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Evaluation of the Impact of Different Combinations of Sustainable Concrete Materials on the Compressive Strength of Concrete Using Machine Learning Techniques

Chandra Shekhar Kumar, Sujit Kumar,
Dr. Bimal Kumar
Government Engineering College Jamui
India"

Dr. Sanjay Kumar
National Institute of Technology Patna
India

Abstract - Nowadays, the application of Machine Learning (ML) techniques has gained significant popularity across various research domains. Concrete compressive strength (CCS) is a critical parameter for ensuring the long-term safety and durability of reinforced cement concrete (RCC) structures. Concrete is a composite material consisting of cementitious materials, fine aggregates, coarse aggregates, water, and chemical admixtures, and its compressive strength depends on the combination and proportion of these constituents. In this study, a dataset comprising 125 samples was used for the development of ML-based prediction models. The data were collected from laboratory experimental investigations conducted in the laboratory and the relevant published literature. Several ML algorithms, including Linear Regression, Ridge Regression, Lasso Regression, Decision Tree, Random Forest, Gradient Boosting, Support Vector Regression (SVR), XGBoost, and Multi-Layer Perceptron (MLP) regression, were employed to predict the compressive strength of concrete.The results indicate that the MLP regressor achieved the highest coefficient of determination (R^2) among all the models considered. It was also observed that the type of concrete materials used, selected input features, target variable, dataset size, and choice of ML algorithm significantly influence model performance. All results and graphical analyses were generated using Python programming on the Google Colab platform. The optimized performance metrics for the MLP regressor include an R^2 value of 0.839, a root mean square error (RMSE) of 6.656, and a mean absolute error (MAE) of 5.414.

Keywords Concrete Compressive Strength, MLP regression, Gradient Boosting, Coefficient of determination

INTRODUCTION

Concrete is the most widely used construction material in the world due to its durability, versatility, and relatively low cost. One of the key indicators of its performance and structural integrity is compressive strength, which directly influences the safety, serviceability, and longevity of concrete structure

Accurate evaluation of concrete compressive strength is therefore essential during both construction and maintenance phases. A critical aspect of ensuring the structural integrity and service life of concrete structures lies in accurately evaluating their compressive strength and overall quality. Traditionally, this evaluation has relied on Destructive Testing (DT) methods such as compression tests on concrete cylinders or cores, which, while highly accurate, can be time consuming, costly. To overcome these limitations, Non-Destructive Testing (NDT) technique such as ultrasonic pulse velocity (UPV), rebound hammer, and ML models have gained popularity. These NDT methods allow for in-situ evaluation without damaging the structure, though they often require calibration and interpretation based on empirical correlations. In recent years, the integration of Machine Learning (ML) in civil engineering has introduced new opportunities for predicting concrete properties with high accuracy and efficiency.

The objective is to enhance the reliability, speed, and cost effectiveness of concrete strength and quality assessments in modern construction and maintenance practices.

The work primarily provide a thorough overview of the state of the art in computer vision-based defect detection and condition assessment for civil infrastructure made of asphalt and concrete.

The researchers works are based on without requiring knowledge of the concrete's composition or history, the researchers classified and predicted concrete strength based only on UPV and RH values.

An early attempt to estimate the compressive strength of lightweight foamed concrete using the Extreme Learning Machine, or ELM, a regression-based soft computing model that is an enhanced version of neural network models. A novel crack detection framework is proposed to automatically assess the cracking in concrete post-fire conditions .

The researchers optimized artificial neural networks using metaheuristics to predict the compressive strength of concrete, we saw a significant improvement in test RMSE values of 39% to 48%. Combining NDT tests with various

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mix percentage designs and curing ages is an efficient way to forecast the compressive strength of concrete. In particular, back propagation neural network (BPNN) and support vector machine regression (SVR) models are developed .

The machine learning models demonstrated a strong correlation with the test results, achieving a R2 value of 0.84 for the XGBoost, in order to examine the synergistic effects of a cement-based mixture consisting of RHA and FA in various proportions on concrete's fresh, hardened, non-destructive, and microscopic properties.

The long-term effects of mixing different chemical admixtures on concrete's compressive strength using sophisticated experimental data and machine learning models with a degree of accuracy and detail that has been comparatively understudied.

The assessment, repair, and retrofitting of masonry structures are described along with the latest developments in machine learning approaches.

With an emphasis on two main methods—destructive testing (DT) like core drilling and non-destructive testing by calibration (NDTBC)—this study methodically examines the concrete strength testing systems in China and Europe. A comparable database is created by standardized processing using 360 component rebound and 240 core specimens with concrete strength classes ranging from C30 to C70 from eight large datasets (24 small datasets) of four typical Chinese projects .

The effects of using quartz powder (QP) and snail shell powder (SSP) in place of some cement can lessen the environmental impact of concrete. The study evaluates the mechanical, microstructural, fresh, and non-destructive qualities of SSP and QP contents at 2.5–10% as an additional cementitious material (SCM) in the creation of environmentally friendly concrete.

Overall, the results demonstrate the efficacy of moisture-aware, integrated non-destructive testing techniques for accurate on-site strength evaluation and validate the structural viability of recycled aggregate concrete. These results support the idea that recycled aggregates should be used more widely in sustainable concrete applications.

587 concrete mix samples were gathered from the literature to create a dataset. Seven prediction methods were used: Multi-Layer Perceptron, Linear Regression, Support Vector Regression, Decision Tree Regressor, Random Forest Regressor, Gradient Boosting Regressor,,and Extreme Gradient Boosting. Missing data treatment, outlier detection encoding, and feature normalization for Principal Component Analysis were all part of preprocessing. Coefficient of determination (R2), root mean squared error, mean absolute error, and mean absolute percentage error with cross-validation were used to evaluate performance. Superior accuracy was demonstrated using Extreme Gradient Boosting (R2 = 0.952 for tensile strength and 0.954 for compressive strength). The mechanical qualities of reinforced concrete structures are increasingly being assessed using machine learning (ML) and image processing (IP). This study focuses on hybrid concrete (HC), which improves mechanical performance and promotes sustainability by including cement replacement materials (CRM) such fly ash and silica fume. To enhance two-parameter SonReb-based AI models by adding a binary input variable that indicates the specimen geometry type (cube or cylinder) and examines the impact of model architecture by contrasting three distinct AI algorithms: Artificial Neural Networks (ANN), Deep Neural Networks (DNN), and Adaptive Neuro-Fuzzy Inference Systems (ANFIS).

The results encourage the wider use of alkali-activated concrete (AAC) as an environmentally friendly building material and provide practical insights for improving AAC formulations study applied artificial neural networks to predict the compressive strength of concrete.

The model showed better accuracy than traditional regression methods.It demonstrated the potential of ML for nonlinear material behavior prediction.

They developed several data-mining techniques for predicting concrete strength. ANN models outperformed statistical approaches for complex mix compositions. The study emphasized the importance of dataset quality.

METHODOLOGY

This study adopts the results from the experiment work in the laboratory

Concrete samples were prepared according to standard mix design procedures. The curing process was carried out under controlled conditions for 7, 14, and 28 days to assess strength development over time.

- **Sample Types**: Concrete cubes
- **Sample Sizes:** Standard
  150 mm x 150 mm x 150 mm cubes
- **Curing Periods:** 7, 14, and 28 days

Fig. 1 Cube mould for sample preparation

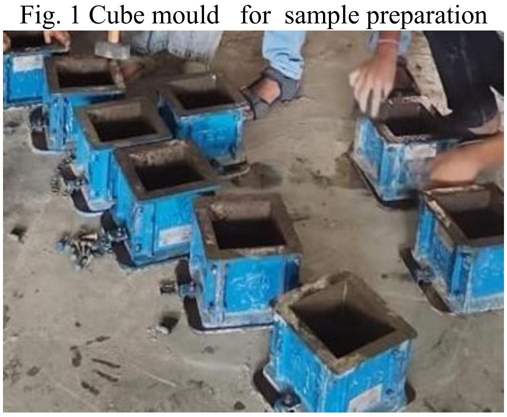

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Fig. 2 Vibration table for sample preparation

Fig. 3 Cube sample preparation

Fig. 4 Cube compressive strength test and compression testing machine setup

Slump Test and Result

Slump Test is applicable for measuring the workability of fresh concrete. Slump Value varies based on the various exposure condition and type of the construction work. CCS results were obtained in Compression Testing Machine by testing the standard cubes after proper curing in 7, 14 and 28 Days.

Fig. 5 Slump test of fresh concrete

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Fig. 6 Reading duration compression testing of cube sample

Results

Table 1 Model performance comparison

Model	R^2 Score	RMSE	MAE
MLP Regressor	0.839	6.656	5.414
Gradient Boosting	0.824	6.964	5.171
SVR	0.804	7.339	6.078
Random Forest	0.799	7.432	5.636
XGBoost	0.698	9.102	6.276
Decision Tree	0.672	9.489	6.483
Lasso Regression	0.263	14.243	12.044
Ridge Regression	0.261	14.259	12.076
Linear Regression	0.249	14.376	12.333

From the table 1 it is found that the coefficient of determination(R2) is minimum in Linear regression model and maximum in MLP Regressor. The two best ML model based on the available data are MLP Regressor and Gradient Boosting based on the value of R2.

Fig. 7 Correlation Heat Map of concrete Features

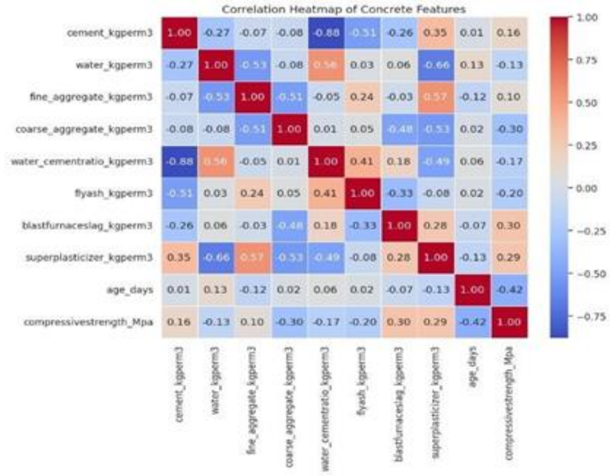
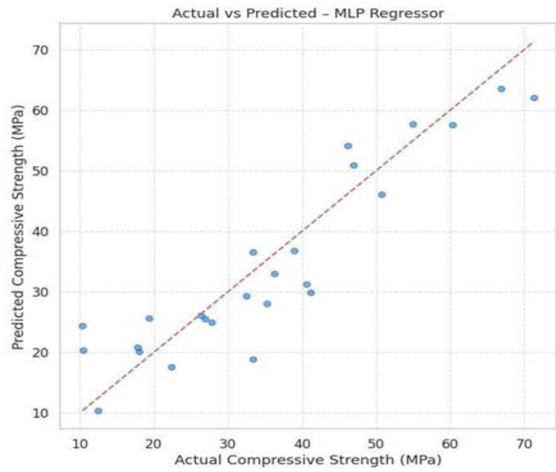


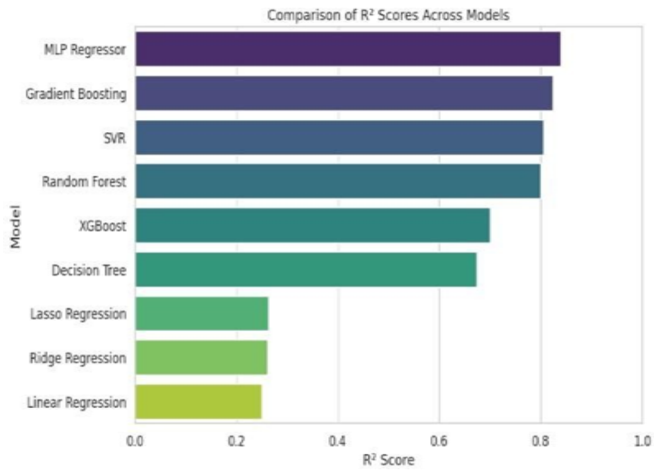
Fig. 8 Actual vs Predicted Values of CCS



The Actual vs Predicted plot in figure 8 compares the model's strength predictions with the real measured CCS values to show how accurately the model performs.

Points closer to the diagonal line indicate high prediction accuracy, while larger deviations reveal modelling errors or noise in the data.

Fig. 9 Comparison of R2 value



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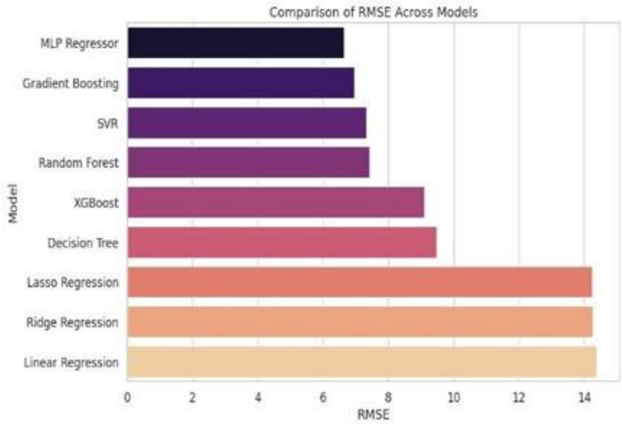
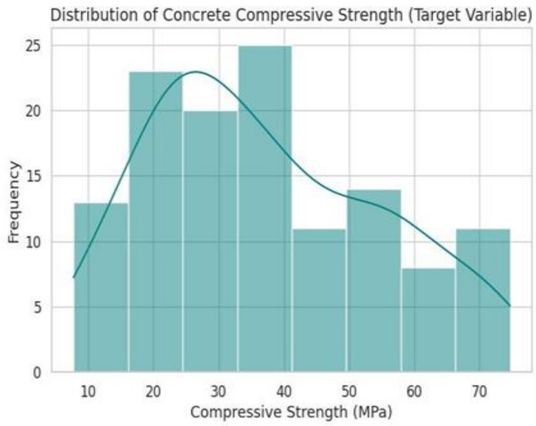
Comparing R^2 values in figure 9 shows how well different models explain the variability in concrete compressive strength. A higher R^2 indicates better predictive performance and a stronger fit between the model and actual data.

Fig. 10 Comparison of RMSE value



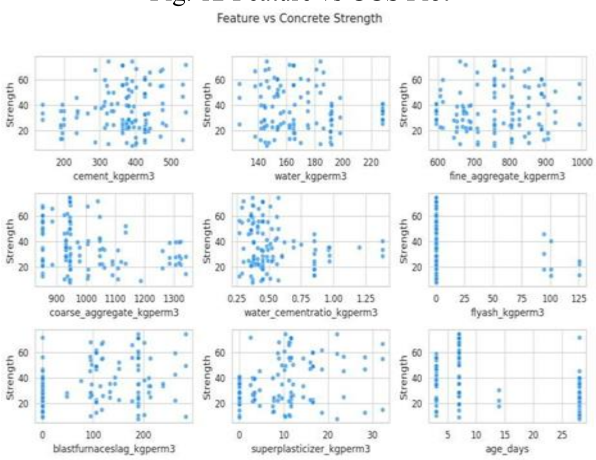
A lower RMSE value in figure 10 indicates better model performance, as it reflects smaller average prediction errors.

Fig. 11 Concrete Compressive Strength distribution



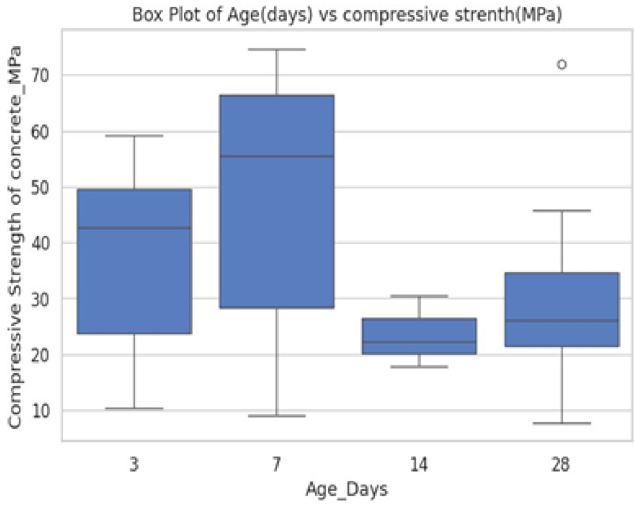
The distribution in figure 11 shows how concrete compressive strength increases with curing age, reflecting the hydration process and strength gain over time.

Fig. 12 Feature vs CCS Plot



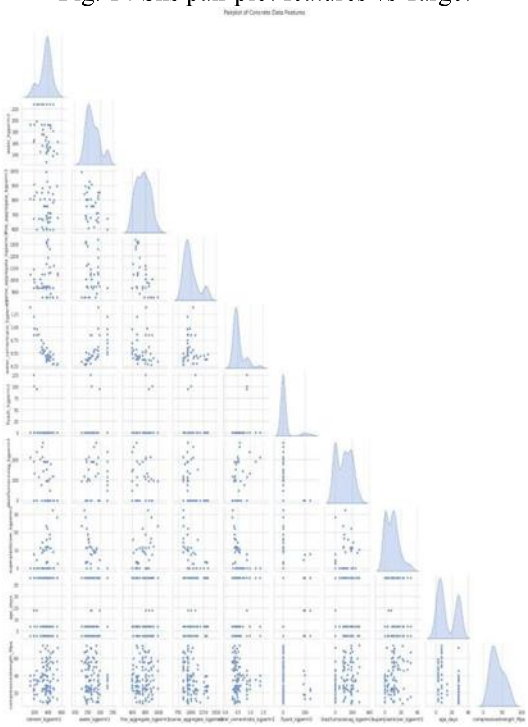
Feature vs CCS plots in figure 12 illustrate how each input variable influences the concrete's compressive strength across its range.They help identify positive or negative relationships, nonlinear trends, and key factors that strongly impact strength prediction.

Fig. 13 Box plot Age vs CCS



The box plot in Figure 13 shows how concrete compressive strength varies across different curing ages, highlighting the median strength and spread of values. It helps identify outliers and understand how strength distribution changes as concrete matures over time.

Fig. 14 Sns pair plot features vs Target



A Seaborn (SNS) pair plot visualizes pairwise relationships between features and the target, revealing correlations, trends, and distributions in one view.

CONCLUSION

The results indicate that the performance of prediction models varies across different machine learning (ML) techniques, with each model exhibiting its own advantages and limitations. The effectiveness of an ML model primarily depends on the selected input features, target variable, and the size of the dataset. Among all the ML models considered, the MLP regressor was found to be the most optimal for model development.

For future studies, it is essential to carefully select the most suitable ML model for predicting concrete compressive strength (CCS) based on different concrete material compositions, while also incorporating standard code guidelines to ensure that all significant features are considered. Optimization techniques should be employed to enhance prediction accuracy. The results further reveal that statistical indicators such as R^2, RMSE, and MAE are key parameters for evaluating ML model performance.

Supplementary cementitious materials (SCMs) represent an emerging and important area of research, as cement production is a major contributor to global carbon dioxide emissions. Materials such as fly ash, silica fume, ground granulated blast furnace slag, rice husk ash, and bagasse ash are increasingly being used as partial replacements for cement in concrete production. Consequently, ML models can be continuously developed and updated to incorporate innovations in concrete materials for accurate prediction of concrete compressive strength. The study demonstrates that machine learning techniques effectively capture the complex nonlinear relationships between sustainable concrete material combinations and compressive strength.

Results indicate that optimized blends of supplementary cementitious and recycled materials can achieve comparable or improved strength performance relative to conventional concrete.

Overall, ML-based evaluation provides a reliable decision-support tool for designing high-performance, sustainable concrete in accordance with material efficiency and strength requirements.

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