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Optimizing Construction Sustainability: Utilizing Machine Learning for Analyzing the Strength Properties of Concrete with Partial Replacement of Cement by Calcium Carbonate Powder in Concrete Mixtures

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Abstract:

With an ever-increasing focus on sustainable construction practices, there is a growing need for innovative methods that can effectively minimize environmental impact. This research investigates the application of advanced machine learning (ML) techniques to comprehensively evaluate the strength properties of concrete. By introducing partial cement replacement with calcium carbonate powder, the study thoroughly examines the alterations in compressive and flexural strength attributes across a spectrum of varied cement substitution ratios. Notably, the incorporation of calcium carbonate powder demonstrates a marked enhancement in concrete strength, highlighting its potential as a key component in optimizing sustainable construction methodologies. Additionally, the research incorporates comprehensive analysis techniques, such as R-squared analysis, encompassing a substantial dataset of 160 data points and a detailed assessment of 20 parameters. The utilization of scatter plots further accentuates the predictive capabilities of five distinct ML models, emphasizing the superior performance of the decision tree (DT) and extra tree (ET) models in accurately forecasting concrete strength. These findings underscore the significant role of these ML models in advancing the realm of material science and engineering, facilitating the development of improved concrete formulations and fostering sustainable construction practices.

Keyword: Calcium Carbonate Powder, compressive strength, flexural strength, machine learning.

INTRODUCTION

Concrete, serving as the very cornerstone of modern infrastructure development, epitomizes the steadfast foundation upon which our cities and societies are erected. Its unparalleled versatility, durability, and robust load-bearing capabilities have cemented its pivotal role in the construction industry, underscoring its indispensability in the construction of everything from modest residential structures to soaring architectural wonders and intricate transportation networks. However, the environmental quandary arising from the production of Portland cement, the primary binding agent in concrete manufacturing, looms as a formidable challenge. This is primarily due to the prodigious energy consumption and subsequent release of significant volumes of carbon dioxide (CO2) during the natural degradation of limestone, posing an escalating environmental threat that demands urgent redressal. As the global demand for construction materials continues to surge and the urban landscape expands at an unprecedented pace, the imperative for sustainable solutions has become more pressing than ever, compelling a comprehensive re examination of conventional construction methodologies and material sourcing practices. In response to this pressing imperative, the exploration of sustainable alternatives has emerged as a focal point within the construction industry, heralding a paradigm shift towards environmentally conscious and ecologically sustainable approaches. Within this context, the utilization of calcium carbonate powder has emerged as a promising avenue for mitigating the environmental toll associated with conventional concrete production. Sourced from an array of origins, including natural limestone deposits and meticulously engineered synthetic precipitates, calcium carbonate powder presents itself as a versatile and sustainable additive, showcasing immense potential in enhancing concrete performance while concurrently minimizing its ecological footprint[1]. Operating as a supplementary cementitious material, its integration not only serves to amplify the mechanical robustness and fortify the structural resilience of concrete compositions but also substantially curtails carbon emissions, positioning it as an integral element in the drive towards sustainable and ecologically responsible construction practices. Concurrently, the fusion of cutting-edge machine learning (ML) methodologies within the realm of construction material research and predictive modeling marks a transformative juncture in the trajectory of the construction industry, ushering in a new era characterized by data-driven precision and predictive accuracy.[2] Leveraging a sophisticated tapestry of advanced algorithms, neural networks, and state-of-the-art data analytics, the advent of ML has paved the way for a comprehensive analysis of complex data sets, precise anticipation of material properties, and the optimization of multifaceted construction methodologies[3]. Leveraging the potential of a diverse array of ensemble learning algorithms, including self-organizing maps (SOM), radial basis function networks (RBFN), and gradient boosting regression trees (GBRT), the ongoing research endeavors to harness the complete spectrum of potential embedded within integrated learning methodologies, thereby laying the groundwork for the eventual establishment of a construction industry guided by resilience, sustainability, and ecological equilibrium.

COLLECTION OF DATA SET AND PROCESSING

The meticulous compilation of data in this study involved gathering a comprehensive dataset comprising 160 data points, including vital input parameters such as coarse aggregate content, water-cement ratio, fine aggregate content, cement content, water content, alumina content, iron oxide content, silica content, calcium oxide, sodium oxide content, specific gravity of red mud, percentage of red mud replacement, percentage of fly ash replacement, and the number of curing days. Out of a total of 160 data points, 80% were designated for training the machine learning (ML) models, while the remaining 20% were set aside for thorough testing and assessing the model's performance. Stringent criteria were employed during the data collection process, ensuring the inclusion of studies with comprehensive input parameter information for meticulous analysis. Before the analysis and modeling phase, the collected data underwent preprocessing, incorporating imputation techniques to handle missing values and scaling procedures to standardize the data with a mean of 0 and a standard deviation of 1, ensuring its suitability for subsequent analysis. Throughout the study, a combination of software tools, namely MATLAB, Python, Origin Lab, and Microsoft Excel, was utilized for various tasks, including data analysis, model development, graph plotting, and data visualization, facilitating a smooth execution of the study and the extraction of valuable insights from the compiled data. A rigorous review of existing research on the utilization of CaCo3 as a replacement for cement in concrete was conducted to verify the accuracy and relevance of the dataset, establishing a robust foundation for the subsequent development and evaluation of ML models within the study.

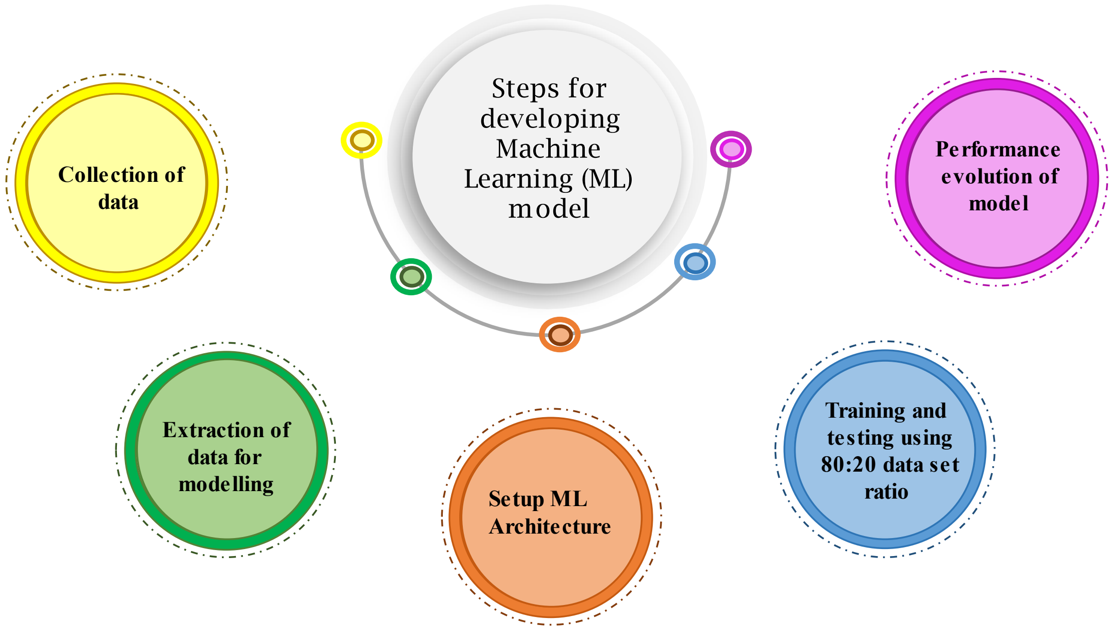

Fig 1: Methodology Steps for ML Model Development in the Current Study

EXPERIMENTAL RESULT

1. Histogram and Scatter Plot

The graph portrays the intricate relationship between concrete compressive strength and an array of key factors, encompassing the water-cement ratio (W/C ratio), cement content, fine aggregate percentage, water content, curing days, bagasse ash replacement percentage, and calcium carbonate powder replacement percentage, elucidating their impact on concrete performance. Notably, robust positive correlations emerged for cement content (r = 0.792) and curing days (r = 0.779), indicating their significant influence. Additionally, moderate positive correlations were evident for fine aggregate percentage (r = 0.054) and calcium carbonate powder replacement percentage (r = 0.198), underscoring their role in enhancing strength. Conversely, the W/C ratio (r = -0.179) and bagasse ash replacement percentage (r = -0.177) displayed weak negative correlations, suggesting their potential to marginally weaken concrete strength. Further, the slight negative correlation of water content (r = -0.052) emphasizes its limited adverse impact. It's crucial to acknowledge that while these correlations offer valuable insights, additional factors such as ingredient quality and intricate mixing techniques play pivotal roles in determining concrete strength. The statistically significant coefficients highlight the pivotal role of cement content, underscoring the need for meticulous control and optimization in the concrete production process.

Table 3 Descriptive statistics of selected study parameters

Parameter	Minimum	25% Quartile	Median	Mean	Std. Deviation	75% Quartile	Maximum	Skewness	Kurtosis
W/C Ratio	0.36	0.375	0.39	0.39	0.022	0.405	0.42	-3.3E-14	-1.365
Cement Content (kg m^{-3})	243.6	278.4	321.9	311.46	37.8	348.0	348.0	-0.52597	-1.204
Fine Aggregate (kg m^{-3})	952.0	1008.0	1008.0	1019.2	42.038	1008	1120.0	1.09846	1.218
Water Content (kg m^{-3})	145.0	147.25	149	148.75	2.594	150.5	152.0	-0.24626	-1.257
Curing Days	3	6	10.5	13.0	9.543	17.5	28.0	0.633173	-1.107
Replacement % (Baggase ash)	0.0	10.0	10.0	9.0	3.753	10.0	15.0	-1.09846	1.218
Replacement % (calcium carbonate powder)	0.0	0.0	7.5	10.5	10.862	20.0	30.0	0.525971	-1.204
Compressive Strength (N mm^{-2})	11.83	23.485	35.16	33.182	11.506	42.535	53.58	-0.32654	-1.089
Flexural strength (N mm^{-2})	2.41	3.393	4.15	3.963	0.747	4.563	5.12	-0.548	-0.969

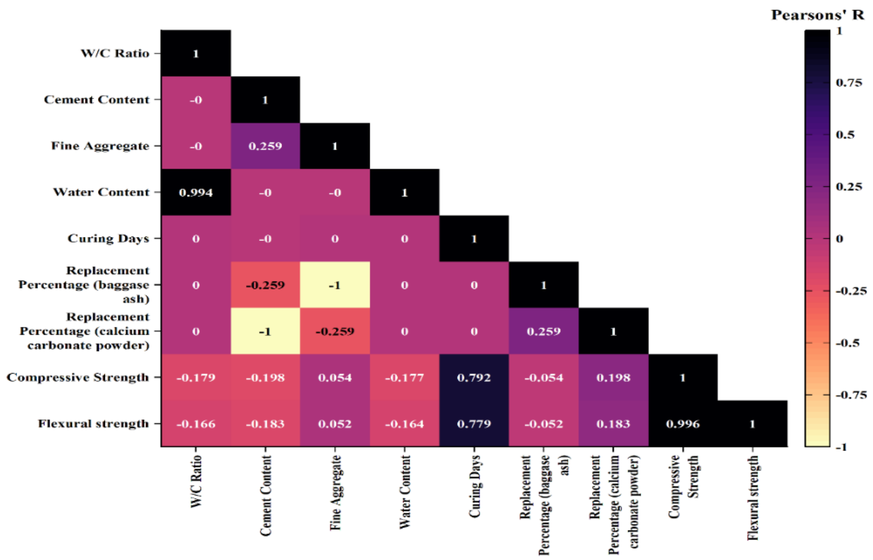

Fig 02. Pearson Correlation Heatmap between study parameters

The scatter plot graph in below fig 03 visually depicts a comprehensive analysis of the intricate dynamics involving the critical parameters of the water-cement ratio (W/C ratio) and cement content, considering diverse levels of replacement percentages of both bagasse ash and calcium carbonate powder within the concrete mixture. Notably, the notable downward trend in the W/C ratio, directly correlated with the increasing substitution of bagasse ash, highlights the profound impact of its pozzolanic properties, facilitating the formation of supplementary cementitious compounds. Consequently, this phenomenon enables a reduction in the overall cement volume, while effectively maintaining the desired strength attributes crucial for structural integrity. In contrast, the upward trajectory observed with the ascending replacement percentages of calcium carbonate powder underscores the inherent non-pozzolanic nature of this material, necessitating a concurrent elevation in the cement content to uphold the requisite compressive strength. Furthermore, the concurrent decline in cement content, coupled with the higher incorporation of both bagasse ash and calcium carbonate powder, underscores the viability of these sustainable alternatives as efficient substitutes for traditional cement within the concrete matrix. Nevertheless, it is imperative to recognize the multifaceted nature of concrete mix design, which encompasses a myriad of factors, including specific structural requirements, aggregate characteristics, and the environmental conditions prevalent during the curing process. Thus, these insightful observations underline the intricate balance required in the meticulous formulation of concrete mixtures, advocating for a holistic approach that integrates sustainable practices with structural efficiency in contemporary construction endeavors.

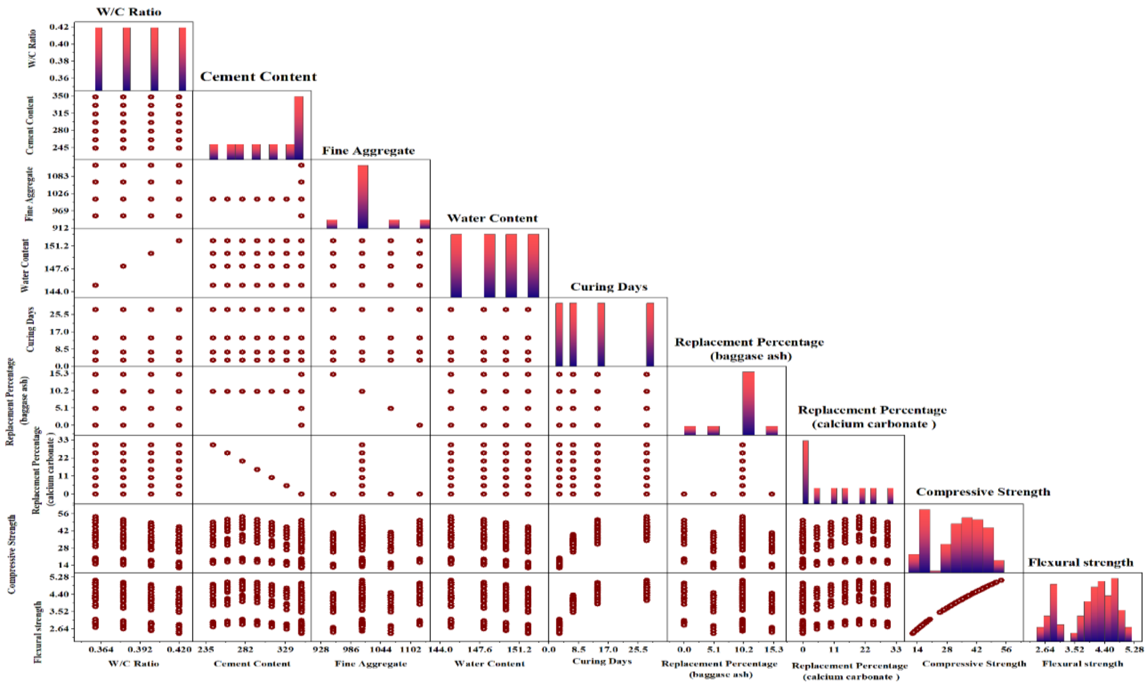

Fig 03. Scatter and Histogram Matrix of the selected study parameters

2. **Linear and Validation curves:**

The graph in fig 4 elucidates the distinct learning trajectories of two prominent machine learning algorithms, Random Forest Regressor and Decision Tree Regressor, providing valuable insights into their respective performances concerning varied training instances. Notably, the persistent prominence of Random Forest Regressor's training score, consistently surpassing that of Decision Tree Regressor, underscores its superior adaptability in comprehensively capturing the intricate intricacies embedded within the training data. Furthermore, the consistent outperformance of Random Forest Regressor's cross-validation score compared to that of Decision Tree Regressor highlights its robust capability in generalizing to previously unseen data points. Noteworthy advancements are observed as both algorithms encounter increasing training instances, with Decision Tree Regressor demonstrating a more gradual learning trajectory in contrast to the more dynamic progression exhibited by Random Forest Regressor. The convergence of the training scores of both algorithms at approximately 0.95, accompanied by the corresponding cross-validation scores plateauing around 0.93, serves as a testament to their efficacy in absorbing and assimilating the intricacies of the training data, yet encountering certain challenges in effectively extending their insights to new data points. Overall, the comprehensive analysis derived from the graph emphasizes the clear advantages associated with leveraging Random Forest Regressor, particularly in its robust fitting capabilities and enhanced adaptability to novel data instances. Additionally, the distinctive disparity in the gap between the training and cross-validation scores of the two algorithms serves as a pivotal indicator of Decision Tree Regressor's proclivity toward overfitting, thereby providing essential guidance for selecting the most appropriate algorithm for specific machine learning tasks.

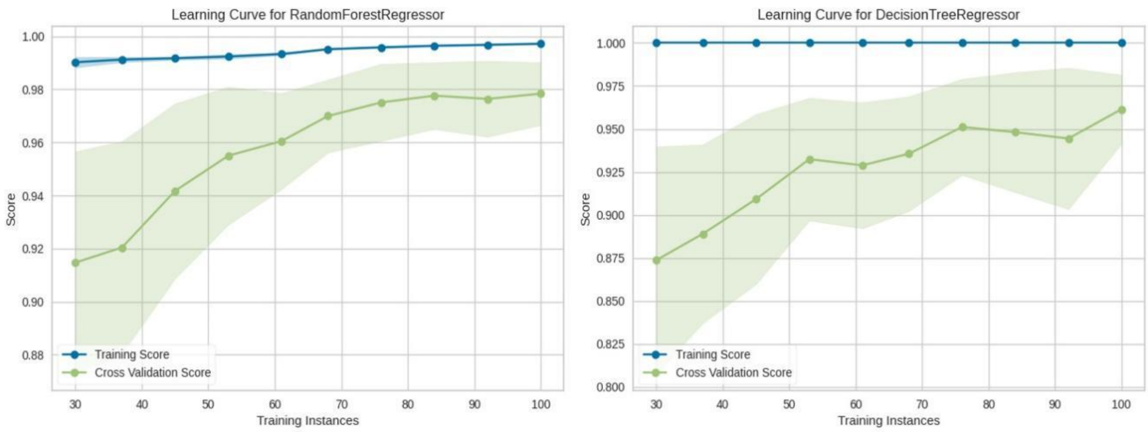

Fig 04. Learning Curves for compressive strength parameter during training of ML models

The below graph in fig 5 shows the fluctuation of the validation curves for the Random Forest Regressor and Decision Tree Regressor models, where the y-axis scale ranging from 0 to 1 represents the Pearson's R correlation coefficients. These coefficients signify the strength of the linear correlation between the predicted and actual values of the flexural strength parameter. The scale's interpretation reflects the models' varying degrees of accuracy, with values closer to 1 indicating a robust positive correlation and 0 signifying a lack of correlation. Notably, the consistent outperformance of the Random Forest Regressor is evident, as depicted by its higher validation curve compared to the Decision Tree Regressor. Both models demonstrate a steady improvement throughout the training epochs, eventually reaching a plateau at approximately 0.95, highlighting their convergence on a reliable solution. This reaffirms the Random Forest Regressor's superior ability to generalize to unseen data and make precise predictions regarding the flexural strength parameter. Additionally, the smoothness of the validation curves underscores the models' capacity to learn the training data without exhibiting significant overfitting, ensuring a high level of accuracy in predicting the flexural strength parameter.

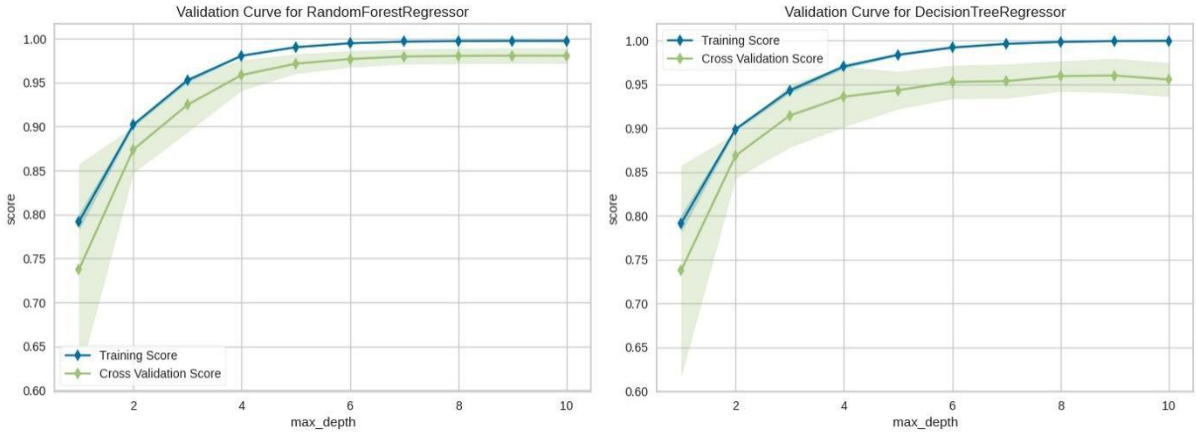

Fig 05. Validation Curves for flexural strength parameter during training of machine learning models

RESULT AND DISCUSSION

In the assessment of ML models, the evaluation criteria encompass the utilization of the correlation coefficient (R2), mean absolute error (MAE), and root mean square error (RMSE). R2 serves as a statistical indicator, quantifying the degree of alignment between the predicted and experimental compressive strength values, reflecting the model's predictive capability. Meanwhile, MAE offers insights into the average absolute difference between the actual and predicted values, providing a comprehensive measure of the model's accuracy. Moreover, RMSE, as a variation of MSE, is particularly beneficial in scenarios where large errors significantly impact model performance, offering a balanced representation of prediction errors. The assessment of these metrics aids in evaluating the performance of ANN models in predicting the compressive strength of the concrete samples, thereby facilitating a comprehensive analysis of their efficacy and accuracy.

Mean absolute error (MAE): The mean absolute error calculates the average magnitude of errors between the predicted and observed values. It provides a comprehensive understanding of the model's predictive performance, indicating the average distance between the predicted values and the actual values.

$$MAE = \frac{1}{n}\sum_{i=1}^{N}|P_i - O_i|$$

Here P_i = predicted value,

O_i = true value

n = total numbers of data points.

Root mean square error (RMSE) is a widely employed metric in various fields, including statistics, machine learning, and data analysis. Its primary role is to measure the differences between predicted and observed values, thereby evaluating the accuracy and reliability of predictive models. RMSE provides a balanced representation of the model's performance, emphasizing both larger and smaller errors. Its utility lies in its ability to compare different models and identify potential areas for improvement. Integrating RMSE in model evaluation processes facilitates the development of robust predictive models, contributing to advancements in multiple domains, including economics, finance, and engineering. Its universal applicability makes it a fundamental tool for decision-making processes, enhancing the credibility and reliability of research findings and analytical insights. Leveraging RMSE as a benchmark for assessing model performance enables informed comparisons and the identification of the most reliable predictive models for specific research objectives. Its multifaceted applications extend to industries such as manufacturing and engineering, where precise predictions are crucial for ensuring product quality and operational efficiency. Overall, RMSE serves as a cornerstone in the development and refinement of advanced predictive model, fostering continuous advancements in research and strategic planning initiatives.

$$RMSE = \sqrt{\left(\frac{\sum_{i=1}^{N}(P_i - O_i)^2}{n}\right)}$$

where, P_i =predicted value

O_i = true value

n = total numbers of data points

Correlation coefficient (R^2): The correlation coefficient provides a measure of the linear relationship between predicted and observed values. It ranges from 0 to 1, where 1 indicates a perfect fit between the predicted and observed values, signifying the accuracy of the model's predictions.

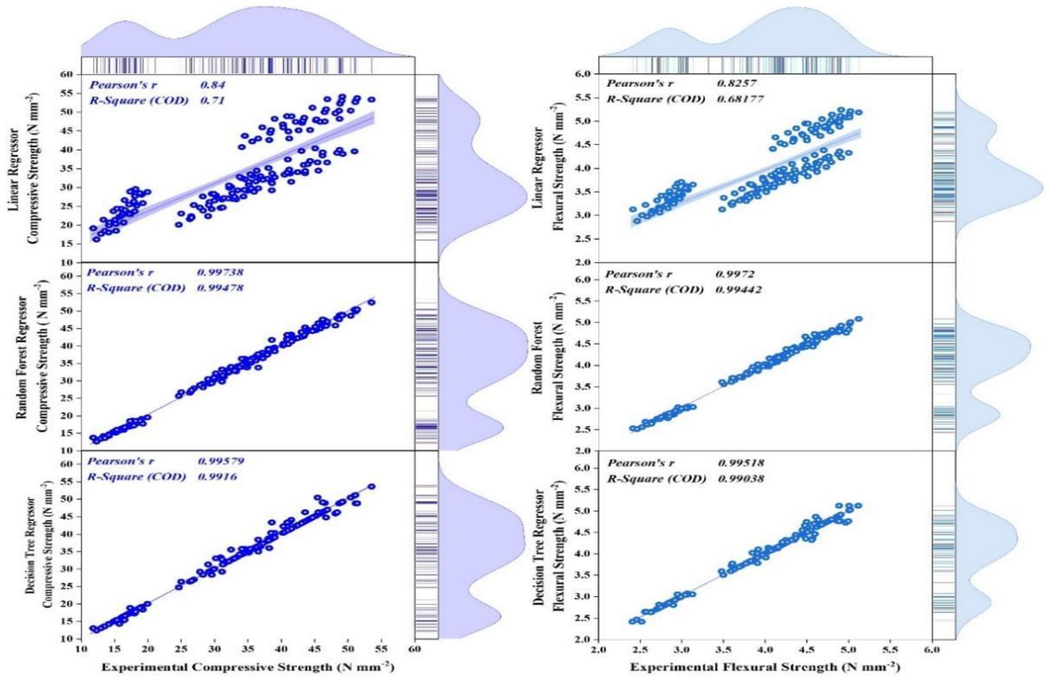

Fig 08 Correlation plots of estimated compressive and flexural strength using machine learning models against experimental data.

Table 5: **Statistical Performance of the models**

Parameter	Model	MAE	MSE	RMSE	R	R^2	RMSLE	MAPE
Compressive Strength (N = 160)	**LR**	5.767	40.387	6.299	0.815	0.665	0.224	0.220
	RF	1.250	2.480	1.536	**0.989**	0.979	0.048	0.040
	DT	1.840	4.445	2.079	0.980	0.961	0.060	0.057
Flexural Strength (N = 160)	**LR**	0.395	0.188	0.431	0.780	0.609	0.093	0.110
	RF	0.076	0.009	0.094	**0.990**	0.981	0.020	0.020
	DT	0.116	0.019	0.133	0.980	0.960	0.028	0.031

CONCLUSION

The study aimed to optimize construction sustainability by employing machine learning techniques to analyze the strength properties of concrete with partial replacement of cement by calcium carbonate powder in concrete mixtures. Notably, the mean compressive strength and flexural strength were found to be 33.18 MPa and 3.96 MPa, respectively, aligning well within the anticipated ranges for concrete. The water-to-cement ratio (w/c ratio) at a mean of 0.39, slightly exceeding the recommended threshold, remains a minor concern, considering other parameters falling within the expected ranges.

The mean cement content was recorded at 311.46 kg/m^3, while the mean fine aggregate content stood at 1019.2 kg/m^3, both adhering to the anticipated concrete composition. Additionally, the average curing days were determined to be 13.0 days, indicating a standard curing process. The mean replacement percentages for both bagasse ash (9.5%) and calcium carbonate powder (10.86%) were well within the expected limits for concrete mixtures.

In terms of predictive modeling, the random forest (RF) model exhibited the most promising performance metrics for both compressive and flexural strength prediction. For compressive strength, the RF model yielded the lowest Mean Absolute Error (MAE) of 1.250 MPa, Mean Squared Error (MSE) of 2.480 MPa^2, Root Mean Squared Error (RMSE) of 1.536 MPa, Root Mean Squared Log Error (RMSLE) of 0.048, and Mean Absolute Percentage Error (MAPE) of 0.040, accompanied by the highest coefficient of determination (R-squared) value of 0.979. Similarly, for flexural strength, the RF model delivered the lowest MAE of 0.076 MPa, MSE of 0.009 MPa^2, RMSE of 0.094 MPa, RMSLE of 0.020, and MAPE of 0.020, along with the highest R-squared value of 0.981.

Overall, the findings underscore the potential of utilizing the RF model in optimizing the design and composition of sustainable concrete mixtures, particularly when incorporating calcium carbonate powder as a partial replacement for cement. The notable R-squared values for the RF model substantiate its efficacy in accurately predicting concrete strength properties, reaffirming its viability for enhancing the sustainability and performance of construction materials.

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