Machine Learning Models for Concrete Compressive Strength

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***Abstract*—A new estimation approach is proposed to overcome the disadvantages of traditional approaches. In this approach, compressive strength estimation is made using nonlinear regression and optimization technique.**

I. INTRODUCTION

Concrete basic strength is determined as a result of testing samples taken from wet concrete in buildings that are still under construction. The aim here is to measure the compressive strength capacity of concrete and to determine its service life. In the compressive strength test, a pressure is applied to the sample with certain dimensions (15/30 cm cylinder or 20 x 20 cube) with the help of a pressure press device, without impact, at unchanging values. It is continued until the sample is broken, this process is stopped at the time of breakage, the compressive strength is determined by proportioning the amount of force that causes the fracture of the sample whose cross-sectional area has been found before, to the cross-sectional area. The values differ according to the necessity of the construction. Concrete in each structure has certain compressive strength values that must be satisfy. Such as dams, detached houses, bridges, roads, industrial floors. These values are of vital importance for construction because concrete is the most fundamental building block of construction. The sample taken is subjected to various tests. These experiments take a long time to perform and require a lot of laboratory equipment. Therefore, it is a costly approach. It is also prone to human error, and as a result, the already long experimentation times can be even longer. As a result, delays occur in production. What is wanted to be done here is the materials we use while preparing the concrete and their amounts are certain, as a result, we can estimate the concrete compressive strength in the new concretes by looking at the past concrete contents and compressive strength tests.

In the study, the concrete strength data set of 1030 samples, which was made in 17 different laboratories, was analyzed by SVM, Decision Trees, Linear Regression, ANN, etc. methods and as a result of the estimations made with these methods; Consistency and estimation accuracy were compared. It has been observed in the literature that ANN and decision tree models are widely used for the estimation of concrete compressive strength.

II. CONCRETE COMPRESSIVE STRENGTH

A. Why is concrete compressive strength tests used?

As single axis, resistance of the concrete material against compressive loads as specified in the relevant standards is called the compressive strength of the concrete. In other words, it is defined as the highest pressure that occurs in a concrete structure subjected to a compressive load in the axial direction. With another definition, it is called the resistance of the concrete against fractures and shape differentiation that may be caused by the amount of load formed in the concrete. The pressure continues until the first break. When a reinforced concrete structural element is exposed to loads, it must withstand loads such as pressure, tensile, shear, etc. The compressive strength of concrete material is the one with the greatest value and the most important place among the mechanical strengths of concrete. Therefore, concrete is used in buildings by subjecting it to compressive strength tests.

B. How are test done?

Small concrete cylinders are created by using different combinations of raw materials, accompanied by engineers. These cylinders are tested for strength changes with the change in each raw material. The recommended waiting time for testing the cylinders is 28 days. In order to obtain the correct results, attention should be paid to the times specified in the standards. In Turkey, concrete compressive strength tests and classes are obtained according to TS500 standards.

C. What is problem with that?

The recommended waiting period is 28 days to get accurate results. This takes too much time. A lot of labor and equipment is required to prepare and test different experimental prototypes. Also, this method is prone to human error and a small error can cause the wait time to increase significantly. Waiting times can also be a hindrance for the next production. These waiting times cause delays in business plans.

There are ways to reduce the wait time and reduce the number of combinations to try. One of them is to try to estimate concrete compressive strength accurately using machine learning models. The focus here will be to provide data on what is known to the computer and make use of digital simulations where machine learning models try different combinations to predict compressive strength. In this way, the number of combinations that can be physically tested and the time required for the experiment can be reduced. But to design such a model we need to know the relationships between all the raw materials and how a material affects the result. It is possible to derive mathematical equations and make simulations based on these equations, but we cannot expect the relationships to be the same in the real world. Also, these tests have been performed many times and we have enough real-world data that can be used for predictive modeling.

D. Concrete's Components (input variables)

This features affect the quality of concrete. Same time this features are model's input variables.

Cement(kg amount in 1m3), is a material whose main raw materials are limestone and clay and which is used as a binder for mineral pieces (sand, gravel, brick, briquette, etc.). In order for cement to fulfill this binding property, water is absolutely necessary. Cement is a binder that hardens by reaction with water.

Blast Furnace Slag(kg amount in 1m3), It is a by-product released during iron production in blast furnaces in iron and steel plants. The blast furnace slag is granulated by abrupt cooling and then ground. This grinded material can be added to cement or used separately in concrete.

Fly Ash (kg amount in 1m3), It is the waste material that is produced as a result of the burning of hard coal or lignite coal in thermal power plants established to produce energy and is retained by electro-filters in the chimneys. It is an additive material that has almost no binding properties on its own and gains hydraulic binding properties by chemical reaction with slaked lime.

Water(kg amount in 1m3), It is the material that enables the concrete mixture to reach the desired consistency and strength.

Super-plasticizer(kg amount in 1m3), Plasticizer, additive that increases the plasticity or fluidity of the substance to which it is added. They are generally used in plastic, cement or concrete mixtures.

Coarse - Fine Aggregate (kg amount in 1m3), It is stone, natural stone or crumbled rock pieces of certain sizes. The structures, sizes, shapes, physical and chemical structures of the aggregates are selected according to the properties expected from the mixtures (concrete, asphalt, etc.) to which they will be incorporated. By bonding to each other with cement, it creates a hard and dense mass and constitutes 60-80% of the concrete by volume. Fine (natural and artificial sand) aggregate between 0-6 mm in diameter. 6~63 mm is thick (gravel and crushed stone) aggregate.

Age(1-365 days), Number of days since the concrete mix was created.

E. Dataset Informations

The dataset consists of 1030 instances with 9 attributes and has no missing values. There are 8 input variables and 1 output variable. Seven input variables represent the amount of raw material (measured in kg/m³) and one represents Age (in days). The target variable is Concrete Compressive Strength measured in (MPa — Megapascal). We shall explore the data to see how input features are affecting compressive strength.

Component	***Range of Components of data sets***		
	Minimum (kg/m³)	***Maximum (kg/m³)***	***Average (kg/ m³)***
Cement	102	540	281.167
Blast Furnace slag	0	359.4	73.895825
Fly Ash	0	200.1	54.188350
Water	121.8	247	181.567282
Superplasticizer	0	32.2	6.204660
Coarse Aggregate	801	1145	972.918932
Fine Aggregate	594	992.6	773.580485
Age	1	365	45.662136
CC_Strength	2.33	82.6	35.817961

Table 1. Ranges of components of data sets.

III. SIMILAR STUDIES IN THE LITERATURE

It has been observed in the literature that ANNs are widely used for the estimation of concrete compressive strength [1]-[2]. Yeh [1] showed that ANNs can be used as an effective method in the estimation of concrete strength and that ANNs can achieve much higher estimation success than regression analysis. Fazel-Zarandi et al. [3] proposed a fuzzy polynomial neural network model consisting of a combination of fuzzy neural networks and polynomial neural networks for the prediction of concrete strength. Cheng et al. In [4], genetically weighted pyramid operation tree (GWPOT), which is a genetic decision tree consisting of genetic algorithm, weighted operation structure and pyramid decision tree (GWPOT), and HPC pressure performed the endurance estimation. The success of the developed model was compared with ANN, SVM and evolutionary support vector machine inference model (ESIM) and it was stated that better results were obtained.

The most comprehensive study on concrete strength prediction in the literature is the study of Chou et al.[5]. 5 different machine learning methods; ANN, SVM, multiple regression analysis and 2 different combined learning models (multiple additive regression trees and bagging regression trees) were applied to the prediction of the compressive strength of HPCs and the obtained prediction results were compared. As a result of the study, the superiority of the predictive success of the combined learning models was emphasized.

In this study, regression analyzes were performed using linear regression, decision trees, random forest, etc., various machine learning models. Their accuracy was examined with various parameters and the results were compared. Then, concrete classes determined according to concrete strengths (concrete compressive strength) were assigned and classification models were used according to these classes.

IV. MACHİNE LEARNİNG MODELS THAT USED

In this section, the models used for the problem will be briefly explained.

A. Linear Regression

It aims to create an equation (model) that allows to predict the value of one from the other based on the relationship between two variables. linear regression establishes a relationship between the dependent variable (Y) and one or more independent variables (X) using the best-fit straight line (also known as the regression line). The number of independent variables determines the degree of the equation. This method focuses on the cause-effect relationship between the variables. Regression techniques often differ in the number of independent variables and the type of relationship between independent and dependent variables. For the values that are far from the determined regression line, loss is used as a measure. We can identify this loss by looking at the difference between the estimate and the actual value for a given x-value. The farther a prediction is from the determined regression line, the greater the error of the model will be, ie the greater the loss. The aim here is to try to minimize the losses. Thus, the model will make more accurate predictions.

B. Decision Trees

Decision trees are tree-based algorithms used in Classification and Regression problems. The first node of a decision tree is called the root. There are internal nodes under the root nodes. Each observation is classified with the help of nodes. It is classified as “Yes” or “No” according to the condition in that node. As the number of nodes increases, the complexity of the model also increases. The leaves are at the bottom of the decision tree. The leaves give the result. This means leaf node represents a classification or decision. A decision tree is a structure used to divide a dataset containing a large number of records into smaller sets by applying a set of decision rules. In other words, it is a structure used by dividing large amounts of records into very small record groups by applying simple decision-making steps. Decision Trees are highly resistant to noise generation during the application of overfitting avoidance methods. The presence of redundant variables does not adversely affect the accuracy of Decision Trees.

C. Random Forest

To solve a problem, the random forest model randomly selects 10s to 100s of different subsets from the dataset and trains them. Their number can be adjusted with the given parameters. With this method, 100s of decision trees are created and each decision tree makes an individual prediction. At the end of the day, if the problem is regression, it chooses the mean of the predictions of the decision trees, and if it's problem classification, it chooses the most votes among the predictions. One of the biggest problems of decision trees, which is one of the traditional methods, is over-learning data (overfitting). Since the training takes place on different data sets in the random forest model, overfitting, which is one of the biggest problems of decision trees, is reduced. Another feature of the random forest model is that it can infer how important the attributes are. The importance of an attribute is how much it contributes to the explanation of the variance in the dependent variable. By giving x number of features to the random forest algorithm, the most useful y can be selected and if desired, this information can be used in another desired model. This application will be used later in the random forest model. As a result of the training, cement, water, blast furnace slag and age attributes rank at the top in order of importance. Then the model will be trained again with these 4 attributes. Although this situation is not really true, it was made to try. Because it would not be very logical to think separately from other important elements that make up the concrete. so be careful when using these features. The domain knowledge about the subject should be sufficient and the specialist should be consulted when necessary.

D. Support Vector Machine

Support Vector Machines are basically used to separate data belonging to two classes in the most appropriate way. For this, decision boundaries or in other words hyper planes are determined. Support Vector Machines are one of the supervised learning methods generally used in classification problems. Draws a line to separate points placed on a plane. It aims to have this line at the maximum distance for the points of both classes. It is often used in classification problems. The main purpose of classification problems is to decide in which class the future data will be placed. In order to make this classification, svm draws a line separating the two classes and the region between ±1 of this line is called Margin. The wider the margin, the better the separation of two or more classes. Support vector regression algorithm was used while performing the concrete compressive strength test. Support vector regression is to ensure that the plotted range covers the maximum point. The points where these drawn maximum intervals intersect are called support points. The drawn line may be linear, but it is also possible to draw curves using different methods. So there is linear SVR as well as non-linear SVR. For this, a non-linear range can be drawn when the SVR model is applied together with the Radial Basis Function (RBF) method.

E. K-Nearest Neighbors

KNN (K-Nearest Neighbors) Algorithm makes predictions on two basic values; first of these, the distance of the point to be predicted from the other points is calculated. the second is the number of k neighbors. It is said that the calculation will be made over how many nearest neighbors. K value directly affects the result. If K is 1, the probability of overfit is very high. Even if it is very large, it makes very general predictions. For this reason, finding the optimum K value is the main issue of the problem. In K-NN classification, a point is classified by the majority vote of its neighbors; The object is assigned the class most common among its nearest neighbors (k is a small positive integer). In K-NN regression, the output is the feature value of the point. This value is the average of the values of its nearest neighbors.

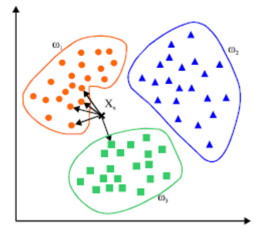

Fig 1. K-Nearest Neighbors[6]

F. XGBooster

XGBoost(eXtreme Gradient Boosting) is a high-performance version of the Gradient Boosting algorithm optimized with various modifications. The most important features of the algorithm are that it can achieve high predictive power, prevent over-learning, manage empty data and do them quickly. Since there is gradient boosting on the basis of Xgbooster, let's talk about gradient boosting. Boosting is a method of transforming weak learners into strong learners. It does this incrementally with iterations. The difference between boosting algorithms is often in how weak learners identify their shortcomings. In Gradient Boosting, the first leaf is created first. Afterwards, new trees are created by taking into account the estimation errors. This situation continues until the number of trees decided or no further improvement can be made from the model.

The first step in XGBoost is to base score. This estimate can be any number as the correct result will be reached by converging with the actions to be taken in the next steps. This number is 0.5 by default. How good this estimation is examined with the erroneous estimations (residual) of the model. Errors are found by subtracting the estimated value from the observed value. Gradient Boosting and XGBoost work on the same principle. The differences between them are in the details. XGBoost shows higher prediction success using different techniques and is optimized to work on large datasets. The main issues that it differs from Gradient Boosting are; Regularization, Trimming, Working with Null Values, System Optimization.

G. Artificial Neural Networks

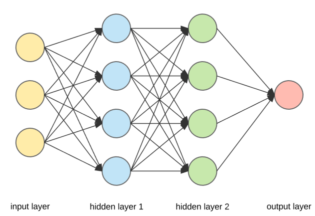

Fig 2. Typical Artificial Neural Network model figure

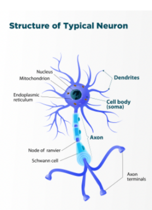

Fig 3. Neuron in Human Brain

Artificial neural networks (ANNs) are computer systems developed with the aim of automatically performing the abilities of the human brain, such as deriving new information, creating and discovering new information through learning, without any assistance[7]. Neural networks in humans are made up of neurons (nerve cells). Neurons have the ability to process information. Neurons connect with each other to form functions. Artificial neural networks have emerged as a result of mathematical modeling of the learning process of the brain based on the human brain. It mimics the structure of biological neural networks in the brain and their ability to learn, remember and generalize. Learning process in artificial neural networks is carried out using examples. During learning, the rules are determined by giving input and output information. Artificial neural networks have some advantages. The main ones are made up of many cells, and these cells work simultaneously and perform complex tasks. It has the ability to learn and can learn with different learning algorithms. They can produce results (information) for unseen outputs. There is unsupervised learning. They have fault tolerance. Can work with incomplete or ambiguous information. In faulty conditions, they show graceful degradation.

V. TRAIN AND TESTS COMPARE

In this section, the models used and the test results will be examined. By means of the models described above, data were trained and various tests were carried out. Some conclusions were made as a result of these tests. While making these inferences, domain information was taken into account. Otherwise, it may cause wrong estimations to emerge as a result of illogical inputs. First of all, data set information is examined. Here, it was checked whether there were missing, abnormal or incorrect data. Then, graphs are drawn for all features. From these graphs, it was checked whether the features were as expected or not and whether they came from their normal distribution. No errors, abnormal or missing are seen. All of the attributes are made up of continuous variables. Categorical variables are not found. When looking at the data summaries, standard scalers were used because there were differences between some features numerically.

Why to standardize before fitting a ML model? Variables that are measured at different scales do not contribute equally to the model fitting & model learned function and might end up creating a bias. Thus, to deal with this potential problem feature-wise standardized (μ=0, σ=1) is usually used prior to model fitting.

Before training machine learning models, the data is separated into train and test data. Attributes can be rescaled to have zero mean and 1 standard deviation, meaning all features fall within the same range. After preparing the data, we can fit different models on the training data and compare their performance to choose the algorithm with good performance. As this is a regression problem, we can use RMSE (Root Mean Square Error) and R^2 score as evaluation metrics. Confusion matrix was used for classification problems and comparisons were made according to f1-scores. Classification models are used for concrete classes. After comparing the regression models, concrete classes were determined according to the standards by looking at the concrete compressive strengths. The standard specified here is TS500, which is valid in Turkey. eg; For concrete class C30, the compressive strength can be at least 27.5Mpa and at most 32.5MPa. In this way, after dividing into classes, the target variable was made categorical. For more detailed information, table 2 can be examined.

Beton Sınıfları ve Dayanımları (TS500)

Beton Sınıfı	Karakteristik Silindir (150 mm x 300 mm) Basınç Dayanımı, fck MPa	Eşdeğer Küp (150mmx150mm) Basınç Dayanımı,fck MPa	Karekteristik eksenel çekme Dayanımı, fctk MPa	28 Günlük Elastisite Modülü Ec MPa
C16	16	20	1.4	27000
C18	18	22	1.5	27500
C20	20	25	1.6	28000
C25	25	30	1.8	30000
C30	30	37	1.9	32000
C35	35	45	2.1	33000
C40	40	50	2.2	34000
C45	45	55	2.3	36000
C50	50	60	2.5	37000

Table 2. Concrete Classes and Strengths[8]

To briefly summarize the values used for the predictive success of regression models;

Root Mean Square Error (RMSE) is the standard deviation of the residuals (prediction errors). Residuals are a measure of how far from the regression line data points are; RMSE is a measure of how spread out these residuals are. In other words, it tells you how concentrated the data is around the line of best fit.

The Mean Squared Error (MSE) is a measure of how close a fitted line is to data points. For every data point, you take the distance vertically from the point to the corresponding y value on the curve fit (the error), and square the value.

MAE measures the average magnitude of the errors in a set of predictions, without considering their direction. It’s the average over the test sample of the absolute differences between prediction and actual observation where all individual differences have equal weight.

R-squared is a statistical measure that represents the proportion of the variance for a dependent variable that's explained by an independent variable or variables in a regression model.

A. Linear Regression

The size of the coefficients in the regression problem equation can be further controlled by using regularization terms to cost functions. By adding the sum of the magnitudes of the coefficients, it is aimed to make the coefficients close to zero, and this linear regression variation is called Lasso Regression. Adding the sum of the squares of the coefficients to the cost function ensures that the coefficients are in the same range, and this variation is called Ridge Regression. Both of these variations help reduce model complexity and reduce the possibility of overfitting.

If the predicted values and target values are equal, the points on the scatterplot will lie in a straight line. This situation can be observed in fig.4. As we have seen here, the Compressive Strength of the models cannot be predicted very accurately. This may be because the prediction model is trying to do it linearly. This is the general problem of linear regression. It was mentioned when describing linear regression.

Model	***Error Scores***			
	RMSE	***MSE***	***MAE***	***R2***
Linear	10.28	105.76	8.23	0.57
Lasso	10.68	114.11	8.65	0.54
Ridge	10.29	105.84	8.24	0.57

Table 3. Error scores for Linear Regression models

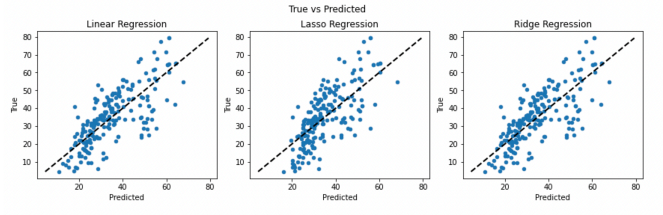

Fig 4. Linear-Lasso-Ridge Regression Prediction results

If we look at the error scores in Table 3, we can observe that there is not much difference between the models. In this case, we will look at other models.

B. Decision Trees

The error is basically how far the predicted values are from the actual values of the dataset. If we look at the error values from fig.5, we can see that it gives better results than linear regression. If we look at the results in Table 4 according to this graph, we can observe that it is equally successful.

Model	***Error Scores***			
	RMSE	***MSE***	***MAE***	***R2***
Decision Tree	6.60	43.51	4.46	0.82

Table 4. Error scores for Decision tree Regression models

In this case, we can make some comments about it. As can be seen from the distributions in the pair plot graphs we made before, there are many zeros in some input properties. This will help decision trees build trees based on some conditions on features that can further improve performance. We can observe that the estimated values are closer to the expected line.

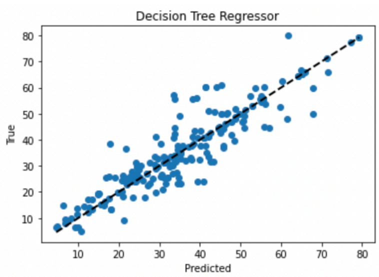

Fig 5. Decision Tree Regression Result

In fig.6, the order of importance of the inputs on the model is examined, it can be observed that the effect of cement, water and wet inputs mentioned above on the compressive strength is more than the other inputs. From this it can be deduced that this is the case in reality. The most important factor affecting the strength of concrete is the cement/water ratio. This ratio should be at the optimum level. Over or under use of either water or cement reduces the strength of concrete. From the feature importance table here, we can say that this situation is provided. In addition, the age factor is at the top in order of importance. The strength of concrete is increasing day by day. Concrete reaches 65% of its strength on the 7th day and 99% on the 28th day. in other words, we can observe from here how important the day is in terms of concrete strength.

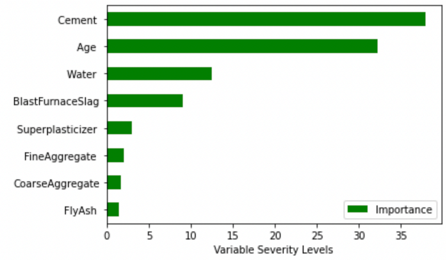

Fig 6. Feature Importance for Decision Tree

C. Random Forest

Model	***Error Scores***			
	RMSE	***MSE***	***MAE***	***R2***
Random Forest	5.12	26.20	3.5	0.89

Table 5. Error Scores for Random Forest model

While the RMSE value of the decision tree was 6.60 in the previous title, it can be observed that the RMSE value decreased to 5.12 in the random forest model. In this case, it can be said that the Random forest Model predicts better than the Decision Tree Model. This is because the Random forest model consists of multiple single trees, each based on a random sample of the training data. All inferences other than this will be the same as made in the decision tree.

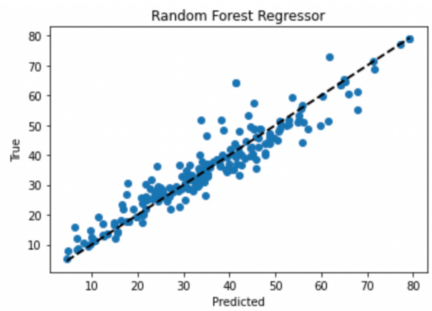

Fig 7. Random Forest Regression result

Similar to decision trees, we can observe the order of importance of the inputs(fig 8). The model can then be retrained using only these inputs. These features can be used to make Feature Selection. It was remodeled with 4 variables that were high, but not much difference was observed in the result values. This variables are age, cement, water, blast furnace slag.

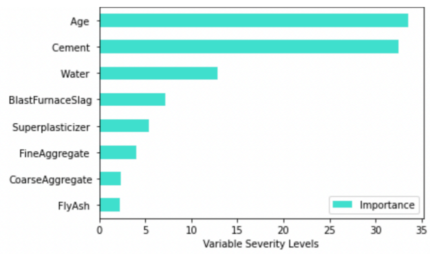

Fig 8. Feature Importance for Random Forest

And also Support Vector Regression and KNN algorithms were used. Looking at the results in Table 7, it can be observed that the results are not very different. According to the decision tree and random forest models, they showed a very bad performance.

Model	***Error Scores***			
	RMSE	***MSE***	***MAE***	***R2***
SVM	10.15	102.98	7.95	0.58
KNN	8.95	80.13	6.85	0.67

Table 7. SVM and KNN regression models

The XGBooster algorithm was also used and the result seems to be better compared to other algorithms. It can be said that the reason for this is that XGBooster uses Boosting, that is, the method of converting weak learners into strong learners. It does this incrementally with iterations. Its purpose is to learn from errors and approach the correct guess. The results can be seen in table 8.

Model	***Error Scores***			
	RMSE	***MSE***	***MAE***	***R2***
XGBooster	4.86	23.63	3.23	0.90

Table 8. XGBooster regression model

Later, artificial neural network algorithm was also used. According to the results, it was checked whether the model could achieve better results by tuning. A small improvement has been observed. It was observed that the score of the model trained with the default parameters was 0.853. Then, using the GridSearchCV library, it was tried to find the most successful model among the following parameters. The model was trained again according to the best parameters returned from here, and this time the score was observed as 0.875.

Comparison of Models:

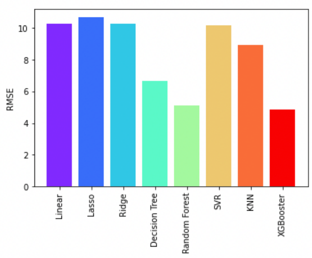

Fig 9.RMSE comparison for regression models

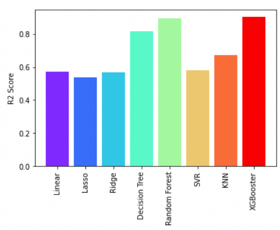

Fig 10.R2 score comparison for regression models

The performances of the methods used can be compared using different statistical criteria. MAE, RMSE and R2 are widely used metrics based on the concept of mean error. R2, which is the level of the relationship between the variables, can be interpreted as very weak if the relationship level is between 0-0.25, weak if 0.26-0.49, medium if 0.50-0.69, high if 0.70-0.89, very high if 0.90-1.00.

Here, we can observe that the Regression models are close to each other and lower than the other models. We can say that algorithms with higher R2 scores have been more successful. XGBooster made better predictions when looking at other models. We can also observe results close to XGBooster in decision trees and random forest algorithms.

Classifier Models

The models used so far were regression models. Here, Concrete class categories were created according to concrete strengths. The class of concrete is assigned according to the compressive strength values. You can see these values in the table 2. eg; For concrete class C30, the compressive strength can be at least 27.5Mpa and at most 32.5MPa. According to this information, the output variable was arranged and classification algorithms were used.

Model	***Accuracy Score(weighted avg)***			
	Accuracy	***Precision***	***recall***	***f1-score***
Decision Tree	0.53	0.56	0.53	0.54
Random Forest	0.56	0.56	0.56	0.56
MLP	0.28	0.41	0.28	0.28

Table 9. Confusion matrix for classifier models

Classification algorithms with various models have been used, but not very successful results have been obtained. Character trees, random forest and MLP classifier models seen in Table 9 were evaluated and compared. When the precision, recall and f1-score values are examined, it is seen that very successful predictions cannot be made.

VI. CONCLUSION

The right combination of components is important to obtain a high quality concrete mix. Reliability and durability are uncompromising factors in construction projects. Using machine learning models, we were able to see the importance of concrete mix components on compressive strength. The Random Forest model showed that cement, age of concrete and water are the main components that affect compressive strength. An important factor in concrete engineering is the water-cement ratio. We can clearly observe this in the importance of the inputs in the random forest and decision trees model.

We have analyzed the Compressive Strength Data and used Machine Learning to Predict the Compressive Strength of Concrete. We have used Linear Regression and its variations, Decision Trees, Random Forests, SVM, KNN, XGBooster, ANN to make predictions and compared their performance. XGBooster Regressor has the lowest RMSE and is a good choice for this problem. Also, we can further improve the performance of the algorithm by tuning the hyper-parameters by performing a grid search or random search.

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