Abstract:
This study has been undertaken to investigate the compressive strength, flexural strength and split tensile strength of concrete of grade M30 and M40 in present investigation by laboratory and predicting the strength through Machine learning technique. Flexural strength and split tensile strength which establishes the concrete class, is one of the most crucial characteristics of concrete. The primary characteristic of concrete's durability and safety is its predictable compressive strength, flexural strength and split tensile strength which is necessary for the use of concrete structures. To explore the time-dependent behavior of concrete strength, considering factors such as curing duration and age. Main aim is to compare the performance of different regression methods, such as linear regression, ridge regression, lasso regression, or machine learning approaches like Random Forest and evaluate their suitability for concrete strength prediction and to find the accuracy of algorithms and regression.

Keywords: machine learning, compressive strength, flexural strength, split tensile strength.

Introduction
In the realm of civil engineering and construction, predicting the fresh properties of concrete is a critical aspect that directly influences the structural integrity and performance of constructed infrastructure. Traditional methods of forecasting these properties often rely on empirical relationships and extensive experimentation, which can be time-consuming and resource-intensive. However, with the advent of machine learning algorithms, there is a paradigm shift towards more efficient and accurate predictions based on experimental data. Machine learning algorithms, such as regression models, and neural networks, will be employed to analyse and interpret experimental data collected from various
concrete mixes. These algorithms can identify intricate patterns and relationships within the data that may not be readily apparent through traditional analytical techniques. Through the utilization of machine learning, the study seeks to develop robust models that can accurately predict crucial fresh concrete properties. The integration of machine learning into concrete forecasting not only enhances accuracy but also provides a scalable and adaptable framework for handling diverse concrete mix designs. As we venture into this exciting intersection of concrete technology and machine learning, the outcomes of this study hold the potential to revolutionize how we approach the prediction of fresh concrete properties, ushering in a new era of efficiency and precision in the field of civil engineering and construction.

Objectives of the Present Study

The main objectives of the present work:

1. To design a mix of M30 and M40 grade of concrete specimen in laboratory and predict the accuracy of present investigation.
2. To analyse the data through machine learning the mechanical property such as compressive Strength, Flexural strength, Split tensile strength of concrete for M30 and M40 grade.
3. Explore the time-dependent behaviour of concrete strength, considering factors such as curing duration and age.
4. Compare the performance of different regression methods, such as linear regression, ridge regression, lasso regression, or machine learning approaches like Random Forest. Evaluate their suitability for concrete strength prediction.
5. To find the accuracy of algorithms and regression.

Literature Review

Alsadey (2012) presented the effect of superplasticizer (SP) on properties of fresh and hardened concrete has studied; the properties of concrete inspected are compressive strength and slump test, hence, an experimental investigation conducted to determine the optimum dosage for the admixture and to study the effect of over dosage of the mentioned admixture, together with one control mixed. Superplasticizer can be added to concrete to make it more workable, and chemical admixtures can be used to decrease slump loss.

Castelli et al. (2013) The main ingredients of concrete, a composite building material, are aggregate, cement, and water. Furthermore, to in addition to the basic components of regular concrete, high-performance concrete contains additional cementitious materials, such as such as blast furnace slag and fly ash, and chemical additives like superplasticizer. High-performance concrete is therefore a very It is challenging to model the behaviour present of complex material.

Shah et al. (2014) calculated the consequences on strength of concrete when water- cement ratio is constant and the increase in slump occurs with the increase in amount of superplasticizer by percentage. The remaining research is done to examine the effects of various superplasticizer dosages under various curing regimes at 45°– 50°C ambient field temperatures. This was accomplished by employing an ASTM C494 type A and F anionic melamine polycondensate non-toxic superplasticizer without chlorides to prepare a concrete mix at 20 MPa while maintaining all other parameters constant.

Salahaldein (2015) superplasticizer use in concrete as a chemical admixture has received a lot of interest recently. To produce high performance concrete, hopresent investigationver, chemical admixtures are frequently used in concrete. The use of chemical admixtures imparts beneficial qualities to concrete in both its fresh and hardened states, according to previous research. This work aims to investigate the effects of concrete performance on superplasticizer doses of 0.6, 0.8, 1.2, 1.8, and 2.5 percentage.

Saad et al. (2016) this work proposes a novel artificial neural network (ANN) method for high strength concrete compressive strength (CCS) prediction. With the help of the actual 1030
datasets from the USI machine learning repository, the suggested method is put into practice for training, testing, and validation.

Muhsen et al. (2016) the qualities of new concrete are negatively impacted by high temperatures in a number of ways, including increased water requirement, accelerated setting, and higher slump loss. Due to the significance of superplasticizer (SP) in improving the workability and setting time of concrete.

Jha et al. (2020) analysing the concrete’s properties requires knowledge of its compressive strength. To determine whether the given concrete mixture satisfies the requirements, the compressive strength is required. The required standards for compressive strength must be met for the construction to be sustainable. Models for machine learning have proven to be a very useful tool for problem analysis across many domains.

Paudel et al. (2023) the study compares the accuracy of various ML models in predicting CS, including non-ensemble models (Multiple Linear Regressor, Support Vector Regressor) and ensemble models (AdaBoost Regressor, Random Forest Regression, XGBoost Regressor, and Bagging Regressor).

Abuodeh et al. (2020) the kind, characteristics, and composition of the materials that make up UltraHigh Performance Concrete (UHPC) determine the material’s compressive strength. Using clever algorithms, like the Artificial Neural Network (ANN), to create a predictive model that fits into an experimental dataset is frequently necessary to empirically capture this relationship.

Chen et al. (2023) extremely cold or oceanic conditions call for high-durability concrete, which makes concrete mix design crucial and challenging. In order to effectively predict concrete durability and optimise the concrete mix ratio, a hybrid intelligent framework for multi-objective optimisation based on random forest (RF) and the non-dominated sorting genetic algorithm version II (NSGA-II) is developed in this study.

Methodology

This present investigation started with reading current things happening in civil engineering and after that deciding the area or field of thesis present investigation want to work on. After arrangement in materials, sampling of the material starts. Then testing of samples is done and all the precautions and follow procedures of experiments properly and accurately.

Materials

1. Cement
2. Sand
3. Coarse Aggregate
4. Fine Aggregate
5. Water
6. Super Plasticizer
7. Bonding Agent

Testing of Materials, Concrete Mix and Specimens

Physical Testing of Materials

Chen et al. (2023) extremely cold or oceanic conditions call for high-durability concrete, which makes concrete mix design crucial and challenging. In order to effectively predict concrete durability and optimise the concrete mix ratio, a hybrid intelligent framework for multi-objective optimisation based on random forest (RF) and the non-dominated sorting genetic algorithm version II (NSGA-II) is developed in this study.
Concrete Mix Design in I.S. Code Practice

Mix design is a process of selecting and proportioning ingredients to produce concrete with the desired properties in both the fresh and hardened states. The mix design process is crucial to ensure that the concrete meets the required strength, durability, workability, and other performance criteria. In India, the Bureau of Indian Standards (BIS) has established guidelines for concrete mix design in the form of the IS 10262:2019 code. Estimating the appropriate quantitative composition and proportion of the components of the concrete mixture is the main objective of concrete mix design. The composition of a concrete mix is chosen to provide the best concrete performance possible. A number of characteristics define the performance of concrete, the two most important being durability and compressive strength.

Essentials

Present goal is to apply machine learning to the design of concrete mixes in the present study. Present investigation would like to construct a regression that can estimate the compressive strength of the concrete mix based on a large number of tested concrete mix recipes. More specifically, the amount of each of the present major constituents of a concrete mix—cement, fine and coarse aggregate, water—is used in the regression to estimate the strength of the concrete.
Concrete Strength Prediction
Regression Models & Recommended Systems

1. **Linear regression**: A variable's value can be predicted using linear regression analysis based on the value of another variable. The dependent variable is the one that you wish to be able to predict. The independent variable is the one you are using to forecast the value of the other variable.

2. **Ridge regression**: A linear regression technique called ridge regression is intended to deal with situations in which the predictor variables show high correlation or high collinearity. Conventional regression models can produce inconsistent or unreliable results when multicollinearity is present.

3. **LASSO regression**: which is also referred to as L1 regularisation, is a widely employed method in statistical modelling and machine learning for predicting and estimating the relationships between investigational variables. Least Absolute Shrinkage and Selection Operator is referred to as LASSO. LASSO regression's main objective is to strike a balance between investigational model accuracy and simplicity.

4. **The Algorithm of Random Forest**: A present investigational-liked supervised machine learning algorithm for classification and regression issues in machine learning is the Random Forest Algorithm. As present investigation all know, a forest is made up of many trees, and the more trees it has, the more robust it is. Similarly, an algorithm’s accuracy and capacity to solve problems increase with the number of trees in the Random Forest.

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![Figure 4. Flow Chart of the Present Investigation](image)

**Results by Machine Learning Approach**

After testing the characteristics strengths of concrete, we put the dataset in machine learning technique to apply different regressions and algorithms to predict the accuracy of our data. The results of different regression methods are shown below.
1. Compressive Strength

<table>
<thead>
<tr>
<th>Regression methods</th>
<th>predicted score</th>
<th>MAE</th>
<th>MSE</th>
<th>RMSE</th>
<th>R2</th>
</tr>
</thead>
<tbody>
<tr>
<td>linear</td>
<td>0.677</td>
<td>2.86</td>
<td>12.99</td>
<td>3.6</td>
<td>67.73</td>
</tr>
<tr>
<td>rigid</td>
<td>0.68</td>
<td></td>
<td>12.76</td>
<td></td>
<td></td>
</tr>
<tr>
<td>lasso</td>
<td>0.677</td>
<td></td>
<td>12.97</td>
<td>3.6</td>
<td></td>
</tr>
<tr>
<td>random forest</td>
<td>0.796</td>
<td></td>
<td>8.2</td>
<td>2.86</td>
<td></td>
</tr>
</tbody>
</table>

Figure 5. Results of All Models of Compressive Strength

It can be seen that the best performance was related to models that could simulate non-linear relationships. The performance of Random Forest approaches 79% was significantly better than the other regression method.

2. Flexural Strength

<table>
<thead>
<tr>
<th>Regression methods</th>
<th>predicted score</th>
<th>MAE</th>
<th>MSE</th>
<th>RMSE</th>
<th>R2</th>
</tr>
</thead>
<tbody>
<tr>
<td>linear</td>
<td>0.69</td>
<td>0.16</td>
<td>0.031</td>
<td>0.17</td>
<td>69.54</td>
</tr>
<tr>
<td>rigid</td>
<td>0.58</td>
<td></td>
<td>0.42</td>
<td></td>
<td></td>
</tr>
<tr>
<td>lasso</td>
<td>-0.281</td>
<td></td>
<td>0.131</td>
<td>0.17</td>
<td></td>
</tr>
<tr>
<td>random forest</td>
<td>0.87</td>
<td></td>
<td>0.013</td>
<td>0.11</td>
<td></td>
</tr>
</tbody>
</table>

Figure 7. Results of All Models of Flexural Strength

The performance of Random Forest approaches 87% was significantly better than the other regression method, so, preset model gives 87% accuracy.
3. Split Tensile Strength

<table>
<thead>
<tr>
<th>Regression methods</th>
<th>predicted score</th>
<th>MAE</th>
<th>MSE</th>
<th>RMSE</th>
<th>R2</th>
</tr>
</thead>
<tbody>
<tr>
<td>linear</td>
<td>0.82</td>
<td>0.2</td>
<td>0.06</td>
<td>0.236</td>
<td>82.52</td>
</tr>
<tr>
<td>rigid</td>
<td>0.79</td>
<td>0.06</td>
<td>0.25</td>
<td></td>
<td></td>
</tr>
<tr>
<td>lasso</td>
<td>-0.28</td>
<td>0.41</td>
<td>0.24</td>
<td></td>
<td></td>
</tr>
<tr>
<td>random forest</td>
<td>0.84</td>
<td>0.052</td>
<td>0.23</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Figure 9. Results of All Models of Split Tensile Strength

Figure 10. Original vs Predicted Value Results of Final Models of Split Tensile Strength
The performance of Random Forest approaches 84% was significantly better than the other regression method. So, preset model gives 84% accuracy.

**Conclusion**

In this study, a prediction model for the strengths of concrete with and without superplasticizers was developed using 4 supervised learning methods from machine learning to address the high-dimensional complex non-linear relationship between the superplasticizer mixing design and the strength of concrete. Using dataset, the prediction of concrete’s compressive, flexural and split tensile strength was carried out with great accuracy. After conducting a statistical analysis of the dataset, a correlation analysis was performed. This study demonstrates a relationship between the mixture design of concrete and its strength in tension and compression, with the help of superplasticizers at different water content and grades of concrete. Using regression analysis in concrete strength can enhance the understanding of the factors influencing strength and facilitate the development of more robust and efficient concrete mix designs.

**References**


