Modelling of the Strength of High Performance Concrete using Machine Learning Models

[1]Sangram Biplab Manabendra Thakur, [2]Paresh Biswal (Guide)

[1]PG Scholar, [2]Assistant Professor
[1]Department of Civil Engineering
[1]GIET University, Gunupur, Odisha, India

***Abstract*: Many research work has shown that High-performance concrete may be a profoundly complex fabric, which makes modelling its behaviour a very troublesome assignment. This paper is pointed at illustrating the conceivable outcomes of adapting the leading conceivable machine learning model to anticipate the compressive strength of high-performance concrete. We are using a data set where the input components are as follows Cement -- kg per m3, Blast Furnace Slag -- kg per m3, Fly Ash -- kg per m3, Water -- kg per m3, SP's -- kg per m3, Coarse Aggregate -- kg per m3, Fine Aggregate -- kg per m3, Age -- Day (1~365). Whereas my output components will be Concrete compressive strength -- MPa. The present study leads to the following conclusion Bootstrap Random Forest classification model performance is better than other machine learning algorithms. Subsequently utilizing the machine learning model will not as it were offer assistance in foreseeing the strength but moreover will be valuable in making a prediction of materials required eventually it'll offer assistance in lessening the wastage of material.**

***Keywords*: Fly ash (FA), Ground Granulated Blast Furnace Slag (GGBS), compressive strength, machine learning models.**

I. INTRODUCTION

High-Performance Concrete (HPC) refers to the type of concrete mixture which has adequate workability, develops high strength and possesses excellent durability properties throughout its intended service life. To ensure eco-friendly and sustainable development, several industrial by-products such as Fly ash, Silica fume, GGBS, Fibers etc., are being utilized in concrete manufacturing as a substitute for either cement or fine aggregate or as an admixture. The mineral materials, when used in HPC, can enhance either or both the physical and durability properties of concrete. Concretes with these cementitious materials are used extensively throughout the world. Some of the major users are power, gas, oil and nuclear industries. The applications of such concretes are increasing with the passage of time due to their excellent performance, low influence on energy utilisation and environment friendliness.

In order to minimize the experimental task for concrete mix design, probabilistic models are generally constructed using Artificial Neural Networks (ANN) and Multiple Regression Analysis (MRA) and constitutive equations are derived. Multiple Regression Analysis (MRA) is one of the traditional methods used to forecast the compressive strength of concrete, by implementing linear or non-linear method. MRA is based on the least-squares fit approach. It is a statistical technique to examine the relationship between one or more independent variables and a dependent variable.

Neural networks are networks of many simple processes, which are called units, nodes, or neurons, with dense parallel interconnections. The connections between the neurons are called synapses. Each neuron receives weighted inputs from other neurons and communicates its outputs to other neurons by using an activation function. Thus, information is represented by massive cross-weighted inter-connections. Neural networks might be single-or multi layered. The single-layer neural networks present processing units of the neural networks, which take input from the outside of the networks and transmit their output to the outside of the networks; otherwise, the neural networks are considered multi layered. The basic methodology of neural networks consists of three processes: Network training, testing, and implementation.

In this study, multilayer preceptor (MLP): a feed forward artificial neural network model is implemented. A large test database has been extensively surveyed and collected. It is then carefully examined to establish the input vectors and the desired output vectors. Finally, a new model is proposed based on ANN and then verified against experimental data which has been collected from different sources.

ANN has the tendency to exploit non-linearity, predict input–output relationship, adapt to the changes in the free parameters and has sufficient fault tolerance. In the current study, the compressive strength of High Performance

Concrete is taken as the dependent variable, whereas, the mix constituents and age of the specimen form the independent variables.

II. LITERATURE REVIEW

The present work is drafted after referring the following previous researches:

Bhanja and Sengupta (2005) worked on Influence of silica fume on the tensile strength of concrete. Extensive experimentation was carried out over water–binder ratios ranging from 0.26 to 0.42 and silica fume–binder ratios from 0.0 to 0.3. For all the mixes, compressive, flexural and split tensile strengths were determined at 28 days.A.

Elahi et al, carried out investigation to evaluate the mechanical and durability properties of High Performance Concrete (W/B = 0.3) containing supplementary cementitious materials (Silica Fume, Fly Ash, Ground Granulated Blast Furnace Slag) in binary and ternary systems. Portland cement was replaced with fly ash upto 40%, silica fume upto 15% and GGBS upto a level of 70%. The ternary mixes containing GGBS or Fly Ash (50%) and Silica Fume (7.5%) performed the best amongst all the mixes to resist the chloride diffusion. Silica fume (7.5%) performs better than other supplementary cementitious materials for the strength development.

B. K. Raghu Prasad et al, proposed an artificial neural network (ANN) to predict 28 days compressive strength of high performance concrete. The high values of R2 demonstrated that the proposed ANN model was suitable for predicting the compressive strength values very closely with the experimental values.

K. E. Hassan et al, carried laboratory study on the properties of super-plasticized high performance concrete by using SF and FA (10%, 30% by weight of cement). The SF concrete showed similar strength development to that of the Ordinary Portland Cement concrete but slight higher values at all tested ages (1, 3, 7, 28, 365 days). FA concrete gave lowest compressive strength at early ages, same at 28 days and higher at 365 days than OPC concrete.

Vaishali G Ghorpade performed tests on four mixes of concrete with 0%, 0.5%, 1.0% and 1.5% by volume fraction of glass fiber, silica fume (0%, 10%, 20%, 30% by weight of cement) with W/B ratio = 0.35, aggregate/binder = 2.0 and super-plasticizer 1% of the weight of cement. The optimum percentage recommended as 1% fiber volume with 10% silica fume for achieving maximum benefits in compressive strength, split tensile strength and flexural strength.

III. MATERIALS USED

Cement

Cement is a binder, a substance that sets and hardens independently, and can bind other materials together. It is one of the most important building materials. Cement for the most part refers to a very fine substance mainly made up of limestone (calcium), sand or clay (silicon), bauxite (aluminium) and iron ore, and may incorporate shells, chalk, marl, shale, clay, impact heater slag, slate. It is used to make concrete as well as mortar. Locally available Ordinary Portland Cement of 53 grade of BIRLA Brand confining to ISI standards has been procured, and the tests have been carried out according 15:8112- 1989.

Fine Aggregate

Aggregates less than 4.75 mm in size are called fine aggregates. Sand falls under the fine aggregate. The fine aggregate ranges from 4.75 to 150 µm is called fine aggregate. The locally available Natural river sand conforming to grading zone II of table 4 of IS 383-1970 has been used as Fine aggregate.

Coarse Aggregate

Machine Crushed granite confining to IS 383-1970 [23] consisting 20 mm maximum size of aggregates have been obtained from the local quarry. It has been tested for Physical and Mechanical Properties such as Specific Gravity, Sieve Analysis, Bulk Density, Cushing and Impact values.

Fly Ash

Fly ash is a fine powder that is a by-product of burning pulverized coal in electric generation power plants. Fly ash is a pozzolan, a substance containing aluminous and siliceous material that forms cement in the presence of water. When mixed with lime and water, fly ash forms a compound similar to Portland cement. This makes fly ash suitable as a prime material in blended cement, mosaic tiles, and hollow blocks, among other building materials. When used in concrete mixes, fly ash improves the strength and segregation of the concrete and makes it easier to pump. The fly ash obtained from Jharsuguda, Odisha is used in the present experimental work. The chemical composition of flyash is rich in silica content which react with calcium hydroxide to form C-S-H gel. This gel is responsible for the strength mortar or concrete. The fly ash used to the specification of grade 1 flyash.

Granulated Blast Furnace Slag

If the molten slag is cooled and solidified by rapid water quenching to a glassy state, little or no crystallization occurs. This process results in the formation of sand size fragments, usually with some friable clinker-like material. The physical structure and gradation of granulated slag depend on the chemical composition of the slag, its temperature at the time of water quenching, and the method of production. When crushed or milled to very fine cement-sized particles, it has cementitious properties, which make a suitable partial replacement for or additive to Portland cement.

Admixture

SP's, also known as high range water reducers, are additives used in making high strength concrete. Plasticisers are chemical compounds that enable the production of concrete with approximately 15% less water content. SP's allow reduction in water content by 30% or more. These additives are employed at the level of a few weight percentage. Plasticisers and SP's retard the curing of concrete. Super Plasticizers are new class of generic materials which when added to the concrete causes increase in the workability. They consist mainly of naphthalene or melamine sulphonates, usually condensed in the presence of formal dehyde.

Water

Concrete is produced by mixing binding materials and inert materials with water. Thus, water and its quality (and also its quantity) play an important role in determining the quality of concrete. The strength and durability of concrete are to a large extent determined by its water to cementitious materials ratio. Tap water has been used in this experimental program for mixing and curing.

IV. METHODOLOGY

Predictive Modeling

A statistical technique using machine learning and data mining to predict and forecast likely future outcomes with the aid of historical and existing data. It works by analyzing current and historical data and projecting what it learns on a model generated to forecast likely outcomes. It has been clearly described below the procedure regarding how to use this technique in the current work.

1. Clean up data by treating missing data and eliminating outliers.
2. Determine whether parametric or nonparametric predictive modelling is most effective.
3. Reprocess the data into a format appropriate for the modelling algorithm.
4. Specify a subset of data to be used for training the model

5. Train model parameters from the training dataset.
6. Conduct predictive model performance monitoring tests to assess model efficacy.
7. Validate predictive modelling accuracy on data not used for calibrating the model.
8. Deploy the model for prediction.

V. RESULTS & DISCUSSIONS

Compressive strength analysis using machine learning models:

Exploratory Data Analysis:

Following are the columns available:

1. Cement - Continuous.
2. Blast FurnaceSlag - Continuous.
3. FlyAshComponent - Continuous.
4. WaterComponent - Continuous.
5. Superplasticizer - Continuous.
6. Coarse Aggregate - Continuous.
7. Fine Aggregate - Continuous.
8. Age In Days - Continuous.
9. Compressive Strength - Continuous. It is the targeted Variable

Correlation between different components of Concrete:

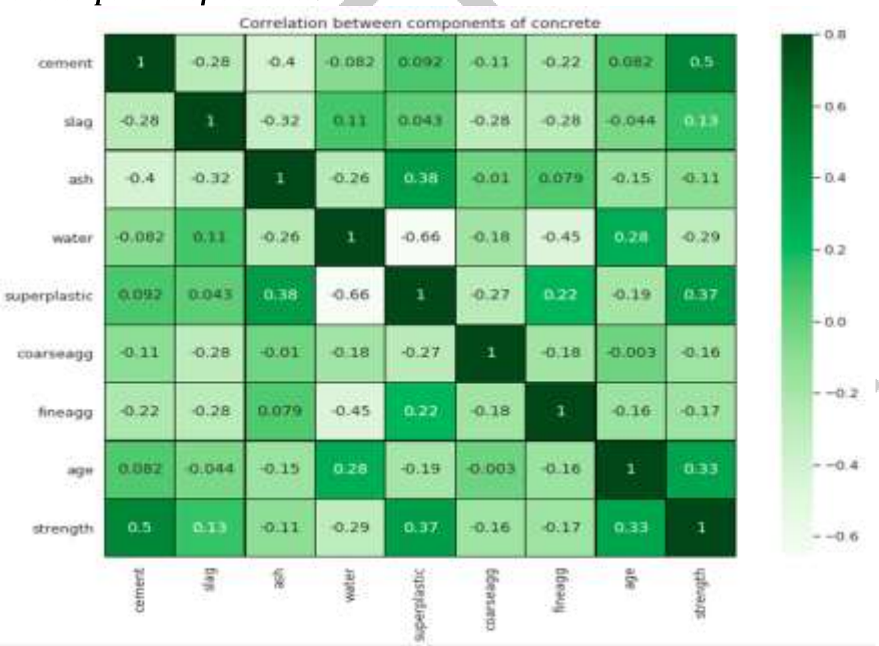

Fig. 1: Correlation between components of concrete

Discussions:

1. Cement and Compressive strength of concrete is positively correlated Compressive strength increases as the amount of cement.
2. Compressive Strength Concrete increases will with increase in age of Concrete.
3. Superplasticiser is also a factor influencing Compressive strength of Concrete.
4. Positive correlations exist between Superplasticizer and Fly Ash, Fine Aggregate.
5. A strong negative correlation exist between Superplasticizer and Water.
6. Compressive strength decreases Fly ash increases

Table 1: Applying Decision Tree Regression

Sl. No.	Components	Importance
1	Cement	0.355173
2	Slag	0.095553
3	Ash	0.011888
4	Water	0.128425
5	Superplasticiser	0.015740
6	Coarse aggregate	0.035993
7	Fine aggregate	0.028619
8	Age	0.328610

1. So, cement, age and water are significant attributes.
2. Here, ash, coarse agg, fine agg, superplastic and slag are the less significant variable. These will impact less to the strength column.

Table 1: Machine Learning Models and their accuracy

Sl. No.	Method	Accuracy
1	Decision Tree	0.833400
2	Random Forest Regressor	0.890072
3	Gradient Boost Regressor	0.891656
4	Ada Boosting Regressor	0.775595
5	Bragging Regressor	0.887433
6	KNN Regressor	0.807882
7	Support Vector Regressor	0.693204
8	Ensamble	0.784919

1. After applying all the models we can see that Random Forest Regressor, Gradient Boost Regressor, Bagging Regressor are giving better results as compared to other models.
2. Now as the dataset have different gaussians, we can apply k means clustering and then we can apply the models and compare the accuracy.

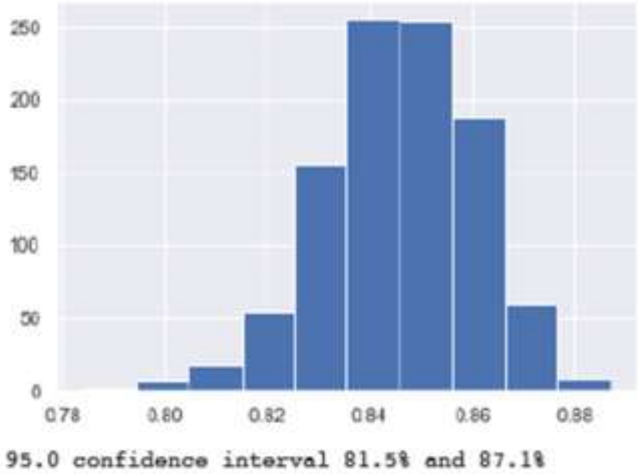

Fig.2: Bootstrap Sampling - Using Gradient Boosting Regressor

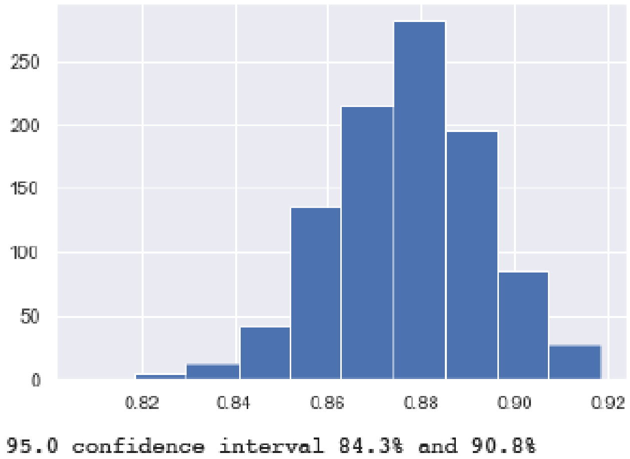

Fig.3: Bootstrap Sampling - Using Random Forest Regressor

VI. CONCLUSIONS

After analysing the Compressive Strength Data using Machine Learning to Predict the Compressive Strength of Concrete. We have used Linear Regression and its variations, Decision Trees and Random Forests to make predictions and compared their performance.. The averaging makes a Random Forest better than a single Decision Tree hence improves its accuracy and reduces overfitting. A prediction from the Random Forest Regressor is an average of the predictions produced by the trees in the forest. Random Forest Regressor has the best accuracy and is a best choice for this problem. The bootstrap random forest classification model performance is between 84%-90.8% which is better than other classification algorithms.

This prediction model can help accurately in predicting and modelling high-performance concrete. Which ultimately helps in reducing the wastage of construction material. Means the High-strength concrete will be more economical.

REFERENCES

[1] Bhanja, B. Sengupta, "Influence of silica fume on the tensile strength of concrete", Cement and Concrete Research, Vol. 35, (2005), pp. 743-747.

[2] Elahi, P. A. M. Basheer, S. V. Nanukuttan and Q. U. Z. Khan, "Mechanical and Durability Properties of High Performance Concretes Containing Supplementary Cementitious Materials," Construction and Building Materials, Vol. 24, No. 3, 2010, pp. 292-299.

[3] V. G. Ghorpade, "An Experimental Investigation on Glass Fibre reinforced High Performance Concrete with Silica fume as Admixture," 35th Conference on OurWorld in Concrete & Structures, Singapore, 25-27 Au-gust 2010, pp. 1-8.

[4] K. E. Hassan, J. G. Cabrera and R. S. Maliehe, "The Effect of Mineral Admixtures on the Properties of High Performance Concrete," Cement & Concrete Composites, Vol. 22, No. 4, 2000, pp. 267-271.

[5] J.A.Peter, M.Neelamegham "Utilization of fly ash as cement replacement material to produce high performance concrete" structural engineering research centres (CSIR) Chennai 1999.

[6] Patil Shreekedar.A and Kumbhar .P.D "Study on effect of mineral admixtures in mix proportioning of HPC", International Journalof Research in Advent Technology", Vol.1,Issue.5,pp.499-504,2013.

[7] B. K. Raghu Prasad, H. Eskandari and B. V. Venkatarama Reddy, "Prediction of Compressive Strength of SCC and HPC with High Volume Fly Ash Using ANN," Construction and Building Materials, Vol. 23, No. 1, 2009, pp.117-128.

[8] Sudarsana Rao.Hunchate, Sashidhar.Chandupall, Vaishali.G.Ghorpode and Venkata Reddy.T.C "Mix Design of High Performance Concrete Using Silica Fume and Superplasticizer" International Journal of Innovative Research in Science, ISSN: 2319-8753.

[9] T.Shanmugapriya , 2,Dr.R.N.Uma, Experimental Investigation on Silica Fume aspartial Replacement of Cement in High Performance Concrete, The International Journal Of Engineering And Science (IJES) ||Volume||2 ||Issue|| 5 ||Pages|| 40-45||2013|| ISSN(e): 2319 – 1813 ISSN(p): 2319 – 1805.

[10] N. Venkateswarao and A. Dattatreya Kumar - Influence of Silica Fume and GGBS on Strength Characteristics of High Performance Concrete, Volume 06 Issue 09, September 2016

[11] P.Vinayagam,"Experimental Investigation on high performance concrete Using Silica Fume and Superplasticizer", International journal of Computer and Communication Engineering, Vol.1, No.2, pp. 168- 171, 2012.

[12] T.V.S. Vara Lakshmi, Prof. S. Adiseshu (05 February 2016), "A Study on Preparing Of High Performance Concrete Using Silica Fume and Fly Ash".