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Speculation of Compressive Strength of Concrete in Real-Time

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Abstract*: Prediction of compressive strength of concrete is a tedious and time consuming progress, so it has to be replaced by means of some modern techniques in order to overcome difficulties. With the growth of the construction industry, there is a need to give quality in it. Improper Testing of the construction materials may lead to the collapse of the entire building. In our Country, most of the construction work is done with concrete, So the first and foremost thing is to examine the compressive strength of the concrete which gives a better idea about durability, reliability, and grade of the concrete. Testing of concrete usually takes place on the 28-day of concrete placement. Human error occurs very commonly in casting the concrete by mixing improper proportions, poor compaction and adapting wrong methods for testing the specimen. If any of the above factors occur it is tedious to obtain the proper process since it has to be carried out from first. Therefore, it has to be taken into consideration that strength yielded to satisfy the strength to be carried. It gives out the speculation of target strength of the concrete using machine learning algorithms with improved accuracy and also a comparison of the result is made between Support Vector Machine (SVM) and Artificial Neural Network (ANN) by 78% and 96%. From the approaches it is found to be, the features can be universal and imparted to all other factors depending concrete strength. The practices of these procedures will lead considerably to concrete quality control.

Index Terms*: Artificial neural networks, Support Vector Machine, Concrete Compressive Strength.

I. INTRODUCTION

Concrete is a composite material and it is the most used binding material for its long-lasting nature, strength, and reliability. Compressive strength is the most important properties of concrete as it resists the compressive stress created by the structure. In concrete construction, it is necessary to ensure the compressive strength, based upon the material proportion added to it. The compressive strength of concrete is tested at the age of 28 days from curing and it is considered as the design strength(Chopra, Sharma and Kumar, 2016)(Young *et al.*, 2019). This traditional process consumes more time and delays the construction work which is not actively implemented in most of the local construction fields. Now it is essential to develop the tool which instantly gives the compressive strength before the concrete is cast in the field with better accuracy(Erdal *et al.*, 2018)(De Melo and Banzhaf, 2016). Machine learning is a science of getting computers to act by feeding data and letting them learn a few tricks on their own. The primary key of machine learning is data, machines learn just like as human. We humans need information that is data to learn similarly machines also needs data to be fed in order to learn and make decisions. The important thing is that when we fed the machine with more data, the machine will learn better and provide high accuracy(Liang *et al.*, 2018). The machine will undergo the process and study the provided data with the help of different algorithms on the data. This paper deals with machine learning with support vector machine and neural networks on concrete compression strength dataset.

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II. RELATED PREVIOUS WORK

Chengyao Liang., *et al.*, (2018) discussed the compressive strength of concrete structures on the marine environment using artificial neural networks. Backpropagation is used for this study since it has wide applications in various fields. Data used in this model were collected from 80 different articles and it includes various factors like water-cement ratio, specimen sizes, initial strength, fly ash dosage, and slag dosage. Statistical analysis has been done and it is recognizable to depict the consistency and conveyance of the information. The dataset was split into training and testing data and hidden layers were fixed and the ANN model is created. Finally, the accuracy of the model has been determined using mathematical parameters and executed.

Saif Salah Alquzweeni., *et al*., (2015) has developed a neural network model to predict the mechanical properties of the concrete with variations of temperature in the compressive strength of concrete. The data of the concrete mix design required for the model has been prepared by casting the concrete. The casted concrete has undergone slow heating at five different temperatures and at different period of time. Finally, its corresponding compressive strength is calculated. The above test has concluded that the compressive strength of concrete with an increase in temperature. The data obtained from the experimental work had been used to create the ANN model by fixing the input and output layer and the number of hidden layers was three. Training and the testing data was fixed and the multi-layer feed forward model was trained.

The mathematical parameter values of RMSE, R2, and MAPE from training in the multilayer feed-forward neural network model were found

Palika Chopra., *et al*., (2016) have employed Artificial neural networks and genetic programming for the concrete strength prediction. The experimental data were classified based on the curing time of the concrete. The trial and error method used to generate true predictions. Genetic programming involves three operation crossover, reproduction, and mutation. The datasets and the categorization are done the same as the ANN model. The values for the parameter Mu and lambda is taken as 100 and 150, hybrid rate and transformation rate have been chosen as 0.70 and 5.*e* – 002. Then the model has been generated and genetic programming model is used to determine the performance of the machine to certain tasks. On comparison of the two models, the ANN model is more accurate in predicting the concrete compressive strength

Vinícius Veloso de Melo., *et al.*, (2015) have used kaizen Programming combined with Ordinary Least Square regression to evaluate the compressive strength of high strength concrete. The kaizen Programming combined with Ordinary Least Square regression to find different non-linear combinations which will provide us with different combinations. Kaizen programming involves the implementation of kaizen event (PDCA) cycle which is used for the continuous improvement process in the business. Three factors have been considered in performing KP is feature construction to expand the current feature dataset, Feature Selection, Model generation. Kaizen programming is the collaborative problem approach, so importance should be at each step and the only issue in kaizen programming is that a large number of models should be generated to achieve better accuracy. The developed Kaizen model is compared with other regression models. The checked accuracy is comparatively better when compared to other techniques and the generated model is considered as the grey box models because it is easy in interpretation techniques.

A Torre., *et al*., (2015) proposed a model to evaluate the compressive strength of concrete using Principle component analysis and artificial neural networks. High strength concrete is one among the revolutionary material and its mix proportion have a great impact on the final strength of concrete.so it should have a tool to numerically model such properties before processing. In this viewpoint, the artificial neural model is proved to be a powerful numerical tool. With 296 concrete specimens, the compression test using the universal testing machine is carried out and data samples are gathered and the model is developed. Principle component analysis was carried out to develop a multilayer perceptron and to improve the performance hyperbolic sigmoid transfer function is used. The network was created using the Mat lab program and the results were computed using regression coefficient r, the coefficient of determination r^2, Root mean square error. The outcome of this paper is ANN is capable of being used to improve in-factory control quality with high accuracy and it opens up a new area of application in the field of construction.

III. MATERIALS

The test and trial data utilized for the forecast of compressive strength of concrete have been obtained from the UCI (University of California), Irvine data repository. To obtain a better prediction model on the target strength of concrete, eight parameters were used. The parameters of about 1030 observations are the measure of cement, water, coarse aggregate, fine aggregate, age, fly ash, blast furnace and finally the compression strength obtained through different mix grade proportions under different curing time period. The correction of the obtained data that is pre-processing is an important step to be done in order to organize and reduce the problems in data that would occur during the model building. In addition to this the standards of material have to be followed as follows: Cement (IS: 269), Aggregates (IS: 383), Water (IS: 3025), Admixtures (IS: 9103), Compressive Strength (IS: 2250).

IV. METHODOLOGY

The machine learning modules are used recently to define material performance in various fields. The methodology implemented in this paper includes aspects which determine the compression strength of concrete in the construction. The methodology followed is slightly similar to other recent studies on concrete. The first step carried out is a literature view of past and recent survey studies. The next step was to collect the required data of concrete mixtures. The collected data is then corrected to required form through data preprocessing techniques and placed. Data scaling has been done with proper split ratio and ready to be tested in the learning modules as shown in Figure 1 and 2.

A. Artificial Neural Networks

An artificial neural network is a fabulous structure imitated over our human brain. Different algorithms can be used to model the network through which several innovations can be made with the learning process. They are generally constructed to overcome the arithmetical, analytical and engineering problems(Liang *et al.*, 2018)(Torre *et al.*, 2015). In this project, neural networks models are used to overcome the difficulties faced in calculating the compression strength of concrete using conventional methods. Multi-layer Perceptron Neural Networks are being used consisting of 3 major layers as input layer hidden layer and the output layer, whereas the input layer acts as a feed of input like concrete characteristics, hidden layer comprising the processes limiting to a threshold and the output layer giving out (Ghanizadeh *et al.*, 2018, Bui *et al.*, 2018, Rajeshwari and Mandal, 2019).

a) Randomly initialize the initial weights to small numbers close to 0 but not 0.
b) Input the first observation of the dataset with the aid of cross-validation in the input layer, each feature in one input node.
c) The set of inputs were treated with a single perceptron with two hidden layers.

Figure 1: Architecture of Compressive strength prediction

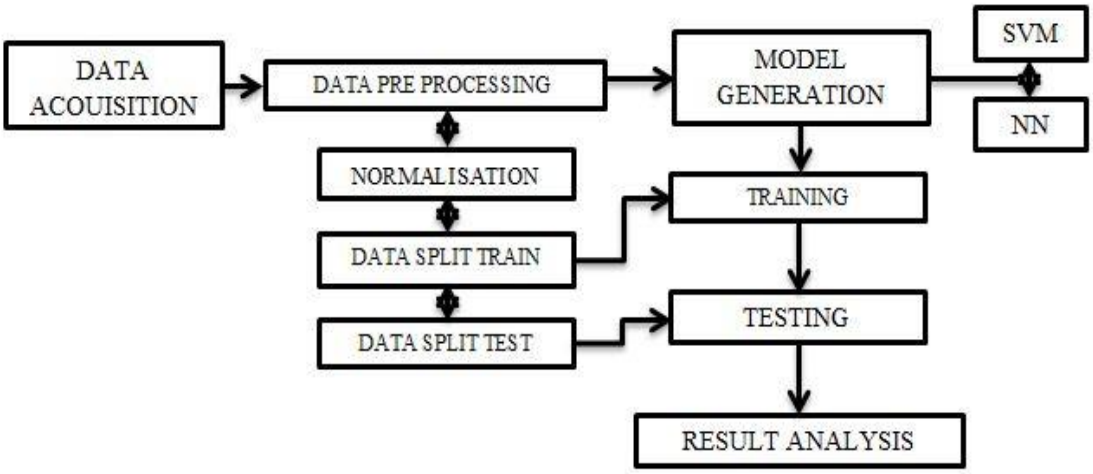

Figure 2: Schematic flow of strength prediction

d) Forward propagation from left to right, the neurons are activated in a way that the impact of each neuron's
e) Activation (Sigmoid) as in eqn (2) is limited by the weights. The activation is propagated until getting the predicted result y.

$$NN_{ccs} = \sum_{j=1}^{p} w_{kj} x_j \quad \dots (1)$$

$$\varphi(v) = \tanh\left(\frac{v}{2}\right) = \frac{1-e^{-v}}{1+e^{-v}} \quad \dots (2)$$

f) Compare the predicted result to the actual result. Measure the generated error
g) Backpropagation from right to left. The error is back propagated and weights are updated according to how
h) Much they are responsible for the error. The learning rate is decided based on the weight updated.
i) Repeat steps 1 to 5 and update the weights after each observation (reinforcement learning) or we will update the weights only after a batch observation (Batch learning)
j) When the whole training set passes through the ANN, which makes an epoch. Redo more epochs.

B. Support Vector Machine

SVM is a predominant technique used to classify contorted datasets. Regression and classification problems can be carried out with the support vector machine which is a supervised learning algorithm. Using SVM, datasets are often classified with the development of the hyperplane that would help to separate the data into several classes. In the case of many hyperplanes, in order to get better veracity of the data, this algorithm will try to stretch the distance of the classified segments which is known as margin maximization. Vapnik in 1992 has suggested Non-linear classifiers that, if a hyperplane cannot be attained with the data then it is categorized and processed a non-linear SVM model with the help of kernel technique (Ghanizadeh *et al.*, 2018)(Mustapha and Mohamed, 2017).

The compression strength of concrete dataset is scattered to a wider area, that is a non-linear data point so to classify this type of data a linear hyperplane cannot be adopted. The better choice to classify and predict this data is suggested to go with non-linear classification. The kernel trick is used to plot our data to a higher dimension. By this, a non-linear data will be converted to a linear one (Prayogo, Wong and Tjandra, 2018)

The initial step of SVM non-linear classification is to employ kernel trick, that is the maximization of the margin is done by the dot product of the support vectors and the final decision line about the hyperplane is based on the margin maximization. The Lagrange multiplier as in eqn (3) is used to find out the maxima and minima of the data points. The dot product of support vectors will result in a function K. (Mustapha and Mohamed, 2017)

- The Lagrange multiplier equation, for optimization, is

$$L = \frac{1}{2}|w|^2 - \sum \alpha_i (y_i(\vec{w}.\vec{x_i} + b) - 1) \quad \dots (3)$$

- Solving the above equation will give w as in eqn (4), band α parameters that gives the margin maximization solution. Then the above equation is partially differentiated with respect to 'w'

$$\sum \alpha_i y_i \vec{x_i} = \vec{w} \quad \dots (4)$$

(Summation contains support vectors in training data points with α_i>0.)

- Then the decision boundaries to compute as in eqn (5) the kernel function $K(\vec{x_i}, \vec{x})$ with each of the support vectors $\vec{x_i}$.

$$h(\vec{x}) = \sum \alpha_i y_i K(\vec{x_i}, \vec{x}) + b \geq 0 \quad \dots (5)$$

- The width of the margin as in eqn (6) is determined from below form

$$\textbf{Width of the margin} = m = \frac{2}{||w||} \quad \textbf{where, } ||w|| = \sqrt{\sum w_i^2} \dots (6)$$

- The most commonly used kernels as in eqn (7) are polynomial kernel and radial kernel, here we have used the radial kernel to transform the nonlinear form of data points and to build the SVM model.The radial kernel function is

$$K(\vec{x_i}, \vec{x}) = exp\left(-\frac{||\vec{x_i} - \vec{x}||^2}{2\alpha^2}\right) \quad \dots (7)$$

RBF kernel is based on the Euclidean distance between the data points. The tuning parameter gamma is used to tune the SVM model. The gamma parameter should not be maximum because this will lead to the minimum value kernel function that would result in overfitting of data points.so gamma value should be minimum than the kernel function. At once the SVM model is built, it is evaluated using learning rules and the accuracy is predicted. The accuracy of speculation of compression strength of concrete using SVM model is 0.7863

V. RESULTS AND DISCUSSIONS

The intention of our study is to inquire about the performance of ANN and SVM models for predicting the compressive strength of concrete. Here we going to discuss the results obtained from the algorithms and their performance of predictive ability. For SVM epsilon regression and Gaussian kernel was adopted with cost = 14, gamma = 0.05 and epsilon = 0.25 is used for training with 561 support vectors and the correlation values are found to be 0.78168. The following plot in Figure 3 to 5 presents the correspondence with actual and predicted values tested in SVM.

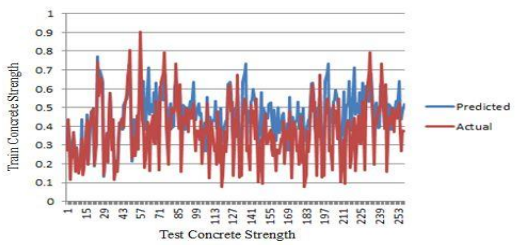

Figure 3: A comparison between Actual and Predicted values using SVM

Table 1: Accuracy from applied approaches

S.No	Algorithm	Accuracy
1	ANN	96%
2	SVM	78%

For Neural network two models have been used with and without cross-validation for data training, then Backpropagation method of training is used with Cross-validated data and with an activation function linear sigmoid with randomized initial weights. In this case, the neural network with 7 and 4 hidden layers is used and the correlation factor obtained is about 0.96244.

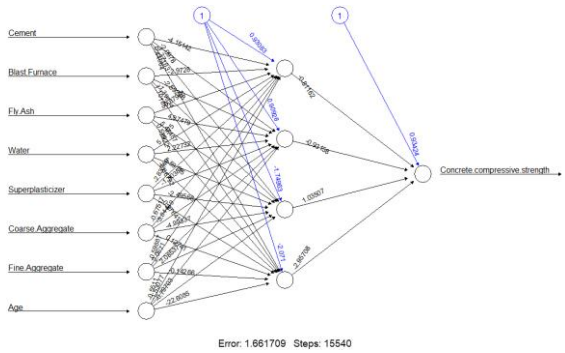

Figure 4: A Schematic diagram of artificial Neural network model

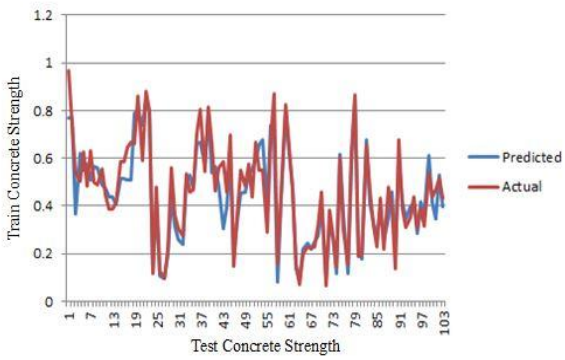

Figure 5: A comparison between Actual and Predicted values using neural nets

VI. CONCLUSION

This investigation provides us a machine learning approach for the concrete strength prediction. In order to predict the compressive strength of concrete two machine learning models ANN model and SVM model are generated. Values from the above techniques give us some fact that the specimen or member produced as per the above factors from the approach gives great practical betterments. The wear and tear, temperature effects will me optimum at most exposure cases. Above all the approaches can be applied to as many factors influencing concrete. The neural network serves as a better tool for calculation of compression strength of various materials in the field of civil engineering and aids most of its applications where predicted results are taken into account. The interactive developments like applications, etc., lead to easier access to testing and deriving results by an unskilled individual.

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