Effectiveness Of Machine Learning Algorithms with Varying Training & Testing Dataset for Prediction of Compressive Strength of Concrete

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Abstract

In this work, various machine learning techniques, which fall under the category of artificial intelligence, are investigated, and an algorithm (model) is created to forecast the compressive strength of concrete at 7 and 28 days. 180 distinct mixtures with 540 specimens are cast with the intention of building the algorithm (model), and the results are gathered. The information employed in the machine learning model is organized into nine input parameters: cement, fine aggregate, coarse aggregate, water, admixture, compaction factor, w/c ratio, slump, age, and an output parameter: concrete's compressive strength. Concrete's 7- and 28-day compressive strength predictions are based on training and testing outcomes.

KeyWords: Compressive strength, Artificial Intelligence, Concrete, Machine learning algorithm, Prediction

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Introduction

Since concrete is the second most used substance on earth after water, its importance can be understood by the amount of time it is used globally each year. All across the world, concrete is utilized in construction. Since of the advantages provided by numerous qualities including strength, stiffness, hardness, porosity, and fire resistance, among all of these qualities compressive strength is crucial because it has a significant impact on durability [1].

Concrete is a heterogeneous material composed of a binder (cement), coarse aggregate, fine aggregate, water, and admixture. Because the properties of the ingredients affect the compressive strength, it is difficult to predict or find the compressive strength of concrete accurately in such a complicated mixture.

By our traditional method, we must first prepare a mix design for the desired concrete grade, then cast a cube of standard dimensions (for cube 150 x 150 x 150 mm & cylinder diameter is 150 mm and height is 300 mm), and finally test the cube/cylinder sample at 7, 28 days by crushing it to determine the compressive strength of the concrete. So our Convention method is time consuming because we have to wait several days to get compressive strength, and different properties of aggregate and batching will result in different compressive strength, making it a costly process.

Artificial Intelligence Overview

The human brain is highly inventive. The invention of various machines that simplify our tasks has resulted from the human brain's creativity. However, intelligence distinguishes humans from machines. Humans gather information, and our brains analyze it. Machines, on the other hand, are not by nature intelligent. Machines cannot analyze data or make decisions on their own. The desire for intelligent machines began in the middle of the twentieth century.

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Present day research in machine and deep learning stresses on computer vision, hearing, NLP, emotional understanding, Computer vision, image processing, pattern recognition, cognitive computing, knowledge representation etc. the objective is to provide machines with abilities to gather data through senses like human senses and then processing the gathered data by using computational intelligence tools. The task is to conduct predictions and decision making at the same level as humans.

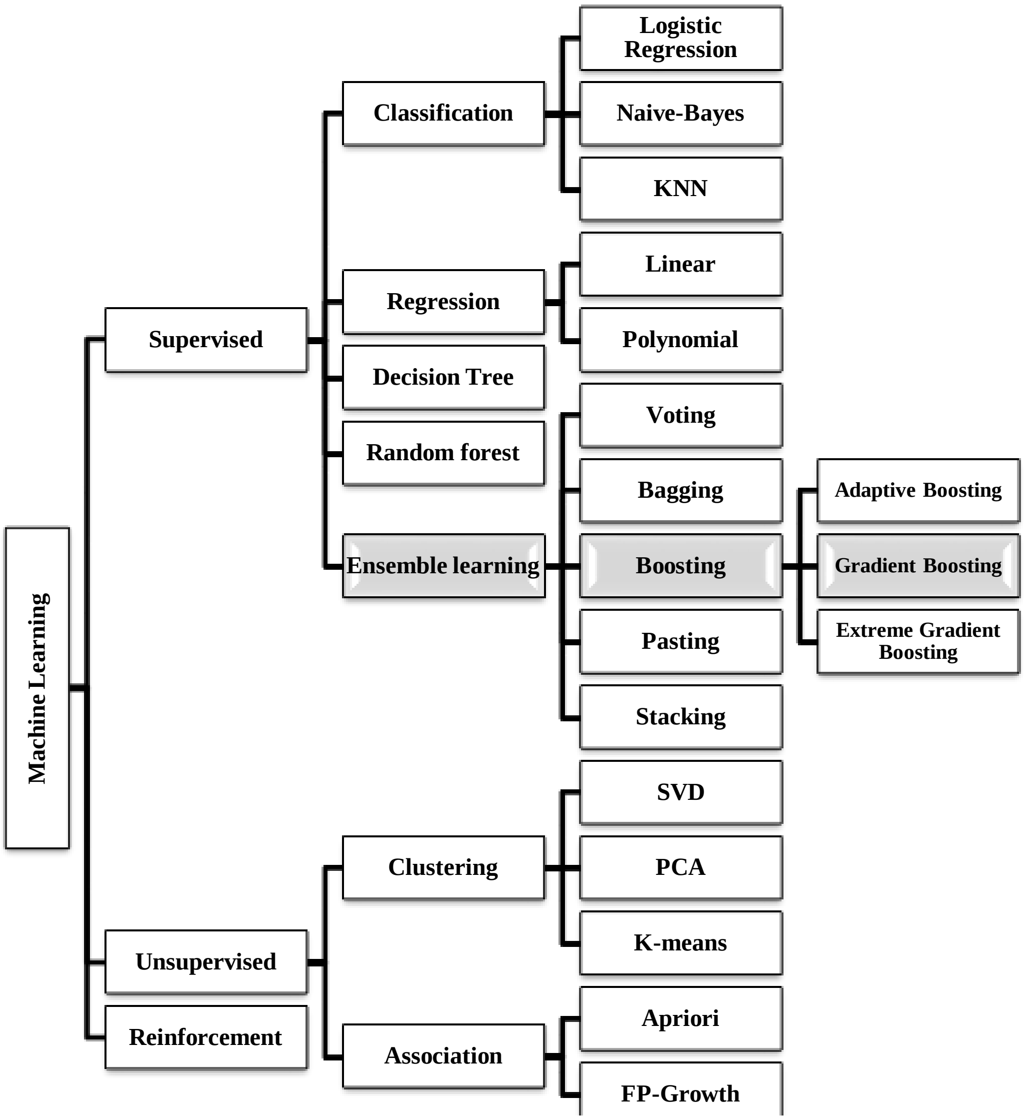

Figure 1: Classification of Machine learning according to methods

Machine learning techniques with literature review

By reviewing literature we know that many of the researchers have research paper on different Machine learning techniques as well as different conditions like HSC, SCC, also with some other material used and prediction is done for different mechanical properties. Also, they used same type of material for all type of samples. So there is no such work done for different ingredient properties. Many of them used only content of all ingredients as input but if we use content of all ingredients along with properties of ingredients and the fresh properties (slump, compaction factor) then it will give better results than earlier results.

Supervised ML algorithms such as decision tree (DT), artificial neural network (ANN) and genetic engineering programming (GEP) and bagging regressor (BR) were investigated for the prediction of compressive strength of fly ash-based concrete [1]. Explored nine ML methods to predict the compressive strength of field concrete at seven days by exploiting 12,107 observations of field concrete associated with 25 different mix designs of seven constituents [2]. A prediction model was generated to predict the compressive strength of concrete using support vector regression which is a machine learning technique. It has been found out that RBH produces the best prediction output in comparison to other NDT techniques [3]. It investigates the multivariate adaptive regression splines model (MARS) as a feature extraction method to extract the optimum inputs that use to design the HPC. The extracted feature is feed to a gradient tree boosting machine (GBM) learning technique to predict the CCS [4].

Objectives

To study Artificial Intelligence which are used in strength prediction of concrete.

To prepare the database of mix design results to frame the model.

To predict strength of concrete at early age so that trails of that mix design will be reduced.

Research Methodology

Experimental Investigation- Concrete Mix Design

In the experimental study, we prepared concrete mix designs of M20 and M25 grade concrete for various ingredient properties and tested the specimen to determine the actual compressive strength of concrete at various ages. In addition, the properties of the ingredients must be determined using traditional methods. We studied different types of materials with different ingredient properties in the experimental work, as well as relevant IS codes for determining ingredient properties and referring to IS 10262:2019 for mix design calculation.

Figure 2: Photographs of experimental work

Description of data with the experimental procedure

As shown in the tables below, the various properties of the materials used in the preparation of 180 mixes, such as cement, fine aggregate, and coarse aggregate, have been conformed to the specification as per the IS standards. The reference section contains a list of all the IS codes used to determine the physical properties of ingredients (cement, fine aggregate, and coarse aggregate).

Table 1: Physical properties of Cement

Material	Properties		Value Range			Standard followed
Cement	Consistency (%)		29.5 to 32			IS 4031:1988 (P-4)
	Initial setting time (min)		90 to 210			IS 4031:1988 (P-5)
	Final setting time (min)		180 to 335			
	Fineness (%)		2 to 6			IS 4031:1988 (P-1)
			OPC43	OPC53	PPC	IS 4031:1988 (P-7)
	Compressive strength (Mpa)	(3 days)	>23	>27	>16	IS 8182:2013 - OPC43
		(7 days)	>33	>37	>22	IS 12269:1987-OPC53
		(28 days)	>43	>53	>33	IS 1489:1991(1)-PPC

Table 2: Physical properties of Fine and Coarse aggregate

Properties	Fine aggregate	Coarse aggregate	Standard followed
Fineness modulus	3.61 to 4.43	6.61 to 7.32	IS 2386:1963 (P-1)
Specific gravity	2.80 to 3.02	2.9 to 2.94	IS 2386:1963 (P-3)
Water absorption (%)	1.29 to 1.67	0.9 to 1.90	
Bulk density of loose weight (kg/lit)	1.54 to 1.80	1.44 to 1.58	
Bulk density of compacted weight (kg/lit)	1.7 to 1.98	1.65 to 1.74	
Percentage of void	0.39 to 0.47	0.46 to 0.51	
Silt content	6 to 8	-	IS 2386:1963 (P-2)

Program of testing

A total of 540 cube specimens measuring 150 x 150 x 150 mm were made. To achieve the desired workability, the trail method and varying super plasticizer demand use a w/c ratio ranging from 0.40 to 0.53. After 24 hours, the specimens were de-molded and water cured at room temperature. Compressive strength tests were performed at 7 and 28 days according to Indian Standard to evaluate the strength progression of the designed formulation to achieve the desired strength.

Modeling aspect description

The dataset consists of 9 inputs (cement, fine aggregate, coarse aggregate, water, admixture, slump, compaction factor, w/c ratio and age in days) with one output (concrete compressive strength). Below tables show the distribution of all parameters.

Table 3: Descriptive analysis of parameters

	Cement	Fine aggregate	Coarse aggregate	Water	Adm.	C.F	Slump	W/C	Age (days)	Compressive strength (Mpa)
Count	180	180	180	180	180	180	180	180	180	180
Mean	364.42	708.09	1174.35	179.01	0.37	0.84	104.48	0.49	17.50	23.48
Std	18.86	96.87	46.32	6.26	0.37	0.03	48.10	0.01	10.52	5.68
Min	335	532.50	1081.29	162.80	0	0.76	0	0.40	7	12.38
Max	407	941.20	1305.94	193.06	1.50	0.96	210	0.53	28	35.77

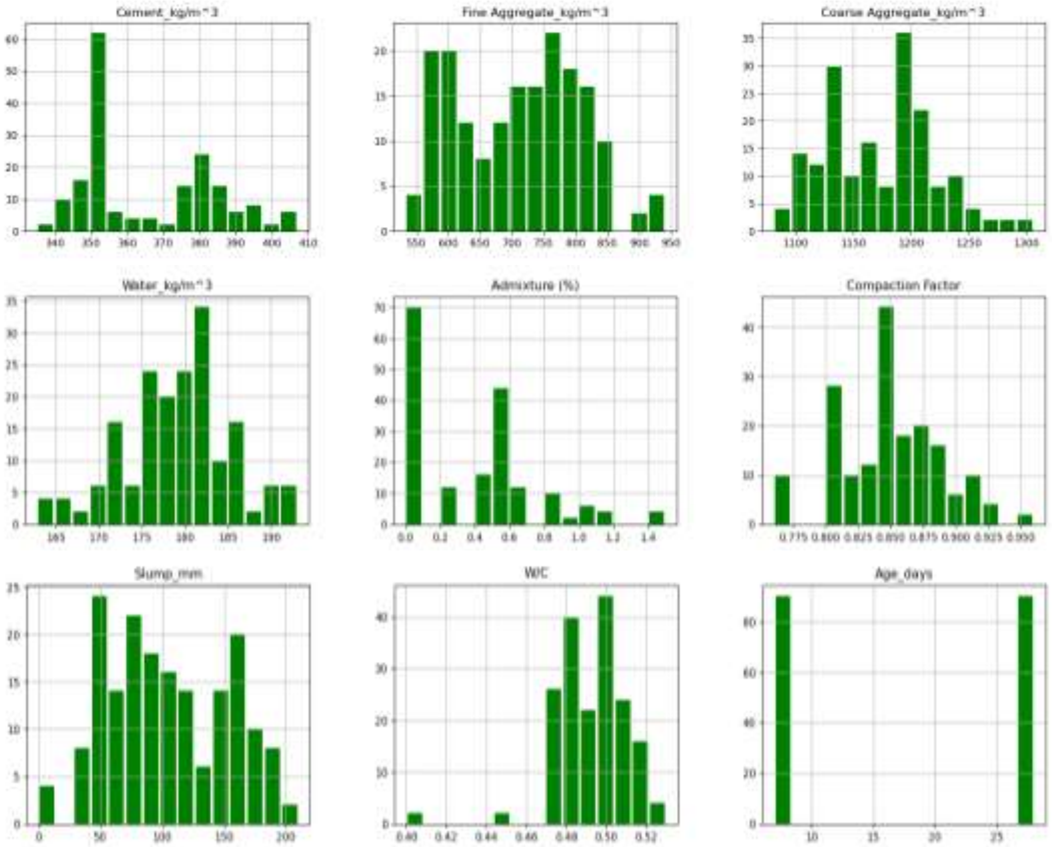

Figure 3: Histogram showing the concentration used to get compressive strength

Model-making Methodology

The models were run using Jupyter Notebook. We know from previous literature and study material on artificial intelligence that machine learning algorithms are used for predictive analysis. Machine learning is classified into three types based on learning methods: supervised learning, unsupervised learning, and reinforcement learning. Because our dataset contains labeled data, we will use a supervised learning algorithm. Supervised learning contains many algorithms, as shown in fig.1. For our model, we chose Linear regression, Ridge regression, Decision Tree, Random Forest, Gradient Boosting, and AdaBoost algorithms, and we will run the model with variation in training and testing datasets.

Results And Discussion

Model Selection

On the basis of value of R2 out 5 algorithms (Linear regression, Ridge regression, Decision Tree, Random Forest, Gradient Boosting and AdaBoost) Gradient Boosting algorithm shows highest accuracy for testing dataset. So gradient boosting algorithm is selected and further we tried 3 combinations which containing variation in training and testing data a) Model-1(65-35), b) Model-2(70-30) and c) Model-3(75-25) for better results

$$R^2 = \frac{\sum (Y_p - \bar{Y})^2}{\sum (Y_a - \bar{Y})^2} \quad (1)$$

Where, Yp = Predicted value, Ya = Actual value, $\bar{Y}$= Mean

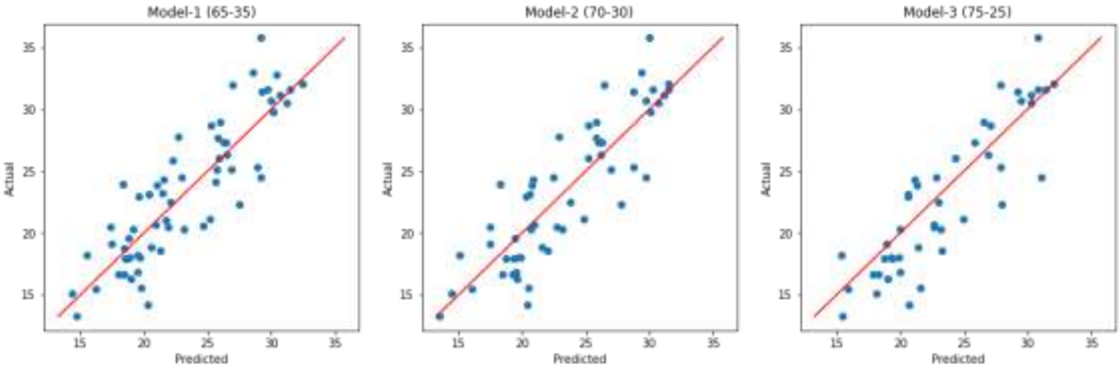

Figure 4: Results obtained using Gradient Boosting algorithm: Relation between the predicted and experimental values of the compressive strength for (a) Model-1 (b) Model-2 (c) Model-3

Table 4: Error for Model-1, Model-2, and Model-3 for M20 and M25 grade of concrete

		Model-1(65-35)	Model-2(70-30)	Model-3(75-25)
For M20 grade of concrete				
Error	Maximum	6.08	7.13	9.66
	Minimum	0.15	0.09	0.20
	Average	2.28	3.02	3.18
For M25 grade of concrete				
Error	Maximum	5.19	8.29	8.74
	Minimum	0.15	0.35	0.29
	Average	2.05	2.91	3.14

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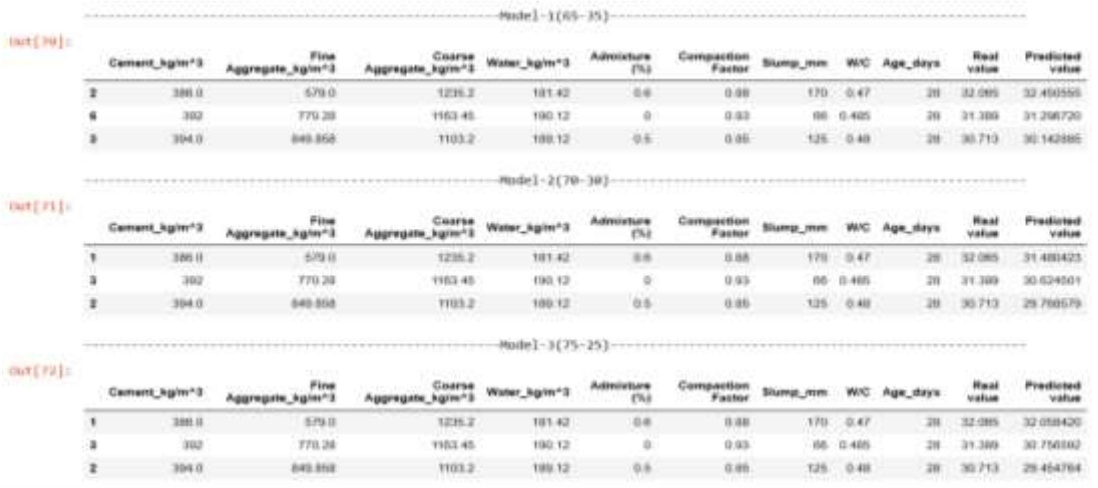

Figure 5: Program output

Conclusion

This research work is based on the performance comparison of the selected machine learning algorithms and combination of training and testing dataset. The predication of result is always complex phenomenon in engineering problems. The strength of concrete depends and deviates with several factors. However the different parameters are leading to vary the compressive strength of concrete.

In this has regard the project work has been done consisting of experimental & computational investigations both. The coding, software training, processing are the parts of computational investigations which are based on experimental results. Collaborative investigation performed in this project reveals following conclusions.

General conclusion

This study shows Supervised Learning is

appropriate method for prediction of compressive strength of concrete.
Linear regression, Ridge regression, Decision tree, Random forest, Gradient Boosting, Ada boost are various algorithms available among these, the Gradient boosting algorithm has given highest accuracy.
The value of R2 is 0.7606 for Model-1(65-35), R2 is 0.7423 for Model-2(70-30) and R2 is 0.7614 for Model-3(75-25) means near about 75% accuracy is shown by models.

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