COMPRESSIVE STRENGTH OF CONCRETE USING DEEP LEARNING

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ABSTRACT
Concrete is the most important material in civil engineering. The concrete compressive strength is a nonlinear function of the concrete age and some constituents. These constituents include cement, blast furnace slag, fly ash, superplasticizer, coarse aggregate, and fine aggregate. The concrete is the only constituents that can be delivered to the working site in the plasticity form. This feature turns it into a notable construction material because it can be cast in any form. We are going to analyze here using ANN . The ANN usually, are used in the classification of a bunch of data.

KEYWORDS
Concrete compressive strength, DeepLearning, ANN, Concrete,

1. INTRODUCTION

The Compressive Strength of Concrete determines the quality of Concrete. This is generally determined by a standard crushing test on a concrete cylinder. This requires engineers to build small concrete cylinders with different combinations of raw materials and test these cylinders for strength variations with a change in each raw material. The recommended wait time for testing the cylinder is 28 days to ensure correct results. This consumes a lot of time and requires a lot of labour to prepare different prototypes and test them. Also, this method is prone to human error and one small mistake can cause the wait time to drastically increase.
One way of reducing the wait time and reducing the number of combinations to try is to make use of digital simulations, where we can provide information to the computer about what we know and the computer tries different combinations to predict the compressive strength. This way we can reduce the number of combinations we can try physically and reduce the amount of time for experimentation. But, to design such software we have to know the relations between all the raw materials and how one material affects the strength. It is possible to derive mathematical equations and run simulations based on these equations, but we cannot expect the relations to be the same in the real-world. Also, these tests have been performed for many numbers of times now and we have enough real-world data that can be used for predictive modeling

2. THE RELATED LITERATURE

1. I-Cheng Yeh, "Modeling of strength of high performance concrete using artificial neural networks," Cement and Concrete Research, Vol. 28, No. 12, pp. 1797-1808 (1998).
2. Tattersall and etc. all; described the advantages and disadvantages of the applied tests in determining the concrete strength and efficiency. He pointed to the main problems in these tests and also determined how much increasing the percentage of the superplasticizer, which retains the w/c ratio, increases the slump, and also determined its effect on the concrete strength.
3. There is also a precious study done by the Erdogdu. He tried to find a solution for recovering the initial slump of the concrete on the working place. He used water and superplasticizer to remix the concrete (re-temper) and compared the results. The concrete recombined with the superplasticizer, notwithstanding the mixing time [6, 7, 8].

3. Dataset Description

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 — Mega Pascal). We shall explore the data to see how input features are affecting compressive strength.

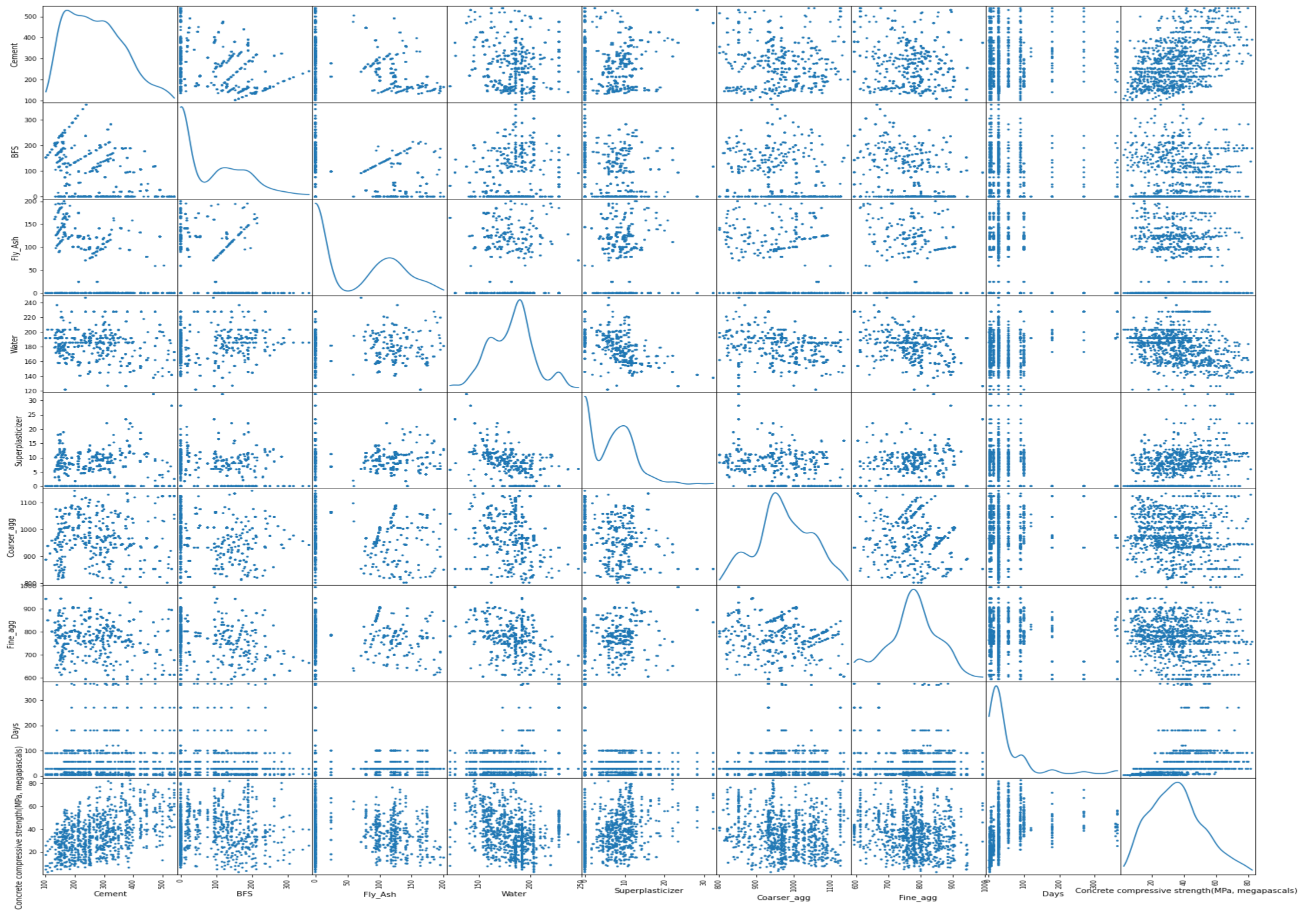
4. DATA PREPROCESSING

(i) Normalization -: Normalization is used to scale the data of an attribute so that it falls in a smaller range, such as -1.0 to 1.0 or 0.0 to 1.0. It is generally useful for classification algorithms.

$$\hat{X}[:,i] = \frac{X[:,i]-\min(X[:,i])}{\max(X[:,i])-\min(X[:,i])}$$

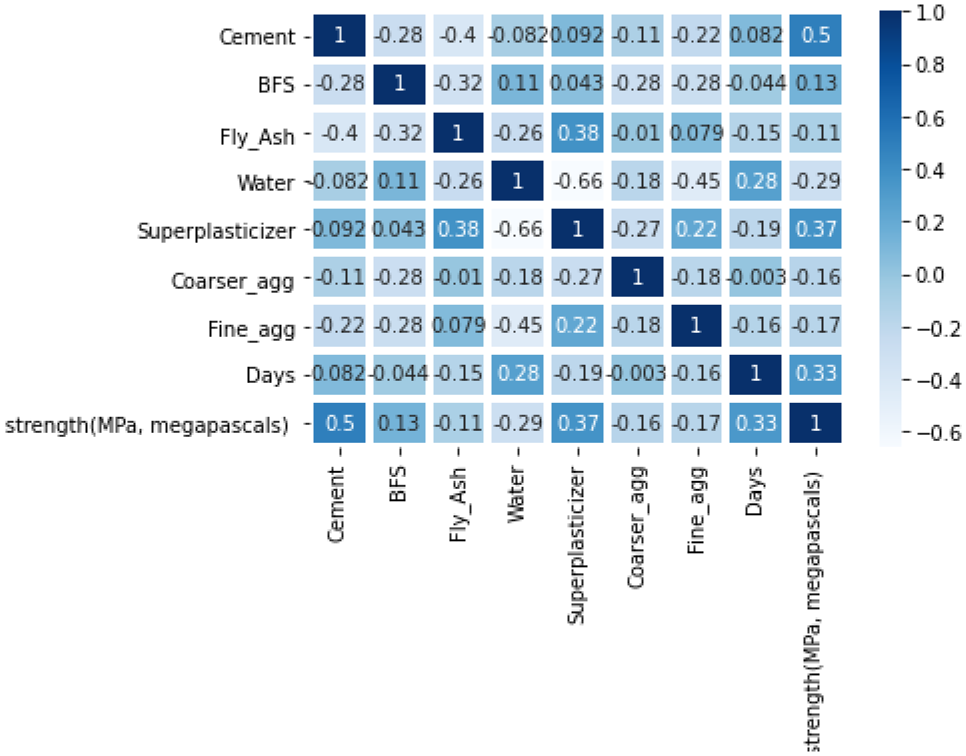
This method rescales the range of the data to [0,1]. In most cases, standardization is used feature-wise as well

(ii) Data Visualization -: Data Visualization tools and technologies are essential to analyze massive amounts of information and make data-driven decisions. This use to check correlation between two quantity. A scatterplot helps us to understand discrete distributions of each feature and provides us with the correlation coefficient (Pearson).



The scatterplot matrix shows us that there are some features such as ‘Age’ are less evenly distributed than other features.

(iii) Correlation Factors-: Data correlation is the way in which one set of data may correspond to another set. In ML, think of how your features correspond with your output.t is important to discover and quantify the degree to which variables in your dataset are dependent upon each other. This knowledge can help you better prepare your data to meet the expectations of machine learning algorithms, such as linear regression, whose performance will degrade with the presence of these interdependencies.



5. CONSTITUENTES

1. **Cement**
2. **Blast Furnace Slag**
3. **Fly Ash**
4. **Water**
5. **Superplasticizer**
6. **Coarse Aggregate**
7. **Fine Aggregate**
8. **Age**

6. CONCRETE COMPRESSIVE STRENGTH

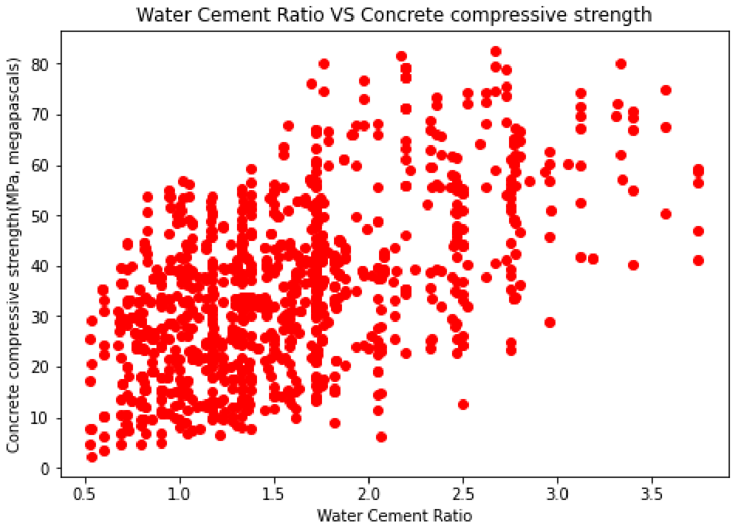
Concrete is the most important material in the civil engineering. The concrete compressive strength is a non-linear function of the concrete age and other elements. Feature turns it into a notable construction material because it can be moulded in any form. It creates a great variety in the surface textures and colours and can be used in the construction of the highways, streets, bridges, dams, big buildings, airport runways, jetties, bulwarks, silo and farm buildings, houses, and even boats and ships.

Two main constituents of the concrete are cement paste and neutral materials. The cement paste consists of the Portland cement, water and some air in the form of the trapped bubbles. And the neutral materials include the fine aggregate like sand and coarse aggregate like grovel, broken stone or slag.

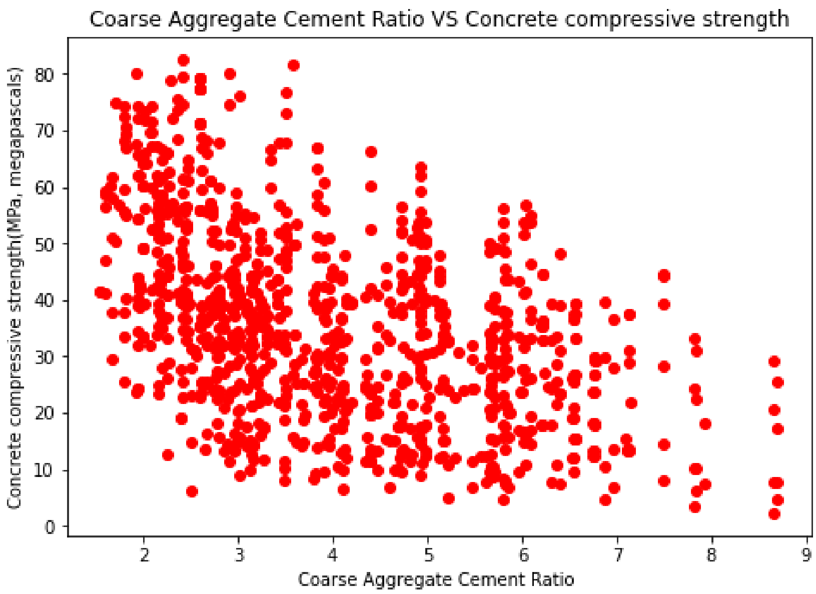
The concrete compressive strength is sorted in the batching plant for each classification, to keep the concrete's high quality during the casting. The cast concretes' samples are tested under the compressive loads to determine the concrete compressive strength. The compressive strength is calculated by applying the failure load on the surface usually after 28 days of curing. It is controlled by the ratio of the cement, coarse and fine aggregates, water and other various constituents.

6. ADDING EXTRA FEATHERS

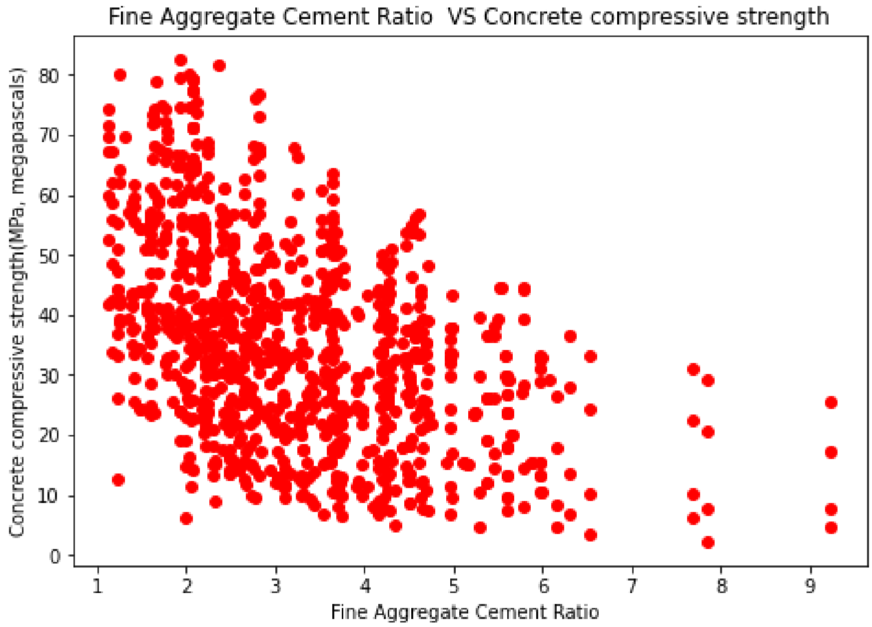
1. **Water Cement Ratio -:** The ratio of the weight of water to the weight of cement used in a concrete mix. Cement hardening depends on the correct chemical reaction of its constituents and accordingly it needs the minimum of water possible. The excess water may increase the fluidity but decreases the strength A lower ratio leads to higher strength and durability, but may make the mix difficult to work with and form. Workability can be resolved with the use of plasticizers or super-plasticizers.this ratio lies generally in the range of 0.35 to 0.65, although the purely chemical requirement (for the purpose of complete hydration of cement) is only about 0.25.Abram law states that compressive strength of hardened concrete is inversely proportional to the water-cement ratio, provided the mix is of workable consistency.



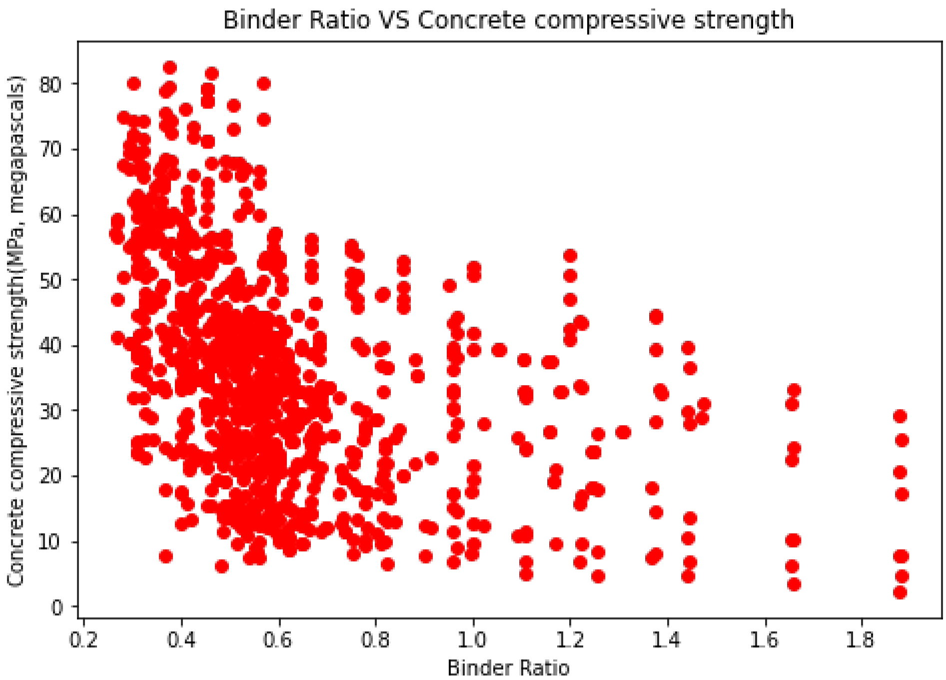
2. **Coarse Aggregate Cement Ratio -:** The ratio of the weight of Coarse Aggregate to the weight of cement used in a concrete mix.



3. **Fine Aggregate Cement Ratio -:** The ratio of the weight of Fine Aggregate to the weight of cement used in a concrete mix.



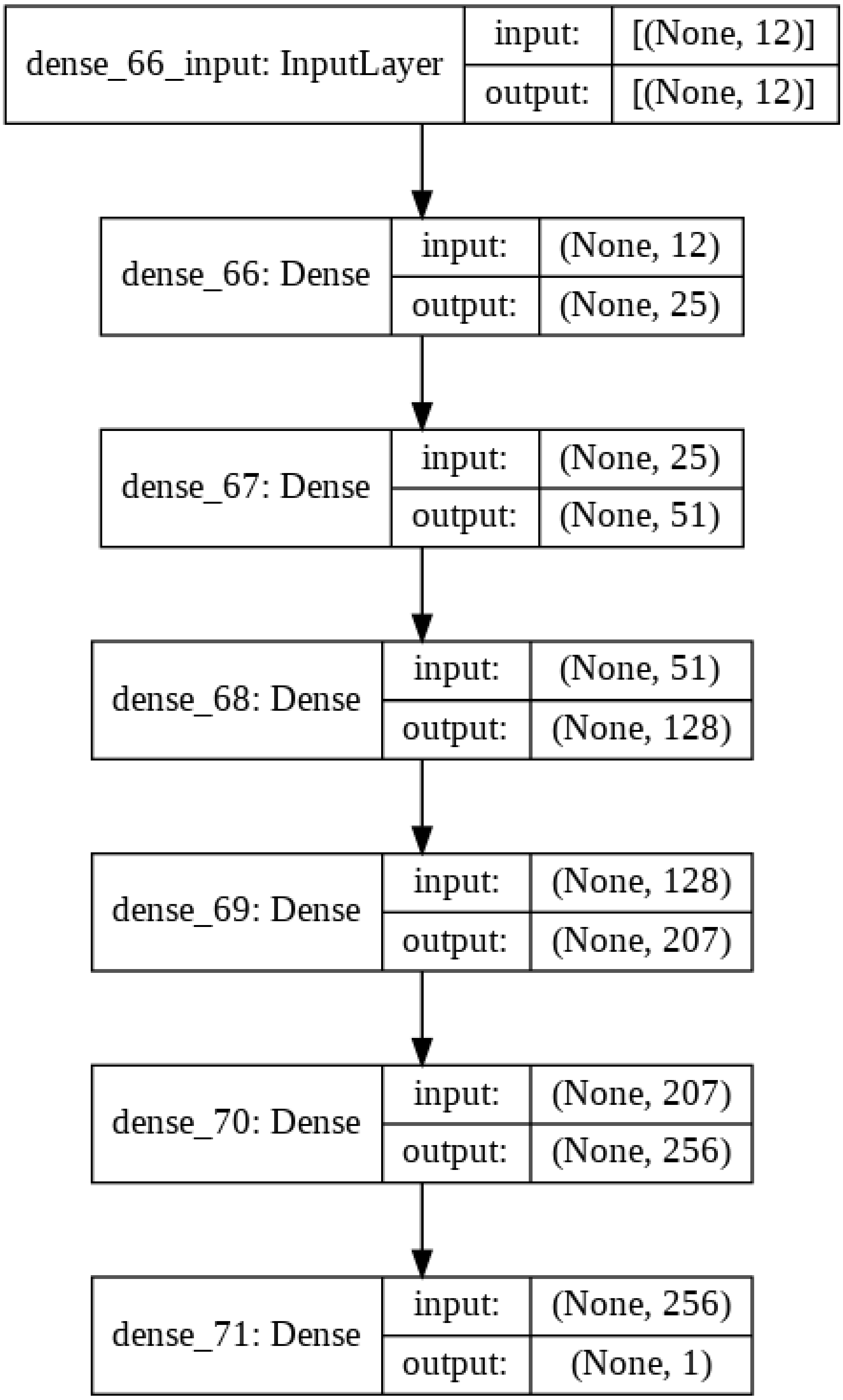
4. **Binder Ratio -:** The ratio of the weight of water to the sum of weight of cement and fly ash used in a concrete mix.



7. MODELLING

Artificial Neural Network -: An artificial neural network is a computational model that attempts to simulate the structure and/or functional aspects of biological neural networks. Various ANN applications can be categorized as classification or pattern recognition or prediction and model-ing. ANNs are widely used in many industrial areas, including process engineering, control and monitoring, technical diagnosis and nondestructive testing, power systems, robotics, transporta-tion, telecommunications, remote sensing, banking, finance and insurance, forecasting, document processing, and construction engineering. The use of ANNs specifically for predicting concrete compressive strength has been studied intensively

Researchers have also explored the use of ANNs to construct concrete compressive strength models that are more accurate than regression models (Yeh 1998).The advantages of ANNs are the unrestricted number of inputs and outputs and the clearly defined number of hidden layers and hidden neurons. The primary drawback of ANNs are the consid-erable time needed to determine the number of layers and hidden neurons, which requires repetitive trial and error-tuning processes.The solution proposed by Hegazy et al. (1994) is to use only one hidden layer to generate arbitrary mapping between inputs and out-puts, and the number of neurons in the hidden layer is 0∶75m;m,or 2m+1, where a m= number of input neurons



8. PERFORMANCE MEASURES

R-SquareThe R-square coefficient, R2is a measure of how well the indepen-dent variables considered account for the measured dependent variable. The higher the R-square value, the better the predictive power.

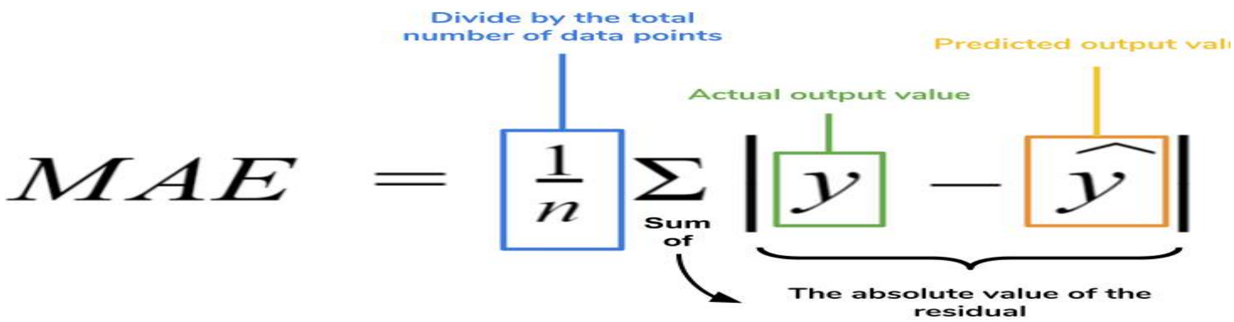
1. **Root Mean Squared Error** -: Root mean squared error (RMSE) is the square root of the mean square error. The RMSE is thus the average distance of a data point from the fitted line measured along a vertical line. The RMSE isgiven by the following equation:

$$RMSE = \sqrt{\sum_{i=1}^{n} \frac{(\hat{y}_i - y_i)^2}{n}}$$

2. **Mean Absolute Error** -: The mean absolute error (MAE) is a statistical measure of predictive accuracy. It usually expresses accuracy as a percent-age. The MAE is commonly used in quantitative forecasting methods because it indicates the relative overall fit (i.e., the good-ness-of-fit). The MAE is given by the following equation:

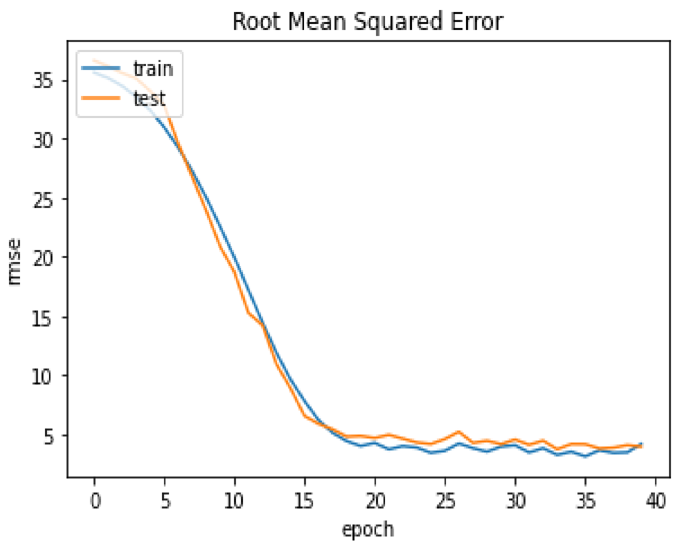
$$\mathrm{MAE} = \frac{1}{n} \sum_{j=1}^{n} |y_j - \hat{y}_j|$$

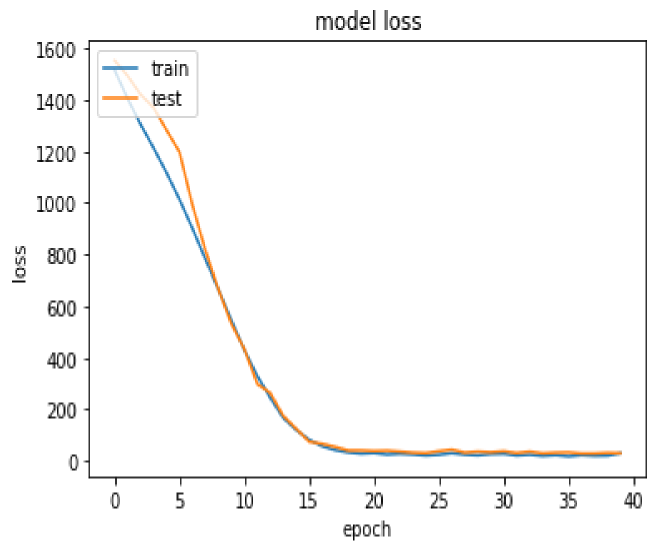
3. **Median_absolute_error** -:



9. EVALUATING MODEL

Model type	R2	MSE	MAE	MSE_true_scale	MAE_true_scale	MedAE_true_scale
ANN	0.8481	39.1193	4.3951	39.1193	4.3951	2.9343





10. Conclusions

This study developed a data-mining approach and performance measures to predict compressive strength and assess the predicted reliability for HPC. Specifically,popular data-mining methods were used: derived from machine learning (ANNs). The experimental data set was acquired from UCI machine learning repository of a 1,030-instance dataset.We also try to extract some additional features like water-cement ratio , binding ratio. In this investigation, the proposed predictive techniques were applied to the prepared data by using nine of the 100-folds for training the models, and the 100th fold for testing. This procedure was repeated 100 times with a distinct fold as test data in each experiment.The proposed approaches were compared for performance out-comes by using four different performance measures (R2, RMSE,MAE) to obtain a comprehensive comparison of the applied predictive techniques. The findings showed that MART achieved the best accuracy forR2and RMSE. The ANN obtained the best prediction power for future unseen data based on the results of MAE, and ANNs performed well in training time.
This study establishes that a predictive model must consider no tonly R2and RMSE, but also MAE and training time. Predicting Compressive strength is a nonlinear problem that cannot be solved by traditional MR techniques. Analytical results indicate that ANN is the most reliable model for high-performance concrete compressive strength in predictive accuracy, speed, ease ofuse, and interpretability.

GitHub Repository -:

This git Repository includes data, code for preprocessing of data and model, and some other graphs and plots.
https://github.com/mlokendra/COMPRESSIVE-STRENGTH-OF-CONCRETE-USING-DEEP-LEARNING