

Compressive Strength Estimation of Concrete Blocks using Fully Connected Deep Neural Network

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Abstract—Compression strength refers to a structure ability to endure loads that cause it to shrink in size. The ultimate load in Newtons scaled by the gross cross section area of the block in square millimeters yields the bearing capacity of a concrete masonry unit. The machine learning technology could extend the interdisciplinary field for the estimation of concrete block compressive strength. With this review, this project aims to estimate the concrete block compressive strength retrieved from the KAGGLE machine-learning repository. The compressive concrete blocks dataset contains 9 features and 1050 concrete block and it is processed with encoding and missing values. The exploratory data analysis is done to analyze the correlation of all the features. The raw dataset is applied to linear regression, Linear Kernel SVR, Polynomial Kernel SVR, Radial Basis Function SVR, Sigmoid Kernel SVR, Decision Tree to analyze the performance of compressive strength estimation of concrete blocks. The proposed model uses Fully Connected Deep Neural Network (FCDNN) where the compressive concrete blocks dataset is applied to estimate the compressive strength estimation of concrete blocks. The performance metrics utilized for analysis are Mean Squared Error, R-Squared error. Experimental results shows that the Fully Connected Deep Neural Network shows Mean Squared Error of 29.5196 and R-Squared error of 0.885 when analyzed with the all regression models.

Index Terms— classifier, oversampling, recall, precision, fscore and accuracy.

I. INTRODUCTION

The quality of the building lies on the power of the solid blocks and its arrangement. Efficiency of the solid block depends on the collective power of the furnished material and its components. The materials involved for the design of concrete blocks includes cement, plasticizer, discharge furnace, glide residue, rough aggregate, adequate aggregate followed by water. The machine learning technology can be used to find the significant features that directly influence the compressive strength of concrete block. When the brickwork is plastered and strengthened to boost the center-most and sidelong capabilities, hollow concrete block masonry is usually used

[1]. One of the most important features for the model of brickwork walls under diverse stress scenarios is compressive strength. Several research investigations on the collective behavior of tangible brickwork masonry have been conducted earlier. The paper is organized in which literature assessment is discussed in section 2 tailed with the paper contributions in section 3. The application execution setup and out-comes are discussed in section 4 and concluded in section 5.

II. LITERATURE REVIEW

Because it allows for grouting and reinforcing resisting larger axial and lateral forces, tangible muffled brickwork architecture is commonly utilized in America and Australasian republics, allowing for the construction of multistory stonework constructions. As a result, only particular scores of mortar are suggested for brickwork masonry in the guidelines, mostly due to certainty about durability. However, there is a paucity of understanding about the properties of brickwork with various scores of materials, and there are substantial differences in design guidelines. [1]. This research provides a forecasting model with neural networks to address the current issues in forecasting the collective power of reprocessed aggregate solid material. The deep characteristics of the water-cement ratio, fly ash replacement ratio, fine recycled aggregate replacement ratio, and their mixtures are first learned using a deep neural network. The prediction model is then developed using the softmax regression. The trials used a variety of masonry mix ratios, and the findings demonstrated that the prediction was accurate. Increased precision, efficiency, and efficacy are just a few benefits offered by deep learning-based models. A novel computing strategy might leverage neural network models with stronger generalization [2]. Machine intelligence methods like neural networks (NN) and support vector machines (SVM) are now often exploited in the prediction of concrete strength. The artificial neural network is used in to forecast the association between numerous factors involved and recycled concrete compressive strength. In reinforced concrete constructions when concrete mixture ratio data are not yet accessible, the suggested method enables the practical calculation of concrete strengths. As a result, using UPV measurements, researchers may quickly assess the workability of the concrete rigidity specimens. The technique can be employed in situations when there are a large number of buildings to examine and exams must be completed in a short amount of time. This strategy also adds to a significant decrease in processing time without sacrificing accuracy [3]. The complexity of NSC to its ingredients, mixing percentage, compaction, and other factors make compressive strength prediction problematic. In order to forecast the 28-day strength development of no-slump concrete, several regression, neural network, and ANFIS models are designed, developed, and assessed in this research [4]. In order to predict the compressive strength of concretes containing high-lime and low-lime fly ashes after 7, 28, and 90 days, convolutional neural networks and fuzzy inference system models were developed. 52 distinct mixtures with 180 specimens were obtained from the literature for the aim of building these models. Nine input parameters are employed in artificial neural networks and fuzzy logic models, including the day, Cement content, liquid, gravel, gravels I (4-8 mm), squashed rock II (8-16 mm), top quality liquid lowering agent proportion, rice husk ash proportion, and CaO as an output parameter [5]. The BP (Back Propagation) neural network's nonlinear transformation capability is used to create a nonlinear model between input and output variables. As a result, effective intensity estimation might be achieved with some training and iteration. The link between compression mix, UPV, and hit hardest is evaluated in this continually enhancing observational data from several cores collected from various reinforced concrete members with varying ages and undetermined cementitious material ratios [6]. The uniaxial compressive strength of FRP constrained concrete was predicted using the support vector machine regression (SVR) technique. There were two SVR models constructed, one for carbon fiber reinforced polymer confined concrete and the other for glass fiber reinforced polymer confined concrete. The created SVR models were evaluated to ANN and current empirical FRP strength prediction models in terms of predicting effectiveness [7]. By taking into account the production methods in addition to the remanufactured fraction and reliability of the cement replacement produced, this research aims to anticipate several of the most important aspects of conceptual recycled aggregate. For this purpose, a database of 1831 combinations culled from 81 articles was developed. These characteristics in structural recycled concretes have been predicted using customized, specific expressions. These expressions were created using two different tools: multivariable regression and genetic programming. The statistical parameters used to analyze the proposed expressions were examined to those obtained utilizing the expressions. [8].

III. RESEARCH METHODOLOGY

The overall methodology of the proposed model is shown in Fig. 1. The work of this paper is to access the compressive strength prediction of concrete block with linear regression, Support vector machine, decision tree

and FCDNN by comparing the mean squared error and RSquared error. The compressive concrete blocks dataset contains 9 features which is shown in Fig.2 and 1050 concrete block and it is preprocessed with encoding and missing values. The exploratory data analysis is done to analyze the correlation of all the features. The raw dataset is applied to linear regression, Linear Kernel SVR, Polynomial Kernel SVR, Radial Basis Function SVR, Sigmoid Kernel SVR, Decision Tree to analyze the performance of compressive strength estimation of concrete blocks. The proposed model uses Fully Connected Deep Neural Network (FCDNN) shown in fig. 3 where the compressive concrete blocks dataset is exploited to predict the compressive strength estimation of concrete blocks. The performance metrics used for analysis are Mean Squared Error, R-Squared error.

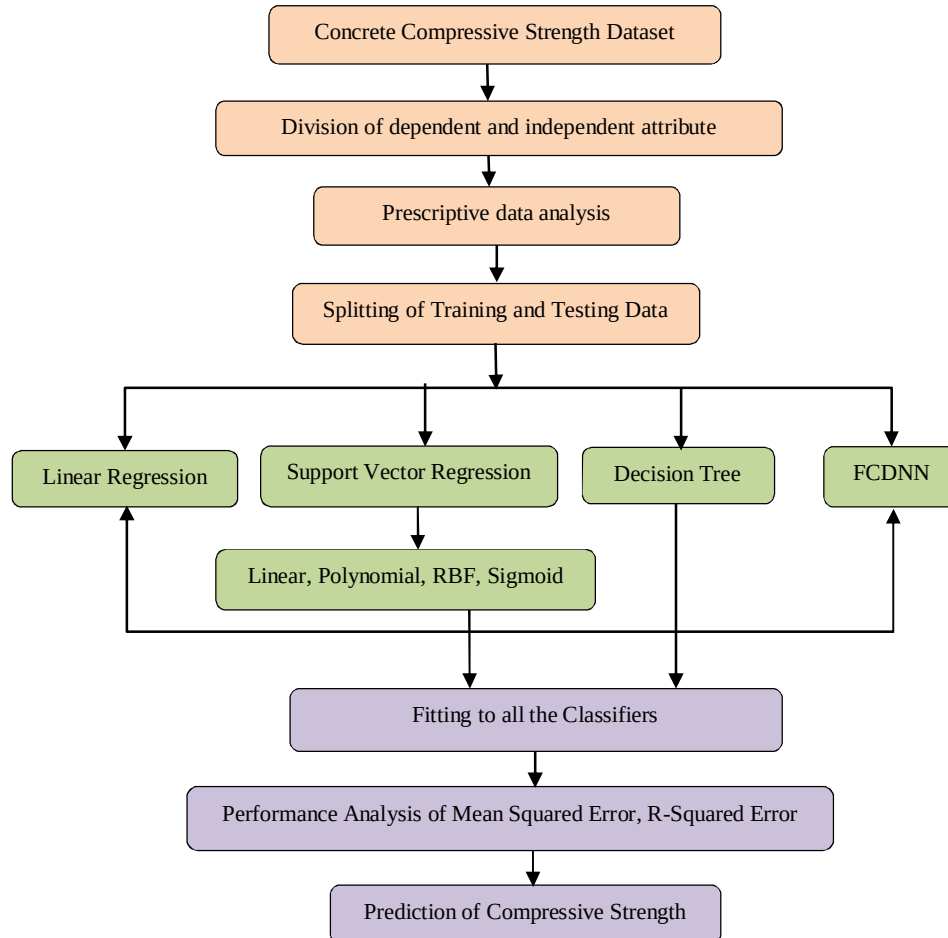


Figure 1. Overall Architecture Flow

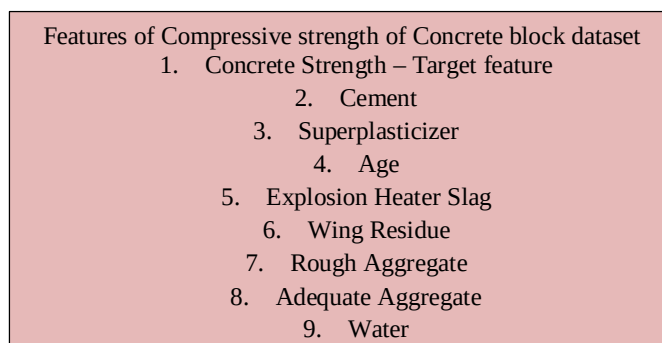


Figure 2. Correlation and Target Distribution

IV. RESULTS AND DISCUSSION

A. Implementation Setup

The KAGGLE repository's compressive strength concrete block dataset of 1050 rows and 9 feature attributes is subjected to data preprocessing such as incomplete data filling and categorical variable encoding. The feature distribution of the dataset is shown in the fig. 4 and the relationship of features is shown in Table I.

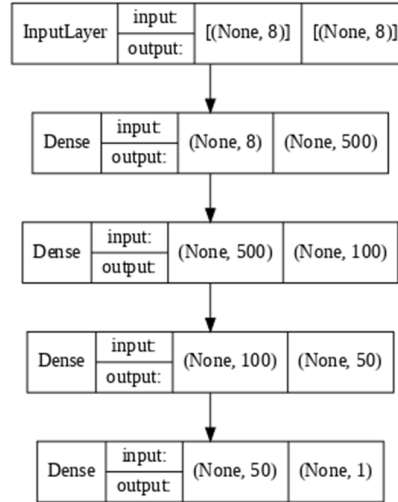


Figure 3. Architecture design of FCDNN

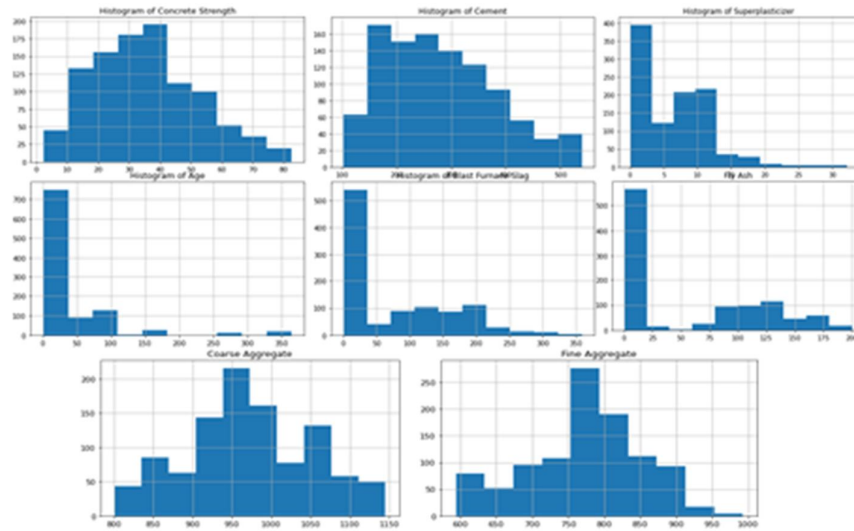


Figure 3. Histogram distribution of the Compressive strength concrete block dataset

TABLE I. CORRELATION OF DATA FEATURES OF COMPRESSIVE STRENGTH CONCRETE BLOCK DATASET

Data Field	Correlation Score
Concrete Strength	1.000000
Cement	0.497833
Superplasticizer	0.366102
Age	0.328877
Blast Furnace Slag	0.134824
Fly Ash	-0.105753
Coarse Aggregate	-0.164928
Fine Aggregate	-0.167249
Water	-0.289613

B. FCDNN Result and Performance Analysis

The compressive strength concrete block dataset is applied to linear regression, Linear Kernel SVR, Polynomial Kernel SVR, Radial Basis Function SVR, Sigmoid Kernel SVR, Decision Tree to analyze the performance of compressive strength estimation of concrete blocks and is shown in Table II. The actual and predicted loss of regression methods and FCDNN is shown in fig. 5, fig. 6 and fig. 7.

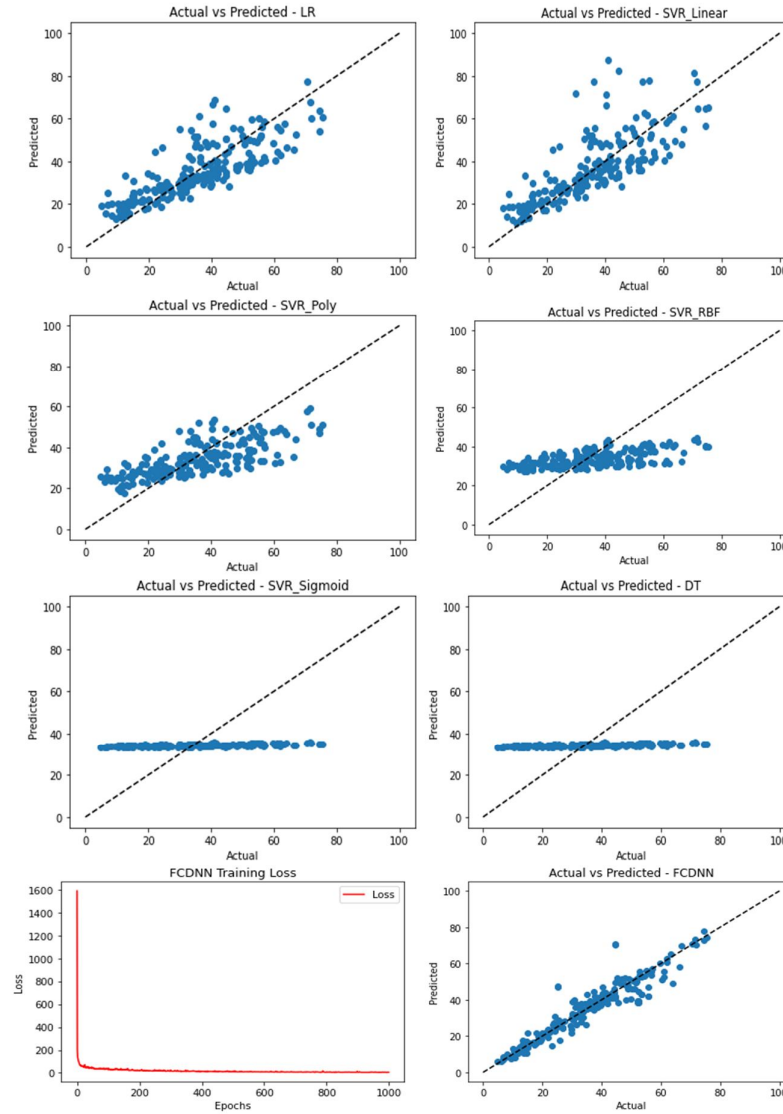


Figure 5. Actual VS Predicted compressive strength for Regression and FCDNN

TABLE II. PERFORMANCE ANALYSIS OF REGRESSION METHODS AND FCDNN

Model	Mean Squared Error	Rsquared Value
Linear Regression	95.975	0.627
Linear SVR	120.571	0.532
Polynomial SVR	135.540	0.473
RBF SVR	197.892	0.232
Sigmoid SVR	249.937	0.030
Decision Tree	249.937	0.030
FCDNN	29.5196	0.885

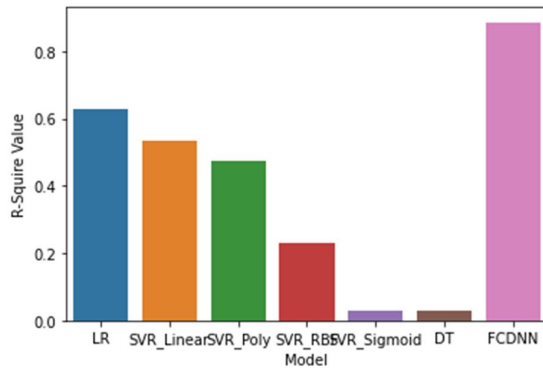


Figure 6. RSquared Value for Regression and FCDNN

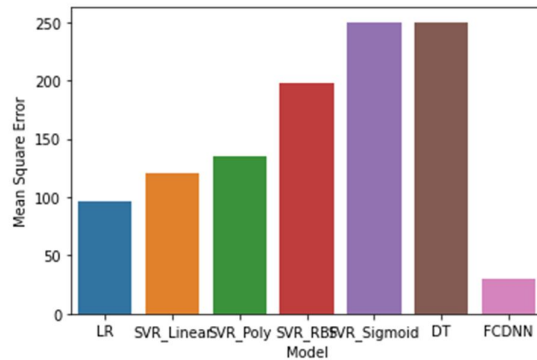


Figure 7. Mean Squared Error for Regression and FCDNN

V. CONCLUSIONS

This paper attempt to analyse how well the prediction of concrete block compressive strength is predicted by the regression algorithms and Fully Connected Deep Neural Network. The exploratory data analysis is done to understand the correlation of all the features in the concrete block compressive strength dataset. The dataset is splitted with 80:20 ratio of training and testing dataset. The raw dataset is applied to linear regression, support vector regression with several kernels like linear, RBF, polynomial and sigmoid and Fully Connected Deep Neural Network. The implementation is done with Python under NVidia Tesla V100 GPU server with training epochs of 1000 and batch size of 32. Experimental results shows that the Fully Connected Deep Neural Network shows Mean Squared Error of 29.5196 and R-Squared error of 0.885 when compared to other regression models.

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