR, which supports vector regressor. Aiyer et al.[26] have predicted, with great accuracy, the compressive strength of self-compacted concrete (SCC) using SVR. Some researchers have used what is called ensemble learning methods, which are a type of machine learning technique that combines numerous base models to create a single best predictive model that has superior prediction compared with a single model[27]. Kaloop et al.[28] have used several algorithms to predict the compressive strength of HPC. Among these algorithms was the gradient tree boosting, which proved to be superior to the others. Han et al.[29] investigated the ability of an improved random forest algorithm to predict the properties of HPC with good accuracy. Anjum et al.[30] have investigated four ensemble learning algorithms, gradient boosting, random forest, bagging regressor, and Adaboost to predict the compressive strength of fiber-reinforced concrete with added nano silica in which good accuracy was achieved.

Many studies were conducted using machine learning to predict the mechanical properties of concrete containing recycled aggregates using different varieties of ML algorithms. Xu et al. [31] have deployed an artificial neural network and multiple nonlinear regressors to predict the mechanical properties of recycled aggregate concrete RAC. In their data, they have taken into consideration the absorption of both the natural and recycled aggregates besides the mixed proportions. For both algorithms, the predicted compressive had the highest R^2 of 0.32 and 0.65 for multiple nonlinear regressors and ANN, respectively. Better results were achieved for the flexural tensile strength. Vasanthalin P and Kavitha N[32] predicted the compressive strength of RAC using ANN and the cuckoo search method. Good results were achieved; however, looking at their results, there is a difference between the R value of the training and the test data, which implies there may be overfitting in the suggested model. The ratio also has taken, as inputs, the weight of recycled aggregate and the recycled aggregate replacement ratio, and both represent the same feature. Duan et al.[33] have studied many inputs, including the specific densities, absorptions, and the maximum size of the natural and recycled aggregates for only 168 data sets. With their model, they have achieved great accuracy for both the training and the testing datasets. The same level of accuracy was reached by Dantas et al. [34], but they also studied the substitution of fine aggregates as well as coarse aggregates, whereas all the previously discussed papers have only researched coarse aggregates.

Looking at the previous studies, the Artificial Neural Network is suitable to model the mechanical properties of normal concrete and recycled aggregate concrete. Duan et al.[35] have used ANN with 324 datasets to predict the modulus of elasticity of recycled aggregate concrete with great accuracy. Surprisingly, Hammoudi et al.[36] trained a model with ANN and response surface method RSM and achieved great accuracy with only three features, which are the cement content, the replacement ratio of recycled aggregates, and the slump value of the concrete mix. For both models, the R^2 was 0.988 and 0.99 for ANN and RSM, respectively, for the compressive strength of RAC at 28 days. We believe that the high accuracy was obtained despite the absence of fine aggregate and coarse aggregate content, as well as their properties, such as absorption and densities as input values because the slump value is the outcome of the previously mentioned attributes.

Similar to normal concrete, many studies have used ensemble machine learning algorithms. Yuan et al. [37] included many features besides the mixture proportions, such as the parent concrete strength water absorption and the Los Angeles abrasion index of the natural and recycled aggregate. They used ensemble techniques, gradient boosting, and random forests. Although the random forest performed better than the gradient boosting, the accuracy level is far below the accuracy of ANN used by other researchers. Khan et al. [38] used decision trees, bagging regressors, and gradient boosting. The best results were obtained for the bagging regressor model with R^2 of 0.91.

In this study, different machine learning algorithms, including ANN, Random Forest, XGBOOST, and Adaboost, will be trained and used to predict the compressive strength of recycled aggregate concrete using data obtained from the literature. Based on the previous studies, the features that will be studied are the content of the mixed components.

III. METHODOLOGY

In this study, eight popular machine learning algorithms, including support vector machines (SVM), artificial neural networks (ANN), XGboost, Tree, Random Forest, Gradient Boosting, CatBoost, and AdaBoost, were used to predict the compressive strength of recycled aggregate concrete. The general approach of every machine learning algorithm includes collecting and analyzing input data, training the algorithm, testing the algorithm, and generating an output/output. The inputs are cement, fine aggregates, natural coarse aggregates, recycled aggregate content, and water content (Kg/m^3). The only output is the compressive strength of the concrete, as shown in Figure 1. The first of the machine learning models was generated using a decision tree, which is a tree-structured model that is simple to grasp and can be effectively generated from data. One of the first and most widely used methods for building discriminating models is the induction of decision trees; this is a technique that has been independently created in the machine

learning community [38, 39, 40]. The method chooses the optimal characteristic for the tree's root, divides the collection of instances into disjoint sets, and then adds nodes and branches to the tree accordingly. The technique is then repeatedly applied to every dataset,,whichch results from dividing the dataset based on the chosen attribute. If all of the examples in a set belong to the same class or if further separation is not achievable. The related node is transformed into a leaf node and assigned the appropriate class label. The methodology involved using machine learning algorithms, including ANN, SVM, RF, and GBM, to predict the compressive strength of RAC at 28 days. Key configurations included optimizing the number of layers in ANN, using an RBF kernel in SVM, setting 100 trees in RF, and applying XGBoost in GBM, with hyperparameters tuned via grid search and cross-validation.
The random forest algorithm, which L. Breiman introduced in 2001 as a general-purpose way to deal with both supervised classification and regression tasks, has proven very beneficial. The strategy, which combines the tree predictors so that each tree relies on the values of an independent, uniformly distributed random vector and then averages their predictions, has shown exceptional performance in scenarios where the number of variables is substantially greater than the number of observations.[41].

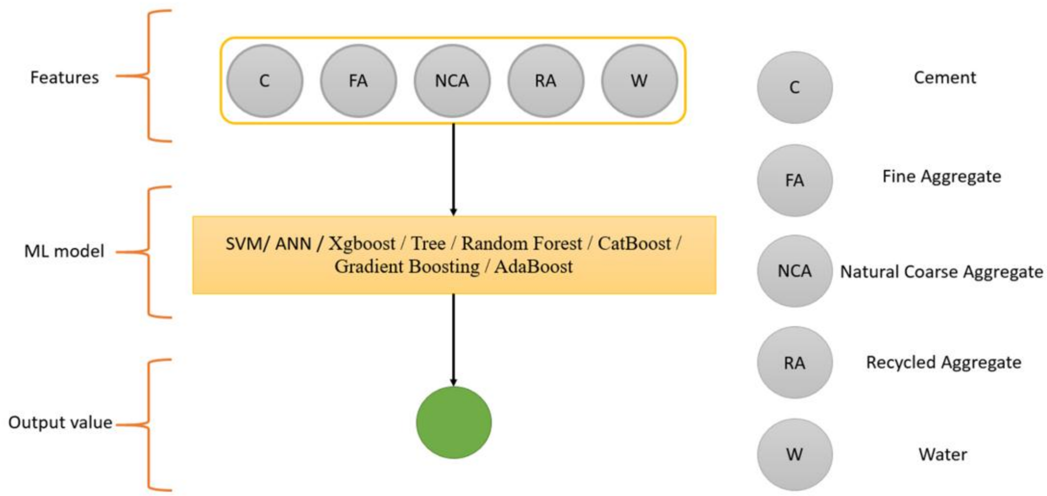

Figure 1. The Machine Learning Model Architecture

The Extreme Gradient Boosting algorithm (XGboost) combines multiple decision tree (DT) models in order to improve the model's efficiency. The implementation of a regularization step distinguishes the XGBoost approach from other gradient boosting algorithms. Regularization is achieved by modifying the loss function with an Ω term as in equation (1) where T is the number of leaves, L is the loss function, and w is the vector of leaf values [42,43]. The regularization parameter of the XGBoost method aids in overcoming the generalization issue and preventing overfitting, hence enhancing its performance.

$$obj = \sum_{i=1}^{n} L(\hat{y_i}, y_i) + \sum_{m=1}^{M} \Omega(f_k) \quad \Omega(f_k) = \gamma\, T + 0.5\gamma \parallel w \parallel^2 \qquad (1)$$

CatBoost uses oblivious trees since they are more resistant to overfitting. Another notable feature of the CatBoost algorithm is its use of the greedy technique at each tree split. Dorogush et al. [44] provide a full explanation of this approach.

In the 1990s, Vapnik and his colleagues at AT&T Bell Laboratories created the SVM, a machine learning model [45, 46, 47] that is still widely used today. The essential notion of SVM is that it maps the input vectors into a high-dimensional feature space using some nonlinear kernel function set a priori, referred to as a "hyperparameter," which is the parameter that is initialized before and fixed throughout the machine learning model's training. In this feature space, a linear decision surface is built with the property of assuring the learning machine's high generalization [45]. For further detail on kernel functions, interested readers might see the "Tutorial on Support Vector Regression" [46].

Gradient tree boosting, first suggested by Friedman [49], is a boosting machine learning model that employs a series of "weak" or "base" learners to create an arbitrarily accurate "strong" learner [49, 50, 51, 52]. To decrease the total training error, the method learns the first weak learner, i.e., the first tree, in the first iteration. The algorithm learns the second tree in the second iteration to decrease the mistake generated by the first tree, as shown in Fig. 2. The algorithm continues this method until it has built a good quality model, such as when the model's loss, i.e., total error, reaches a certain amount. The literature has thorough descriptions of methods and learning algorithms, such as "Greedy function approximation: a gradient boosting machine" [49] and "Gradient boosting machines, a tutorial" [53]. Adaptive boosting (AdaBoost) [54] improves predictor performance by concentrating on samples underfitted by the predecessor and assigning and changing sample weights as functions of prediction error. The last method used is "neural network," which is a notion that arose as a result of scientific interest in artificial intelligence (AI) in the mid-1950s. The ANN-model gives synaptic activity through a weight matrix, which is a set of numerical values that are usually changed by a learning process that is similar to how humans learn. The obvious benefit of this technique is that neuron-computing devices do not need to be programmed; rather, the random selection of starting weights encourages learn-making from the process of modifying the weights themselves by achieving the lowest prediction error. The ANN presents a weight matrix of numerical value and a bias "b" for each neuron, for which various analytical formulae are performed to generate modifications to the matrix itself. The supplied data is processed by successive layers of neurons. The input layer and output layer are always considered. In addition, a certain number of "hidden" levels are presented. Typically, just one hidden layer is considered; however, the addition of two or more hidden layers may occasionally greatly enhance the ANN's performance. Figure 3 shows a made-up model of the human nervous system that was based on the ANN method. In this method, a, and b are input parameters with no size.

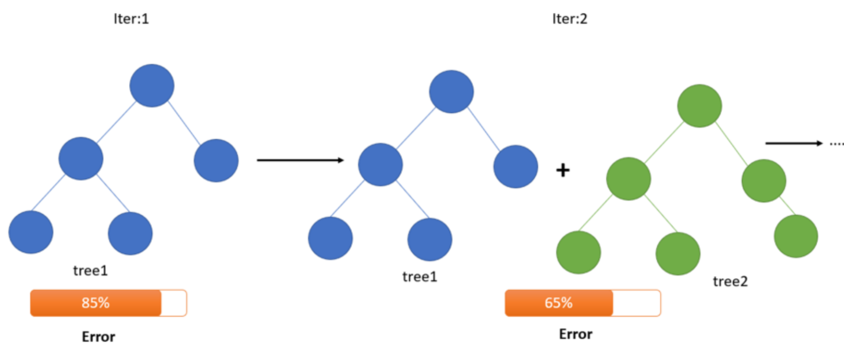

Figure 2. Iteratively Learning Weak Learners (trees).

IV. DATA COLLECTION

The data used in training the machine learning models in this study were collected from the literature. In total, 419 data samples were used in training and testing all the machine learning models in this study. 250 data samples were collected for concrete that includes coarse recycled aggregate, from 30 previous studies[38]– [64]. In addition, an extra 169 data samples were used for normal concrete taken from the data of (Yeh,1998) [18]. This study will only consider the replacement of coarse aggregates with RCA with the use of natural fine aggregates. The considered features that have been considered are the cement, fine aggregates, natural coarse aggregates, recycled aggregates contents, and water content measured in measured in Kg/m^3 and only one output, which is the compressive strength of the concrete. For consistency, it was decided to use recycled aggregate content rather than the replacement ratio. Moreover, the authors did not consider other properties such as density, specific gravity, and water absorption of all the aggregates, not the cement properties, as features based on the previous studies discussed in section 1.2 where adding these features did not increase the model accuracy. Additionally, the data were split into training and testing sets, with a ratio of [80:20]. A cross-validation technique k-fold cross-validation, was also employed to ensure the robustness of the model. Data preprocessing was performed prior to training, including the transfer of compressive strength from cube strength to cylinder strength because the obtained data contained tests for both compressive strength for cubes and cylinders. Therefore, the greater cube compressive strength was transformed into cylinder compressive strength by multiplying it by a factor of 0.8. the value of 0.8 represents the average of the Conversion factors used to get the cylinder's compressive strength from a cube[66]. TABLE I shows the ranges, mean and standard deviations of the features and target.

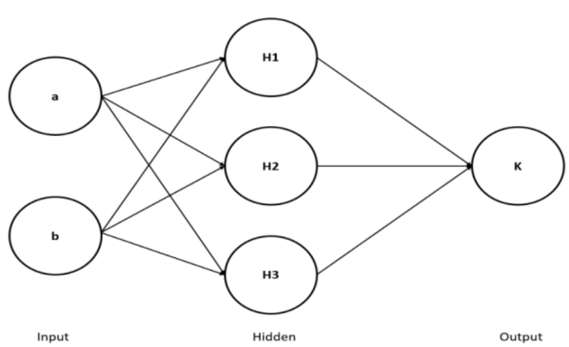

Figure 3. Artificial Neural Networks Inspiration from the Human synapse

V. RESULTS AND DISCUSSION

The algorithms were written in Python 3 and used the open-source libraries listed above. The predictions of eight different machine learning models are discussed in this section. For every model, the data used in was split into training and testing data with ratios of 0.8 and 0.2 of the total data. For each model and after completing the learning process, a variety of evaluation metrics was calculated for both training and testing data to measure the model accuracy in predicting the compressive strength of RAC. The calculated metrics are the Mean squared error (MSE) that can be calculated as follows.

TABLE 1. RANGES, MEAN AND STANDARD DEVIATION OF THE FEATURES AND TARGET

Name	Mean	Median	Min.	Max.
Cement (Kg/m^3)	379.6030	375.00	200.00	539.00
Water (Kg/m^3)	198.2683	192.63	152.14	271.00
Coarse aggregates (Kg/m^3)	710.6555	872.00	0.00	1295.00
Fine aggregates (Kg/m3)	665.4851	647.00	363.00	946.00
Recycled Aggregates (Kg/m^3)	386.8544	265.70	0.00	1252.00
Concrete Compressive Strength (Mpa)	30.39275	31.280	12.250	49.920

$$MSE = \frac{1}{N}\sum_{i=1}^{N}(y_i - y°_i)^2 \qquad (2)$$

where N represents the number of samples, y represents the real value, and $y°$ represents the predicted output value. The other performance evaluation metric was the Root Mean Squared Error calculated by

$$RMSE = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(y_i - y°_i)^2} \qquad (3)$$

The other metrics calculated to evaluate the models are the Mean Absolute error MAE and the coefficient of determination R^2, which are calculated using equations (4) and (5).

$$MAE = \frac{1}{N}\sum_{i=1}^{N}|y_i - y°_i| \qquad (4)$$

$$R2 = 1 - \frac{\sum_{i=1}^{N}(y_i - y°_i)^2}{\sum_{i=1}^{N}(y_i - y^{\wedge})^2} \qquad (5)$$

Tables II and III show the evaluation metrics for all the machine learning models used in this study for both training and testing data. Linear and polynomial regression were also done, but the results were very poor, so they were not included in the study. Looking at the results, it is very clear that Tree Decision and SVM did not perform as well as other algorithms with R^2 equal to 0.695 and 0.688, respectively, and this is in agreement with other studies. As expected, the artificial neural network performance was great, with R^2 of 0.9948 and MSE of only 0.278. as discussed earlier. It appears that Artificial Neural Networks can model the mechanical properties of concrete remarkably. All the other ensemble methods used in this study are able to predict the compressive strength of RAC with good accuracy. However, only one algorithm was able to score better than the Artificial Neural Network, which is the Adaboost, with an R^2 of 0.996. XGBoost algorithm also obtained very good prediction results with an R^2 of 0.991. Lastly, both Gradient boosting and CatBoost have good accuracy with R^2 of 0.947 and 0.978, respectively.

TABLE 2. METRICS FOR TRAINING

Model	MSE	RMSE	MAE	R^2
XGboost	0.462255	0.679894	0.427692	0.991354
Tree	16.96004	4.118256	3.085174	0.682771
SVM	16.94243	4.116119	3.132912	0.6831
Random Forest	3.188919	1.785755	1.269868	0.940353
Neural Network	0.277969	0.527228	0.159495	0.994801
Gradient Boosting	2.838594	1.684813	1.232686	0.946905
CatBoost	1.147411	1.071173	0.803371	0.978538
AdaBoost	0.219607	0.468622	0.094772	0.995892

TABLE III. METRICS FOR TESTING

Model	MSE	RMSE	MAE	R^2
XGboost	0.488148	0.698676	0.436796	0.990801
Tree	16.17095	4.021311	2.969486	0.695252
SVM	16.5457	4.067641	3.106928	0.688189
Random Forest	3.235244	1.798679	1.281519	0.93903
Neural Network	0.285306	0.53414	0.169448	0.994623
Gradient Boosting	2.784651	1.668727	1.209725	0.947522
CatBoost	1.095168	1.046503	0.781274	0.979361
AdaBoost	0.213149	0.461681	0.096477	0.995983

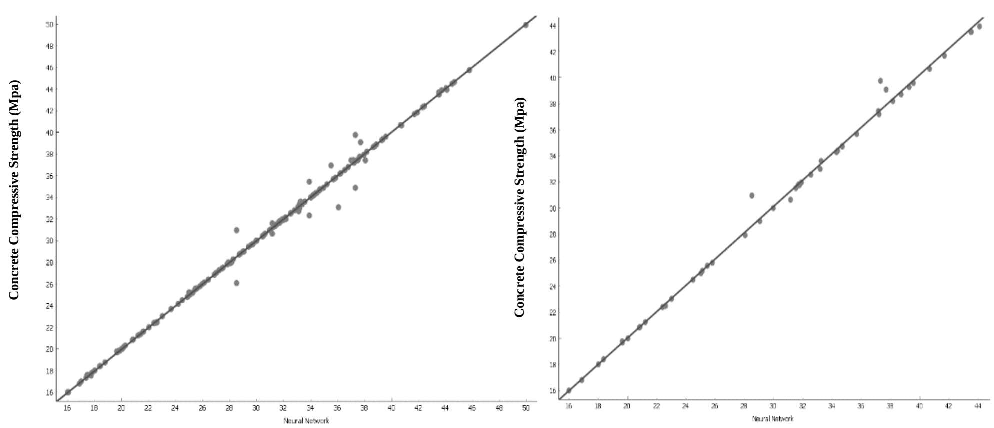

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Figure 4. Neural Network Prediction vs Real results for (a) training Data (b)Testing Data

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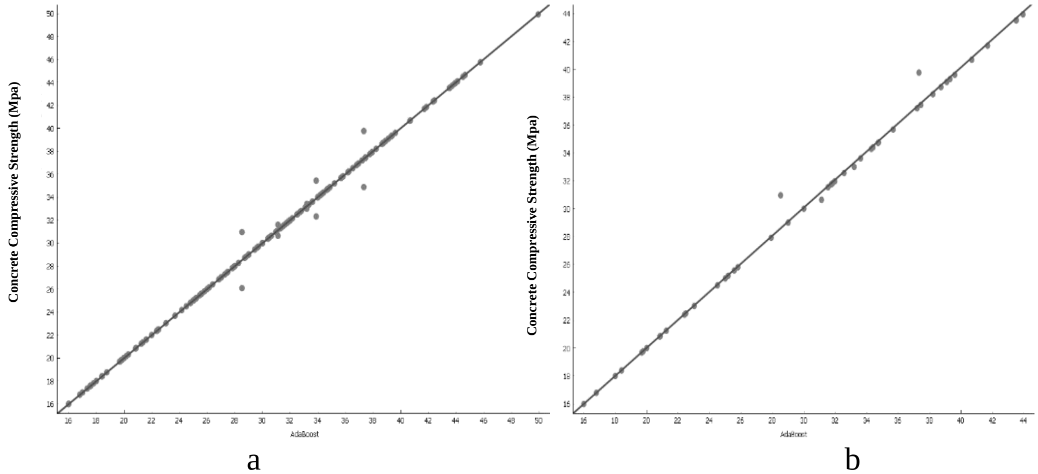

Figure 5. Adaboost Prediction vs Real results for (a) training Data (b)Testing Data

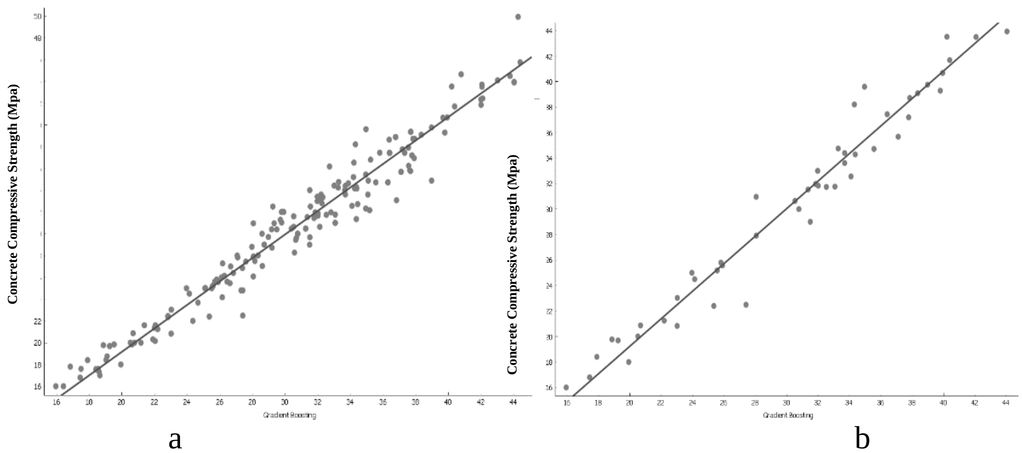

Figure 6. Gradient Boosting Prediction vs Real results for (a) training Data (b)Testing Data

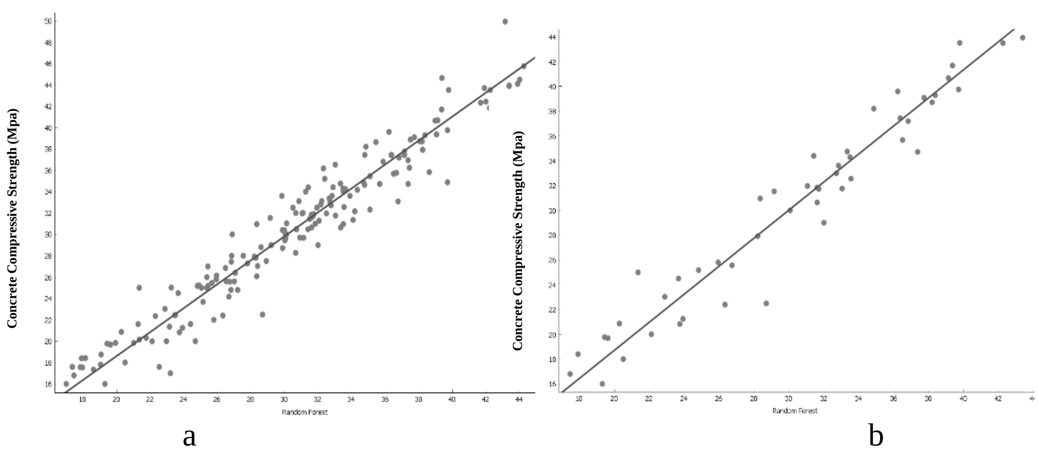

Figure 7. Random Forest Prediction vs Real results for (a) training Data (b)Testing Data

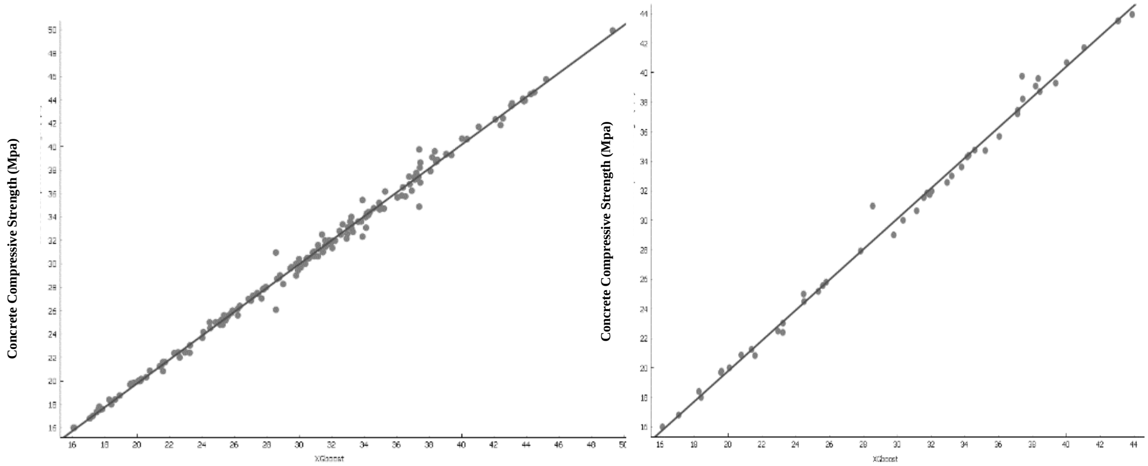

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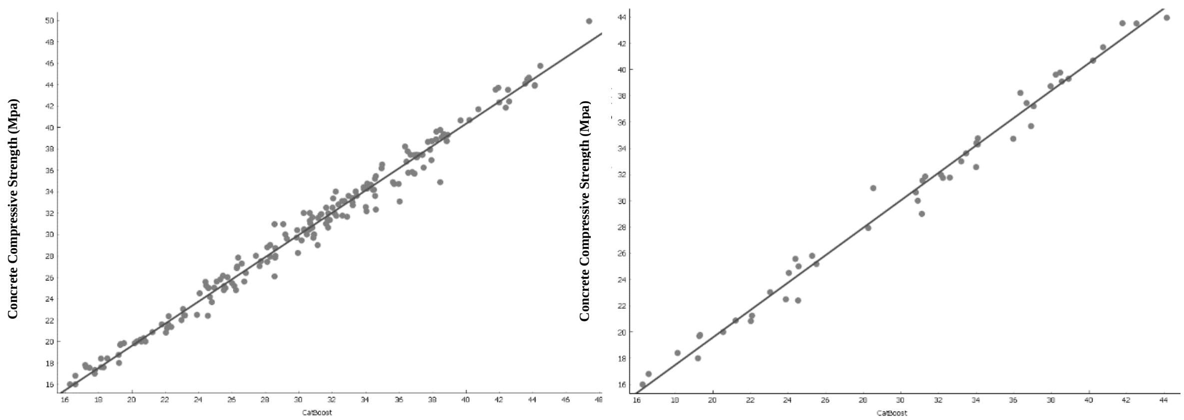
Figure 8. XGboost Prediction vs Real Results for (a) Training Data (b)Testing Data



a b

Figure 9. Catboost Prediction vs Real Results for (a) Training Data (b)Testing Data

Figures [4-9] show the predicted compressive strength versus the actual compressive strength for the training and testing datasets. From the figures, it is clear that Neural Network, AdaBoost, and XGBoost are the best models for predicting the compressive strength of RAC. The other algorithms, the random forest, the gradient boosting, and the Catboost, had good accuracy, while tree decision and SVM performed poorly in predicting the compressive strength of RAC.

VI. CONCLUSION

In this study, different machine learning algorithms have been employed to predict the compressive strength of concrete that contains recycled coarse aggregates at an age of 28 days. The studied features are cement, natural fine aggregates, natural coarse aggregates, recycled coarse aggregates, and water contents. This conclusion was found:

1. Most machine learning algorithms are capable of modeling the compressive strength of normal concrete and recycled aggregate concrete RAC with good accuracy.
2. SVM and Tree decision algorithms did poorly in predicting the compressive strength of RAC
3. Ensemble and Boosting methods considered in this study performed really well compared to SVM and Tee Decision.
4. Implementing Artificial Neural Networks ANN is a great tool for predicting the compressive strength and the mechanical properties of concrete.
5. XGboost, ADABoost, and ANN are the best algorithms to use to model the mechanical properties of concrete.

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