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(RESEARCH ARTICLE)

Prediction of GGBS based geopolymer concrete strength by using machine learning

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Abstract

The aim of the present study is to develop a compressive strength machine learning model that matches the conventional laboratory technique by means of machine learning. The entire operation consists of casting cubes of the 150mm dimension of geopolymer concrete based on the mixture of various Molarities of Ground Granulated Oven Slag. Cube has been evaluated by various laboratory techniques under compression. Data were utilized in machine learning modelling. 80% of the actual data examined were utilized for training and 20% for testing. The modelling is performed in the Python language using linear regression and artificial neural network.

Keywords: Ground Granulated Blast Furnace Slag (GGBS) pellets; Alkali activators (Sodium silicate and Sodium hydroxide); GC (Geopolymer Concrete);Artificial Intelligence (AI); Machine learning (ML); Linear Regression (LR); Artificial Neural Network (ANN)

1. Introduction

In engineering, many AI techniques are utilized and new technologies are introduced. Although there were numerous fields of AI prior to the arrival of computers, applied AI systems demonstrated their progress and effectiveness in dealing with engineering problems compared to their standard counterparts. Over the years, many applications for the prediction of the behaviour and properties of cement-based materials in AI techniques have been reported. For example, an intelligent system for the discovery and forecasting of concrete strength has developed the supported ANN. The results obtained show that the suggested technique properly predicts the strength of the concrete. The results of further research supporting tangible maturity are also contrasted with the system chosen. Maturity is often defined because it is important for your time. The comparison revealed that nearly the experimental outcomes generated by the ANN system. Later, ANN forecasts concrete compressive strength. In this respect, experimental data are used to characterize the concrete. Experimental findings check the correctness and good agreement of the proposed system. Although one of the model's limits is the use of limited test information, the typical mistake of ANN in forecasting test results was considerably less than the previous methods, which are grouped into three major categories, including linear, second and non-linear models. Specific methods, i.e., linear and ANN algorithms, are expected throughout this research [1].

2. Materials Used

- GGBS
- Fine aggregates- Manufactured sand (M-SAND)
- Coarse aggregate- crushed stone aggregates
- Alkali activator solution and wate

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Table 1 Physical properties GGBS

Sl.no	Properties requirement As per is 16714:2018	Test results
I	Specific Gravity	2.93
II	Fineness 320(min)	391

Table 2 Physical Properties of M-Sand

Sl.no	Test Properties	Test Results	Code Standards	Reference Code
I	Specific Gravity	2.65	2.3-2.7	IS:2386 (Part3)- 1963
II	Bulk Density [Kg/m3] Loose Density Compacted Density	1934 2056	1520-1680	IS:2386 (Part3)- 1963
III	Fineness modulus	3.48	2.2-3.2	IS:383-2016
IV	Grading Zone	Zone I	Zone I-IV	IS:383-2016
V	Bulking [%]	41.19	-	IS:2386 (Part3)- 1963

Table 3 Physical Properties of coarse aggregate

Sl.no	Test properties	Test results	Code standard (is:383- 1970)
I	Specific Gravity	2.71	2.75
II	Bulk Density	1705 Kg/m32	-
III	Crushing value	25%	<45%
IV	Water absorption	0.15%	<2%

3. Methodology

3.1. The following sequence steps followed in prediction of concrete strength

- Mix GGBS geopolymer concrete design of grade M25 for alkaline solution differentiation (Molarities) concentration, i.e. 2M to 12M.
- Casting of 150mm standard cubes for various concrete mix proportions.
- Testing cubes after 3 to 90 days by utilizing a compression test machine test till failure.
- 80% of the data utilized for the training of programs from the actual compressive strength tested data and 20% remain for the testing.
- The observed information were Molarity, GGBS content, Fine Aggregation, Coarse Aggregate, Extra Water Content, Na2SiO3 solution quantity, NaOH solution quantity and real compressive strength.
- The compressive strength of the test mixtures is predicted by both algorithms and compared to the actual strength of the compression [2].

3.2. Compressive strength test directed on geopolymer concrete

One of the most basic tests for determining strength is the "Compressive-Strength Test." The concrete cube sizes used for casting are 150 mmX150mmX150mm in accordance with IS 516-1959 part five to evaluate the compressive strength of the concrete throughout the casting process. After exposure to 3, 7, 28, 56, and 90 days ambient conditions, the specimens may be placed on CTMs to evaluate their compressive strength by applying a compressive force. The following is the formula for the compressive strength assessment.

Compressive Strength = [Failure Load /Area] in N/mm^2

3.3. Working of linear regression:

The least quadratic approach is the most frequent technique for fitting a regression line. The Middle-Squared Error feature is used to calculate your loss. This function has three stages:

- The difference between the predicated and actual value: $\bar{y}$, for a given x.
- Perform the squaring operation on the difference value
- For every value of X the average of square is performed.

$$E = \frac{1}{n} \sum_{i=0}^{n} (y_i - \bar{y}_i)^2$$

The greatest match for the data is found with this method by cutting the vertical squares of each point to the line (if a point lies on the fitted line exactly, then its vertical deviation is 0).

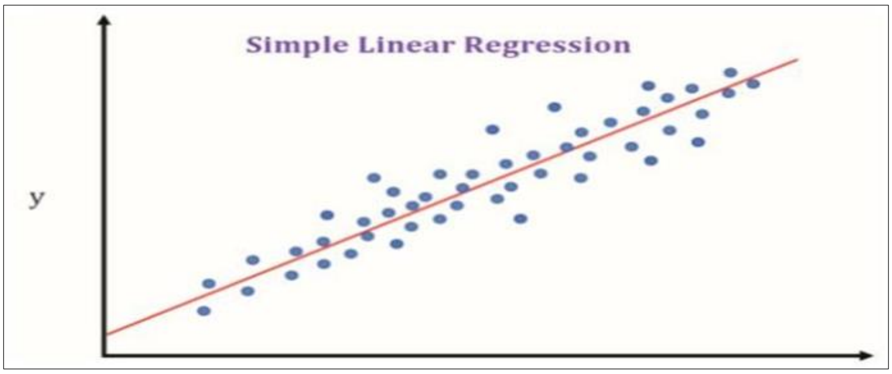

Figure 1 Simple Linear Regression

The discrepancies are squared and summarized, such that no cancellation is made between positive and negative figures.

3.4. Artificial neural network model construction/ methodology:

Here we have built ANN model with 5 layers, out of which one is the input layer and three hidden layers and one output layer. It is represented in below diagram:

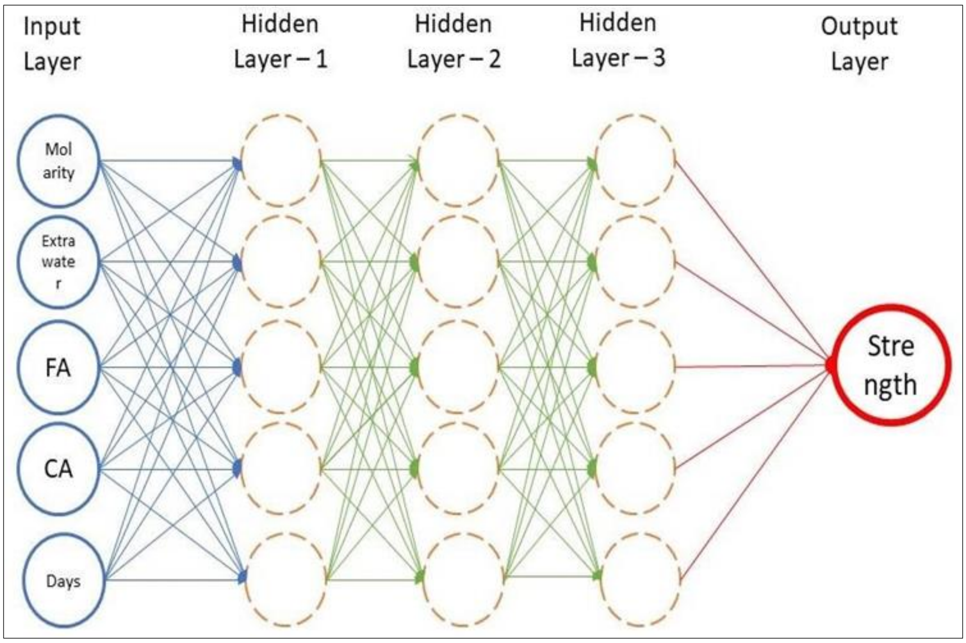

Figure 2 ANN Model Used in the Work

The activation function we have used is **ReLU** and the optimizer used is **Adam.**

- **Data Propagation or feed forward:** It is organized into layers and, as shown in Figure, all the Artificial Neurons in each layer are linked to all the neurons in the above layer. But in later levels, there is no connection between neurons in the same layer or neurons that are not linked. Our ANN model is initialized with random weights (coefficients). When the data is propagated with such weights in the forward direction, it is spread to the ultimate hidden layer[3].
- **Error correction or back propagation:** In neural networks the weights of the network are adjusted according to the error rate obtained in the previous period (i.e., iteration). The proper weight modification allows you to reduce mistake rates and improve the model's dependability. The erroneous values are propagated back in order to adjust the weights to minimize the amount of error.

Table 4 Mix proportions obtained from mix design for different Molarities

Molarity	GGBS (Kg/m^3)	Extra Water Content (Kg/m^3)	Na_2SiO_3 (Kg/m^3)	NaOH (Kg/m^3)	FA (Kg/m^3)	CA (Kg/m^3)
2M	400	16.93	105.71	42.29	874.54	1068.88
4M	400	20.31	105.71	42.29	873.02	1067.02
6M	400	23.70	105.71	42.29	871.49	1065.16
8M	400	27.08	105.71	42.29	869.97	1063.30
10M	400	30.47	105.71	42.29	868.45	1061.44
12M	400	33.85	105.71	42.29	866.93	1059.58

Table 5 The Input and Output quantities used

Input Variable		
Molarity of NaOH	2	12
Quantity of GGBS (Kg/m^3)	400	400
Extra Water Content (Kg/m^3)	16.93	33.85
Na2SiO3(Kg/m^3)	105.71	105.71
NaOH (Kg/m^3)	42.29	42.29
Fine Aggregate (Kg/m^3)	866.93	874.54
Coarse Aggregate (Kg/m^3)	1059.58	1068.88
Output Variable		
Compressive strength (N/mm2)	29.01	71.35

4. Result and Discussion

4.1. Comparison of 4m Actual Strength With ANN Method Predicted Values

Table 6 4M Actual strength with ANN method predicted Strength

Days	**Actual strength N/mm^2**	**Predicted strength N/mm^2**
3	30.75	32.62
7	35.44	33.51
28	36.78	38.18
56	42.66	44.40
90	47.35	51.96

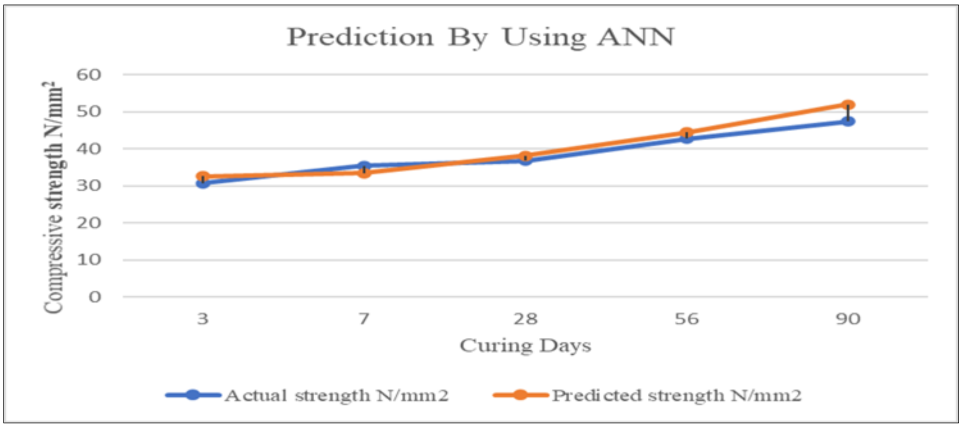

Figure 3 Graph of 4M Actual vs ANN method predicted Strength

- Almost all the predicted values of 4M GGBS based concrete is having least error for tested days.
- Only the 7 Days predicted strength is less than actual strength and remining all are higher values.
- Average error in the prediction is less than 6%.

4.2. Comparison of 4m Actual Strength With Linear Regression (Lr) Method Predicted Values

Table 7 4M Actual strength with LR method predicted Strength

Molarity	Days	Actual strength N/mm^2	Predicted strength N/mm^2
4	3	30.75	32.54
4	7	35.44	33.48
4	28	36.78	38.40
4	56	42.66	44.97
4	90	47.35	52.94

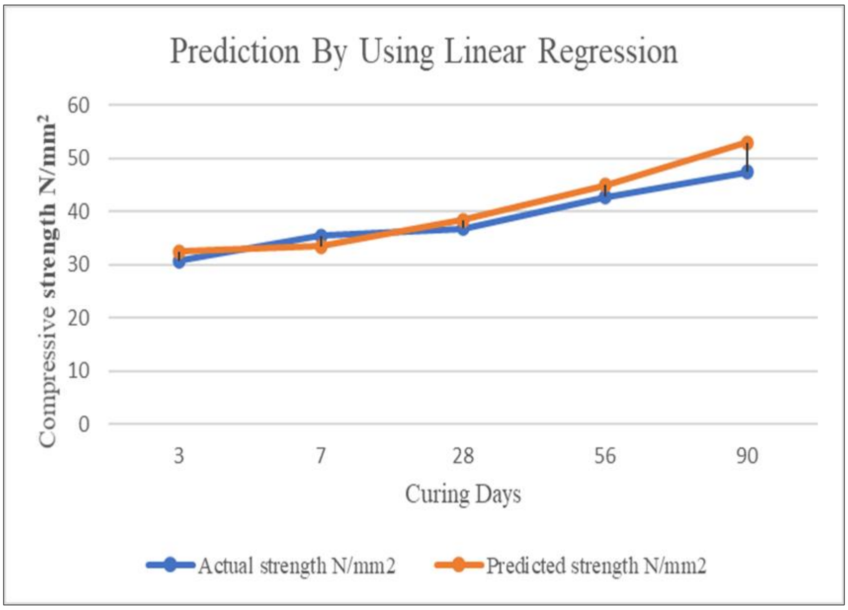

Figure 4 Graph of 4M Actual strength vs LR method predicted Strength

- Using this technique of prediction, the average error is less than 7 percent on average.
- When compared to the ANN model, the error rate in this approach is greater.
- Except for the projected strength for the next 90 days, all other predictions are less than 10%.
- The 28 days predicted strength is having less error compared to all others days[4,5].

4.3. Comparison of 4m Actual Strength With Predicted Values

Table 8 4M Actual strength with predicted Strength

Molarity	Days	Actual strength N/mm^2	Predicted strength by Linear Regression Method N/mm^2	Predicted strength by ANN Method N/mm^2
4	3	30.75	32.54	32.62
4	7	35.44	33.48	33.51
4	28	36.78	38.40	38.18
4	56	42.66	44.97	44.40
4	90	47.35	52.94	51.96

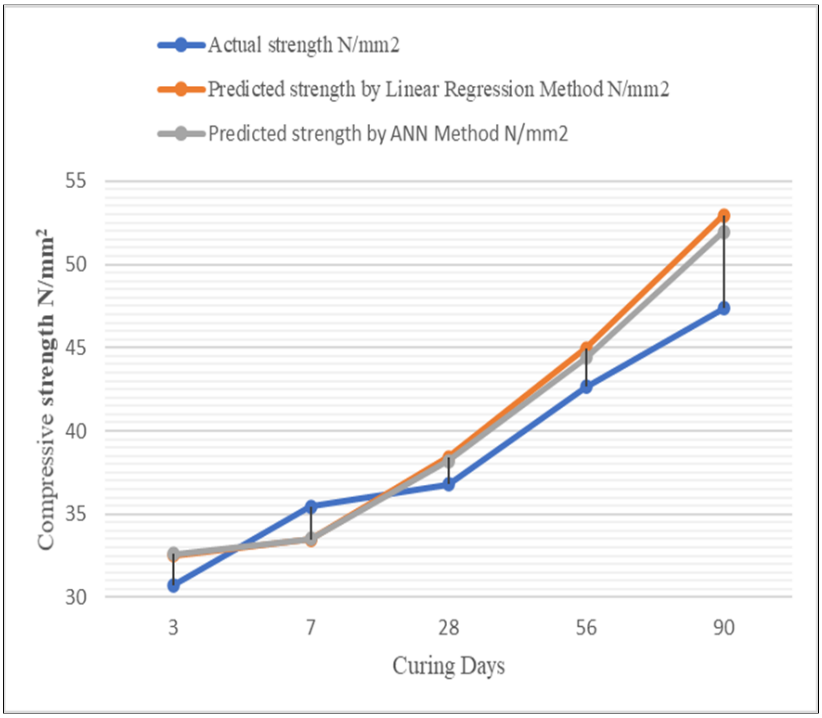

Figure 5 Graph of 4M Actual strength vs predicted Strength

- Both the methods ANN and Linear Regression give similar pattern of results.
- Only for 7 days error is negative remaining all is positive error.
- ANN Method give better results compared to linear regression method[6].

4.4. Correlation of Input and Out Data

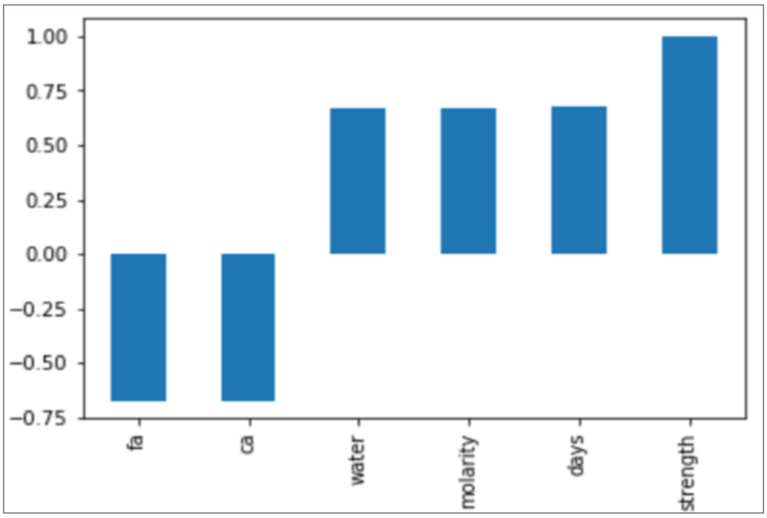

Figure 6 Correlation Graph

- Above graph explains about the input values weightage on the prediction.
- Here we can see that Water content, Molarity and Curing days gives positive impact on prediction.
- Fine aggregate and coarse aggregate content give the negative impact on prediction of strength.

5. Conclusion

In two models created in Machine Learning, a multilayer feed forward neural network in a back propagation algorithm and a basic LR model were utilized in the ANN technique and the LR model, respectively. Compressive strength values of concretes containing slag may be calculated in a short period of time using multilayer feed forward ANN and LR models, and the findings are very accurate and reliable. Machine learning may be used in lieu of expensive experimental research, saving money in the process. For the purpose of predicting characteristics The testing of the material by means of a destructive technique may be substituted by methods based on artificial intelligence. Despite the fact that the ANN approach produced superior outcomes throughout testing in our present research. The overall inaccuracy of the LR technique is likewise quite low.

Compliance with ethical standards

Disclosure of conflict of interest

No conflict of interest to be disclosed.

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