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Modelling and Prediction of Concrete Compressive Strength Using Machine Learning

K Sumanth Reddy*[1], Gaddam Pranith[2], Karre Varun[3], Thipparthy Surya Sai Teja[4]

[1,2,3]Student, Civil Engineering Department, Sreenidhi Institute of Science and Technology, Hyderabad, India

[4]Student, Civil Engineering Department, Vasavi College of Engineering, Hyderabad, India

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ABSTRACT

The compressive strength of concrete plays an important role in determining the durability and performance of concrete. Due to rapid growth in material engineering finalizing an appropriate proportion for the mix of concrete to obtain the desired compressive strength of concrete has become cumbersome and a laborious task further the problem becomes more complex to obtain a rational relation between the concrete materials used to the strength obtained. The development in computational methods can be used to obtain a rational relation between the materials used and the compressive strength using machine learning techniques which reduces the influence of outliers and all unwanted variables influence in the determination of compressive strength. In this paper basic machine learning technics Multilayer perceptron neural network (MLP), Support Vector Machines (SVM), linear regressions (LR) and Classification and Regression Tree (CART), have been used to develop a model for determining the compressive strength for two different set of data (ingredients). Among all technics used the SVM provides a better results in comparison to other, but comprehensively the SVM cannot be a universal model because many recent literatures have proved that such models need more data and also the dynamicity of the attributes involved play an important role in determining the efficacy of the model.

Keywords : Concrete, compressive strength, Artificial Intelligence, Regression, Super Plasticizers

I. INTRODUCTION

The mechanical properties of construction materials play a very important role in achieving the efficiency of the structure the material is made up of1. Predicting the construction materials mechanical properties is vital in achieving durability and lifelong performance of the material, the bonding or the cementing material used in construction materials is made up of many different combination of materials for example the high performance concrete is made of vagaries of materials like cement, fly ash, silica fume, blast furnace, metakaolin etc., these proportions are important to develop the durability and compressive strength of the concrete2. To determine such proportions it is necessary to take help of the computational and prediction models for early predictions to overcome any hazard and improve the efficacy of the design proportions3.

The regression model has been used with respective to mean absolute error (MAE) root mean squared error (RMSE) of more than 85% but still this method has drawbacks in predicting the values because of skewed approach towards the outliers of the sample values4. The noises (like the outliers and inliers) are difficult for handling to get a very R2 value, these few values impact the model and result in irrational predicted values5. To overcome the problems due to linear and nonlinear regressions the recent computational rely on algorithms wherein the outliers are specially treated to obtain the accurate model, also the recent artificial intelligence and machine learning models are very accurate due to their ability to learn and adopt to the new environment of the variables6.

$Y = a + bX$, is a linear regression line equation, where X is the explanatory variable and Y is the dependent variable. Here "a" is intercept and "b" is the slope of the line7.

Artificial intelligence (AI) is the ability of computers to perform a particular task that typically requires some level of human intelligence, the AI works very similar to the human brain the Artificial Neural Network is inspired and modelled in accordance to human brain's tendons and synapses, which has ability to improve its outcome by learning on its own it's a semi-autonomous initially thence becomes totally autonomous thus increasing the computational speed and also in getting better output results8.

Machine learning is a powerful tool which depends upon statistical techniques to enhance the capability of self-learning for the models explicitly without any program or coding9. Deep learning is one such powerful machine learning technique that has been making rounds in the scientific fraternity very loud and powerful. Machine learning encompasses famous learning techniques like Supervised, Unsupervised, Semi-supervised, and reinforcement learning1.

Further to develop an accurate model it is necessary to use algorithms which enhances the dependence of the feature class on the variables and the output of the model, the famous techniques viz., Artificial Neural Network, Support vectors, nearest neighbor, logistic regression, decision tree, random forests are the famous techniques in supervised learning, which have been producing wide variety of application and generating very accurate models10. In civil engineering these techniques have been used in water resources optimization, reservoir optimization, rainfall prediction, flood analysis etc. This paper focuses on predicting the compressive strength of the concrete with commonly used cementing materials used in High Performance concrete11.

WEKA software has been used to solve predictions problem, which is a free open source software with good number of inbuilt tools to develop a prediction model. Earlier literatures have reported that Support vector Machines (SVM) is a better model for deterministically predicting the material properties like modulus of elasticity of many different types of concrete10. Even the Artificial Neural Network (ANN) has equal traits to predict a very accurate models similar to SVM, but it there is no evidence that one is superior to other not only with respect to SVM and ANN in some conditions other supervised learning models have been giving superior results in contrast to ANN and SVM3.

The compressive strength of high performance concrete can be found by a single model consisting of more than one prediction models like stacking bagging and voting which can perform well than any single model of prediction of compressive strength of high performance concrete. In this paper support vector machine, linear regression, tree regression, are compared and tested for mean absolute error (MAE), mean absolute percentage error (MAPE), and root mean square error (RMSE), validating the same with experimental values conducted in laboratory4. Though this paper validates the algorithm the research is open to predict the HPC compressive strength with recent prediction models6. In the support vector machine the hyper plane plays an important role in classifying the data points, the objective should be to find the maximum separation between two distinct points which enhances the capability of classifying the data with more confidence. Further based on inputs the hyperplane can be a line or a plane further if input is more than 3 it becomes difficult to imagine the plane in higher dimensions1.

The neural networks was rationalized to Multilayer perceptron to solve complex problems and save time and effort which were capable of learning autonomously after initial prompting the input data to obtain the best and effective algorithm. The neural are robust based on the training done using training data and hence capable of mapping any function and can be developed as universal approximation algorithm7.

II. MATERIALS USED

Table 1. The chemical and physical properties of cementitious materials

Chemical analysis (%) / Properties	Cement	Silica fume
Calcium oxide (CaO)	62	0.59
Silica (SiO_2)	22.3	92
Alumina (Al_2O_2)	4.0	0.59
Iron oxide (Fe_3O2)	4.8	0.8
Magnesia (MgO)	3.5	1.5
Sodium oxide (Na_3O)	0.8	0.5
Potassium oxide (K_2O)	0.56	1.35
Sulfur trioxide (SO_2)	1.85	–
Bogue's compound in %		
Tri calcium silicate (C_3S)	53.5	–
Di calcium silicate (C_2S)	21	–
Tri calcium aluminate (C_3A)	4	–
Three days compressive strength, kg/cm^2	224	–
Seven days compressive strength, kg/cm^2	308	–
Twenty Eight days compressive strength, kg/cm^2	415	–
Initial setting time	150	–
Min Final setting time	190	–
Min Specific surface, cm^2/g	3294.8	–

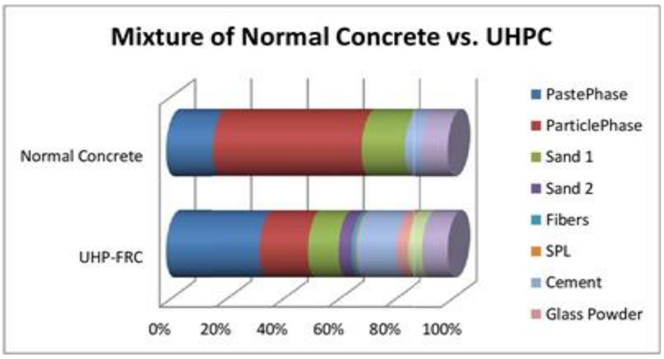


Fig1. Normal Concrete vs HPC

Table 2. The physical and mechanical properties of the aggregates

Table 3. High Performance Concrete Attributes for

Type	Relative Density (g/cm^3)	Water Absorption (%)	Modulus of Fineness	200 sieve (75 μm)
Fine aggregate	2.53	2.6	3.2	1.1
Coarse aggregate	2.56	1.46	-	0.4

Dataset

Coarse Aggregate (kg/m^3)	1190.0	1141.73	1169.0
Fine Aggregate (kg/m^3)	490.0	599.71	699.0
Cement (kg/m^3)	408.0	518.31	661.0
Silica Fume (kg/m^3)	0.0	24.57	61.0
Water (kg/m^3)	160.0	164.74	171.0
Plasticizers (kg/m^3)	2.32	2.73	3.29
Water Reducing Agents (kg/m^3)	7.0	8.90	15.2
Air content in voids (%)	1.28	2.01	3.01
Testing age (Days)	1.0	18.0	60
Concrete Compressive Strength (MPa)	19.8	70.20	115

Table 4. High Performance Concrete Attributes for Dataset 2

Cement (kg/m^3)	101.0	280.50	539.0
Blast furnace slag (kg/m^3)	0.0	69.32	361.4
Fly ash (kg/m^3)	0.0	59.81	259.0
Water (kg/m^3)	121.8	179.98	250.0
Super Plasticizer (kg/m^3)	0.0	6.42	33.10
Coarse Aggregate (kg/m^3)	699.8.0	959.83	1150.0
Fine Aggregate (kg/m^3)	597.0	769.49	991.6
Compressive Strength (MPa)	2.43	35.84	81.6

Table 5. Performance of Model in predicting the Compressive Strength for Dataset 1&2

Dataset 1	**Machine learning Technique**	**Mean Absolute Error (MPa)**	**Root Mean Square Error**	**Absolute Percentage error**	**Index of Synthesis**
1	MLP	5.64	7.65	19.64	0.49
2	CART	6.12	7.48	19.73	0.52
3	SVM	2.87	4.86	11.45	0.01
4	LR	6.52	9.86	27.86	0.87

Dataset 2	**Machine learning Technique**	**Mean Absolute Error (MPa)**	**Root Mean Square Error**	**Absolute Percentage error**	**Index of Synthesis**
1	MLP	3.89	4.98	9.96	0.02
2	CART	3.93	5.01	15.63	0.49
3	SVM	7.56	9.65	12.54	0.14
4	LR	10.87	12.36	22.45	0.89

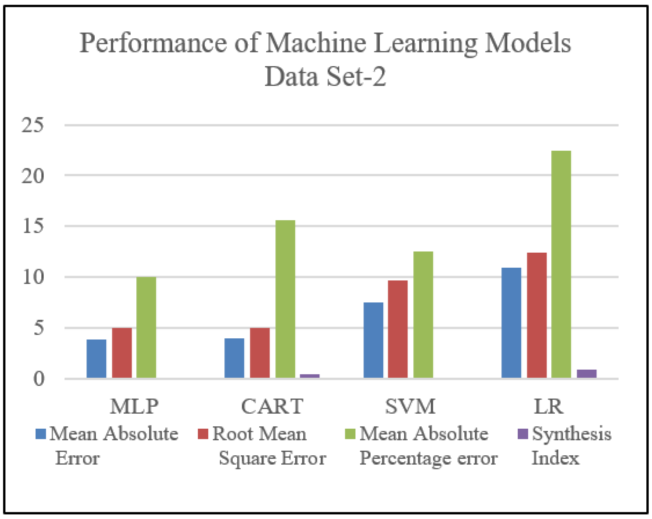


Fig 3. Performance of Machine Learning Models for Data set-1

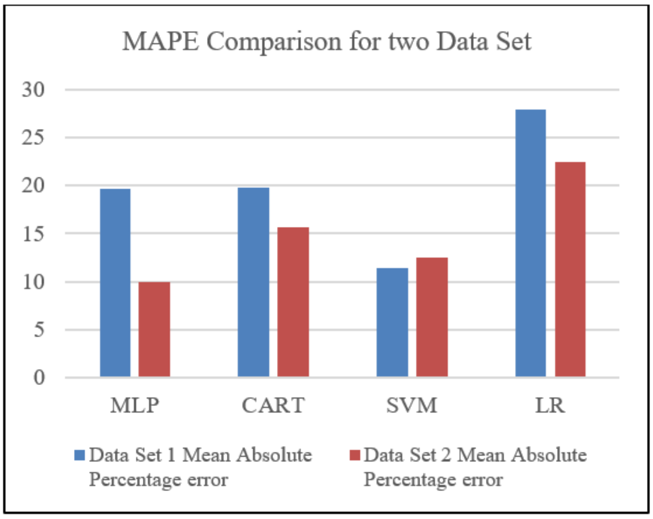
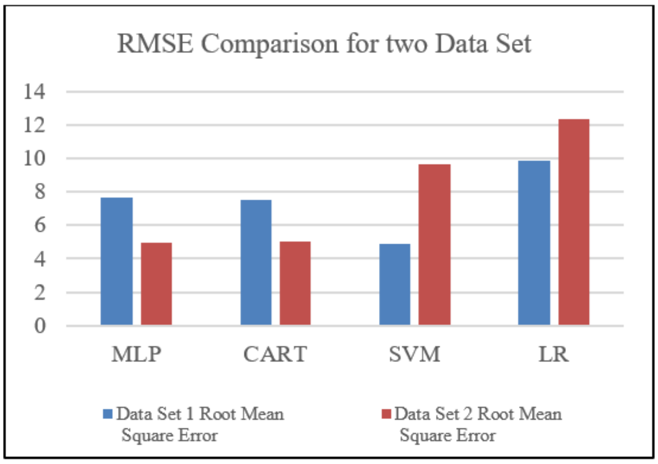


Fig 4. Mean Absolute Performance Error (MAPE) of Machine Learning Models for Data set-1&2



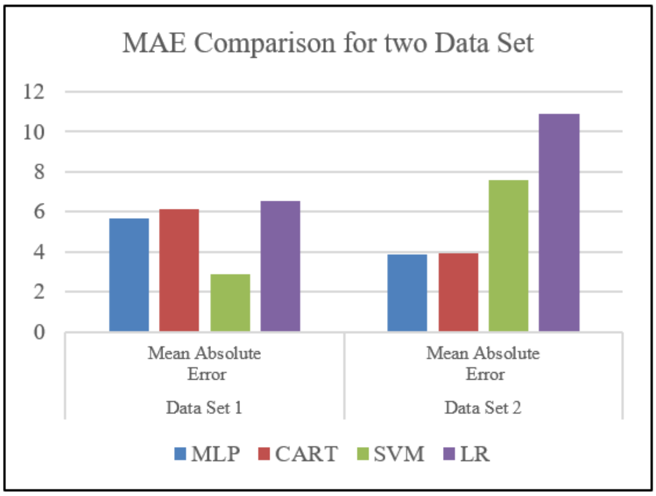


Fig 5. Mean Absolute Performance Error (MAPE) of Machine Learning Models for Data set-1&2

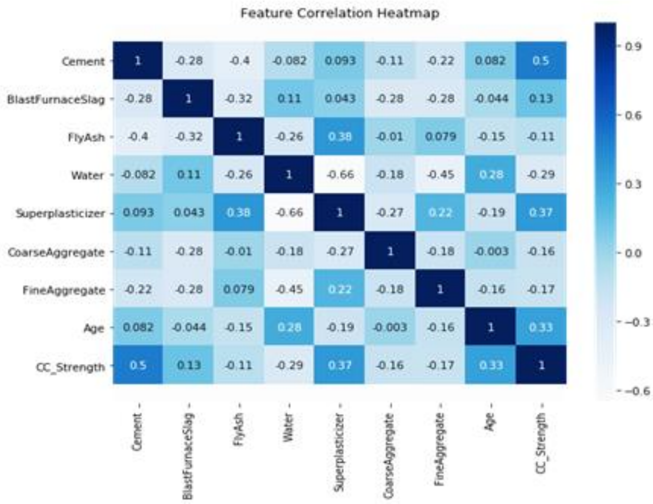


Fig 6. Feature Correlation Heat Map

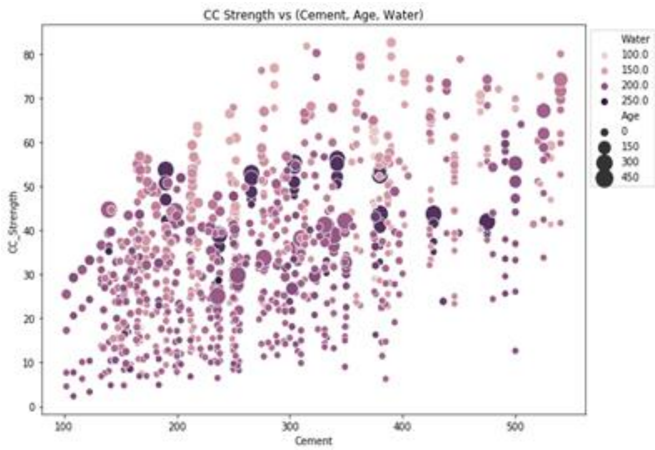


Fig 7. Concrete Compressive Strength (CCS) vs Cement, Age and Water

From Figure 6 it is observed that there high correlation between cement and the compressive which is in fact very true from experimental data and also the compressive strength has good correlation with super plasticizers and Age.

There are other strong correlations between the features,

• Super Plasticizer and Water are strongly negative correlated.

• Fine aggregate, Fly ash and Super plasticizers are positively correlated.

To develop an efficient model such information about the variables relation is necessary as it can save more time and money and can rationalize the decision making process. A pair plot can be drawn to understand the exact relation between each variables (but in this paper it's not included because of the scale of the map).

Further from figure 6 it is observed that,

- Compressive strength increases as the amount of cement increases.
- Cement with less age requires more cement for higher strength,
- The older the cement is the more water it requires,
- Concrete strength increases when less water is used

III.CONCLUSION

The machine learning techniques are making a profound mark in computational techniques and are in need infields of decision-making subjects to enhance the decision-making process and also rationalize the resources distribution in a system for sustenance. In this paper the machine learning models have rationalized many combinations of ingredients towards producing a high-performance concrete for compressive strength it is clear from the above graphs that Support Vector Machine has given a very rational results for both sets of combination of materials. These machine learning techniques can be used further by combining the different techniques to produce a desired output with maximum efficiency. In this paper only two datasets have been used, on other hand it can be used for many datasets for computing the compressive strength of the concrete for many different and latest materials as the material science is making a profound development in the science optimizing the cost as well as manufacturing processes. This work has been done using the WEKA software with default settings which reduces the freedom of the user to explore and innovate new combinations or new feature selections, or try with different attribute selections etc.

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