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PREDICTING THE COMPRESSIVE STRENGTH OF CONCRETE: A MULTIVARIATE APPROACH UTILIZING MACHINE LEARNING REGRESSORS

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Abstract

Concrete's compressive strength is a crucial factor in the design of new concrete structures and the assessment of existing ones in the civil engineering discipline. Precise estimation of concrete's compressive strength is crucial to the advancement and quality of construction. Traditionally, estimating concrete's strength characteristics has required a great deal of laboratory testing. To expedite this process, researchers are increasingly using predictive models. The current study is to apply the machine learning regressor models to predict the compressive strength of concrete. The multivariate analysis comprises of nine independent variables and compressive strength of concrete as a dependent variable. For training and assessing the models, a dataset with 1133 test results of compressive strength of concrete is collected and used. The methodology employs XGBoost, CatBoost, LightGBM, and ensemble/stacked regressor models to predict the compressive strength using nine input parameters. The ensemble/stacked regressor outperforms the other three regressor models, achieving a root mean. squared error (RMSE) of 3.87MPa, a mean absolute error (MAE) of 2.81 MPa, and a coefficient of determination(R2) of 0.955. The results of the models were validated statistically with different pairs of models, and the ensemble/stacked model significantly outperforms the individual regressor models. Finally, a web-based prediction interface was developed.

Keywords: Compressive strength, Machine learning, Prediction.

1. Introduction

Concrete offers significant advantages in construction due to its durability and properties. In addition to the primary components, which include cement, coarse aggregates, fine aggregates, and water, various admixtures may be incorporated as required based on the specific application. The most important factor in evaluating the quality of concrete is its compressive strength [1]. Concrete compressive strength constitutes a critical performance characteristic and is a fundamental requirement for design applications. However, the accurate prediction of compressive strength poses significant challenges, arising from a multitude of influencing factors [2]. An effective and dependable method for predicting compressive strength during the initial phases of a project can significantly reduce the overall project timeline. Concrete's compressive strength can be estimated using statistical and machine learning (ML) models by collecting the necessary data, or it can be evaluated using destructive testing techniques. Typically, destructive testing is conducted within a laboratory environment and is often characterized by substantial time investment, high costs, and impracticality [3]. Conventional approaches for estimating the compressive strength of concrete such as empirical formulas and statistical models, frequently do not adequately address the relations and interactions that are characteristic of concrete mix designs. In the recent past, ML algorithms have been widely used in construction management applications, owing to their capability to model complex relationships and handle extensive datasets. ML algorithms extract patterns from historical data and can generate precise predictions on input parameters rendering them suitable for forecasting the

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compressive strength [4]. The researcher's attention has shifted to the application of ML and deep learning (DL) architectures to predict the compressibility of concrete. Comprehensive investigations have aimed at refining the prediction models for the compressive strength of concrete mixtures, which plays a crucial role in construction management [5]. Recent advancements in the field of ML, particularly in the domain of Artificial Neural Networks (ANNs), provide a promising alternative for various applications.

The investigation of the compressive strength of concrete using different ML models and ANN with a sample set of 1234 samples yielded the highest coefficient of determination by support vector regression [6]. The ML models were effectively applied in predicting the 28-day compressive strength of concrete mixes, self-compacting concrete high-performance concrete, and recycled aggregate concrete [7-9]. Despite the growing development of ML models, accurately predicting compressive strength remains a challenge due to the intricate relationships between the variables, and previous research findings indicate varying results.

A comparison was made between the effectiveness of ensemble and non-ensemble ML models in predicting the compressive strength of concrete containing fly ash. The findings indicated age, cement and water content are the key factors; the study did not offer a thorough investigation of how these factors interacted [10]. In addition to this, ANN model, M5P model tree algorithm and ensemble models were applied to predict the compressive strength of concrete [11-13].

Tree-based ensemble models such as XGBoost, CatBoost, and LightBoost are more appropriate for predicting the compressive strength of the non-time series/tabular data [14]. The majority of research focuses on attaining high predictive accuracy without fully examining the interactions between the input parameters in the models. There is an urgent requirement for research that employs advanced ML models to forecast concrete characteristics while also offering a thorough examination of how features interact and their impact on model predictions. This practice would enhance model clarity, lead to better decision making in optimizing material composition, and foster the development of high performance, resilient, and sustainable concrete [15].

The study follows a structured approach to data preparation, addressing issues such as missing values, outliers, and anomalies before conducting an exploratory data analysis (EDA) to identify patterns and interrelations in the dataset. Methods for feature selection methods are employed to ascertain the key variables that significantly affect the compressive strength, thereby enhancing the accuracy and effectiveness of the model. By incorporating advanced analysis of feature interactions within ML models, this research contributes to the advancement of data driven methods in concrete technology. The results of the study are expected to offer meaningful insight for improving the construction proposals and in attaining quality standards in the construction sector.

2. Materials and Methods

This study adopted an exhaustive approach to assess and predict concrete's compressive strength through a number of regressor models. Collecting information, EDA, feature engineering, and the generation and testing of ML models for regression were all part of the study methodology, as shown in Figure 1. Employing regressor methodology and feature interaction analysis, the objective was finding the best prediction models and comprehend the fundamental elements affecting the compressive strength.

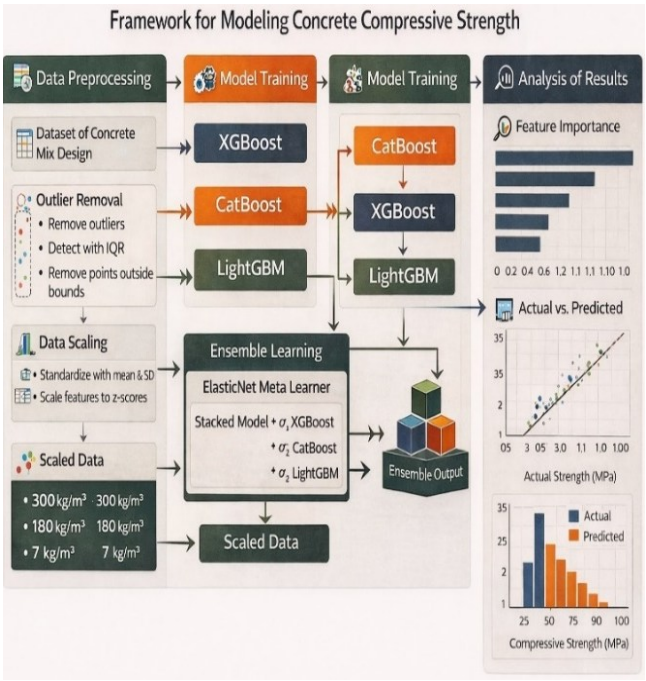


Figure 1. Framework for prediction of compressive strength

2.1. Data Collection

The "Compressive strength dataset of foamed/normal concrete for the prediction model" was used in the investigation [16]. Each of the 1133 observations in the dataset, which include nine variables, represents a different concrete mix design. The eight input characteristics include the age of the concrete in days and the amounts of various concrete

components expressed in kilograms per cubic meter (kg/m³). The concrete's compressive strength, expressed in megapascals (MPa), is the dependent variable.

2.2. Data Preprocessing

To ensure data quality while preparing the datase t ready for modeling, the data preliminary processing phase was crucial. It includes cleaning the dataset for null values, elimination of outliers, EDA, data scaling, feature engineering. The dataset comprising of 1133 was screened for inconsistencies, redundant data, and missing data. It was verified that none of the variables possessed any missing values. Before outlier screening and model training, redundant rows in the dataset were identified and removed using specific row matching to ensure data integrity. The dataset was reduced to 1008 distinct observations after these duplicates were eliminated to ensure data quality. The interquartile range (IQR) approach was used to find and eliminate these outliers in order to minimize their possible effect on model performance [17]. Outliers were eliminated from all input variables, and extreme values were likewise eliminated from the output variable, as seen in the Figure 2.

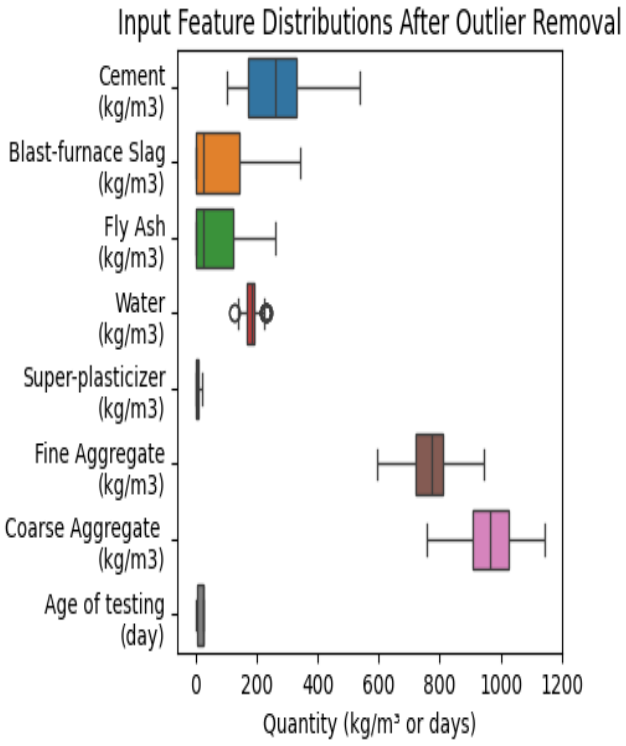


Figure 2. Input feature distribution after outlier removal

To increase the accuracy and generalizability of the model, significant outliers in variables like age were eliminated from the dataset. The final dataset includes 817 observations after outliers were excluded.

2.3. Exploratory Data Analysis

Significant variation in the components of the concrete mix was found by EDA. Compressive strength was strongly positively correlated with cement content and curing age, but negatively correlated with water content. Fly ash and blast furnace slag, two additional cementitious ingredients, showed delayed strength contributions. Age and strength distributions were the main areas where outliers were found, which supported preprocessing before model building. The observed patterns are in good agreement with the known behavior of concrete materials. The EDA of concrete mix variables is shown in Figure 3.

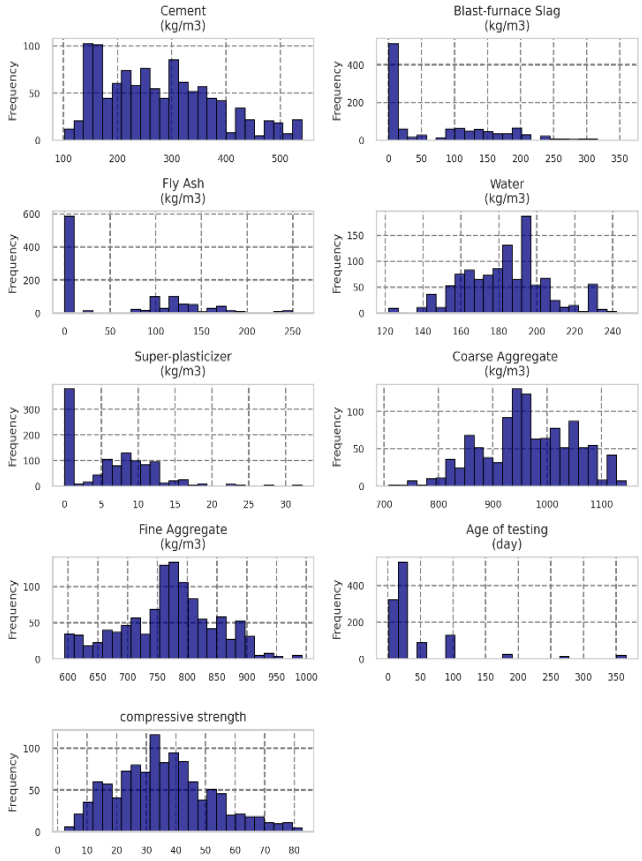


Figure 3. EDA of concrete mix variable

2.4. Correlation analysis

The volume of water has a clear negative correlation with compressive strength, but cement content and curing age have significant positive relationships, according to correlation analysis. Due to their delayed pozzolanic contributions, supplementary cementitious materials such fly ash and blast furnace slag show comparatively favorable associations. Weak correlations between aggregate contents and strength development suggest that these factors have an indirect implication. The dataset's suitability for robust machine learning models is demonstrated by the lack of significant multicollinearity. The correlation matrix

of concrete mix parameters and compressive strength is shown in Figure 4.

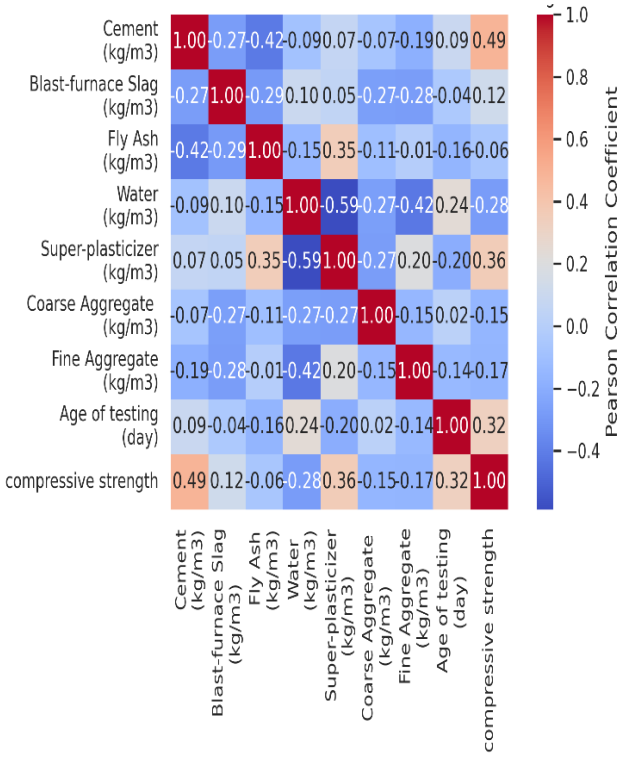


Figure4. Correlation matrix of mix variables and strength

2.5. Feature Engineering and Multicollinearity Analysis

The strength of concrete is influenced by the proportions of materials and the mechanisms of hydration, which are frequently non-linear and based on interactions. Consequently, feature engineering was applied to identify the ratios that are physically significant, mitigate scale dependency, enhance interpretability, and improve performance. This process involved integrating relationships that are meaningful and govern concrete strength [18-19]**.** Variables derived from this process, such as the water-cement ratio, total binder content and logarithmic age transformation, contributed to improved predicted accuracy [20]. An assessment of multicollinearity through correlation analysis and variance inflation factors (VIF) revealed no significant collinearity among the predictors. The features that were engineered bolstered the robustness of the model and resulted in more consistent feature attributions. VIF analysis was performed to evaluate multicollinearity among the independent variables. The original feature set displayed moderate collinearity, especially among the cementitious components. To rectify this, features that are physically meaningful were introduced. The updated feature set showed a significant reduction in VIF values, all remaining below five, which indicates minimal multicollinearity. This enhancement led to improved interpretability and stability of the model without disturbing the predictive performance. The results of VIF for input feature selection is shown in Figure 5.

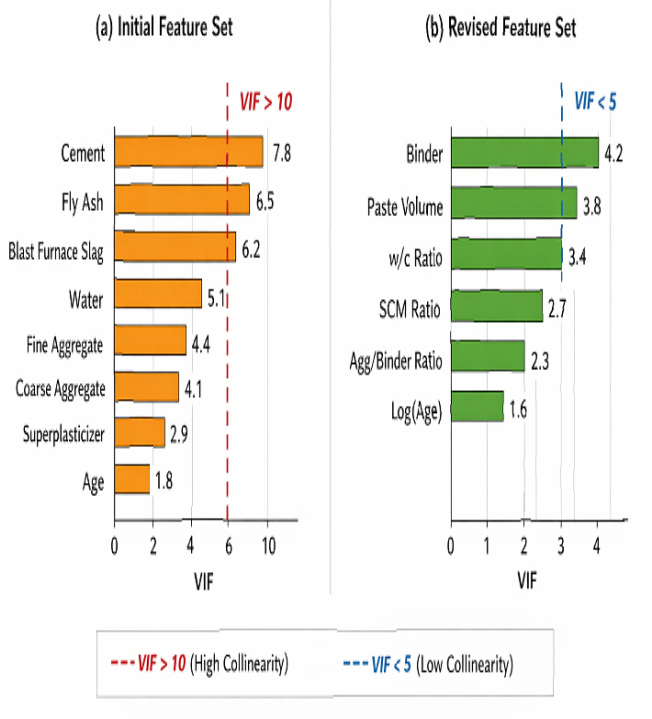


Figure 5. VIF results for input feature selection

2.6. Data Scaling

The independent variables of the dataset reveal significantly diverse numerical ranges and units which include material quantities (kg/m^3) and age in days. In order to maintain the numerical stability and a balanced contribution from features, Z-score normalization (StandardScaler) was utilized on the independent variables [21]. The scaling was carried out after the removal of outliers and engineering of features, and was implemented within each training fold of the K-fold cross validation framework to avoid the data leakage.

2.7. Model Development and Evaluation

The crux of the methodology involved the formulation and assessment of various ML models aimed at regression tasks. The objective was to accurately predict the compressive strength of concrete. The dataset was divided into training and testing sets with an 80-20 split [22]. To accurately represent the complex and interaction-driven behavior of concrete compressive strength, a series of advanced tree-based ML models were adopted.

XGBoost, CatBoost and LightGBM were chosen as base learners due to their established effectiveness in managing the complex feature interactions, robustness

to multicollinearity, and strong performance on structred tabular datasets. CatBoost also helps to mitigate overfitting through ordered boosting, while XGBoost and LightGBM provide efficient gradient boosting frameworks that incorporates regularization. To further improve predictive accuracy and generalization, these base models were combined using an ensemble and stacked learning approaches, wherein the predictions of individual learners were integrated through a meta-learner. Model evaluation was performed using K- fold cross validation, and the performance was primarily assessed using the coefficient of determination(R^2). This multi-model evaluation framework ensures a thorough comparison and reliable identification of the optimal predictive model for predicting the compressive strength.

- CatBoost Regressor

The CatBoost model employs gradient boosting to create ensembles of decision trees, utilizing ordered boosting to lesson prediction bias and prevent overfitting. It is particularly useful for predicting the compressive strength of concrte due to its robustness against multicollinearity, its capability to capture complex interactions among the components of the mix, its reliable performance with minimal need for hyperparameter tuning.

- XGBoost Regressor

XGBoost serves as an efficient gradient boosting framework that employs regularization to regulate the model complexity and avoid overfitting. Its proficiency in capturing complex non-linear relationships and interactions contributes to its effectiveness in modelling how cementitious materials water content, and curing age influence the strength.

- LightGBM Regresso

LightGBM represents a gradient boosting model that prioritizes speed and memory efficiency, utilizing histogram-based learning alongside leaf-wise tree growth. This model demonstrates strong performance on extensive tabular datasets and is proficient in detecting the nuanced patterns in concrete mix proportions, maintaining a high level of predictive accuracy.

- Ensemble / Stacked Model

The ensemble model synthesizes predictions from CatBoost, XGBoost, and LightGBM through a stacked learning methodology, wherein a meta-learner amalgamates the advantages of each individual model. This approach mitigates model -specific bias and variance, resulting in enhanced generalizations and more dependable predictions of strength. The ensemble model combines the s predictions from CatBoost,XGBoost , and LightGBM utilizing a stacked learning framework, where a meta-learner unites the strengths of the individual models.

2.8. Hyperparameters of the models

The hyperparameters applied for the regression models are presented in Table. 1.

Hyperparameters for the models.

Table 1.

Model	Hyperparameters
CatBoost	Iterations (1000), learning rate (0.03), depth (8), loss function (RMSE), random seed (42)
XGBoost	Random seed (42), learning rate (0.03), max depth (6), subsample (0.8)
LightGBM	N estimators (900), max depth (-1), num leaves (31), sub sample (31)
Stacked Ensemble	Base models (CatBoost, XGBoost, LightGBM), meta learner (Linear regression), cv folds (5), final metric (R^2)

2.9. Model Evaluation Metrics

Multiple regression evaluation criteria, which capture both accuracy and error characteristics, were used to thoroughly evaluate the prediction performance of the constructed models. The main performance parameter was the coefficient of determination (R^2), which measures the percentage of compressive strength variance that can be accounted for by the model predictions. Stronger agreement between predicted and experimental values is shown by a greater R^2, which also shows how well the model captures the underlying mechanisms regulating strength.

Prediction error magnitude was also assessed using Mean Absolute Error (MAE) and Root Mean Square Error (RMSE). While MAE offers a reliable indicator of the average absolute variation between observed and predicted strength values, RMSE penalizes higher errors systematically and is vulnerable to outliers. When combined, these measures provide a fair assessment of the accuracy, robustness and generalization capacity of the model. The main metric used to assess the model's performance was R^2, which was supplemented by RMSE and MAE to measure the prediction errors. R^2 quantifies the proportion of variance in experimental compressive strength explained by the predictive model The R^2 is calculated by using the Equation 1.

$$R^2 = 1 - \frac{\Sigma_{i=1}^{n}\left(f_{c,i}^{\mathrm{ex}} - f_{c,i}^{\mathrm{pd}}\right)^2}{\Sigma_{i=1}^{n}\left(f_{c,i}^{\mathrm{ex}} - \overline{f_c^{\mathrm{ex}}}\right)^2} \quad (1)$$

Where, $f_{c,i}^{ex}$ = experimentally measured compressive strength of the i^{th} concrete sample (MPa);

$f_{c,i}^{pd}$ = model-predicted compressive strength of the i^{th} sample (MPa);

$\overline{f_c^{ex}}$ = mean experimental compressive strength (MPa);

n = total number of observations;

The RMSE and MAE are calculated by using the Equations 2 and 3.

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}\left(f_{c,i}^{ex} - f_{c,i}^{pd}\right)^2} \quad (2)$$

$$MAE = \frac{1}{n}\sum_{i=1}^{n}\left|f_{c,i}^{ex} - f_{c,i}^{pd}\right| \quad (3)$$

RMSE emphasizes larger prediction errors and reflects overall prediction accuracy in MPa. MAE represents the average absolute deviation between predicted and experimental strength values.

3. Results

The regression models have been evaluated Usin g their R^2 and MSE values, as indicated in the table.

The table offers an upfront overview of the accuracy with which the regressor models predict the compressive strength of concrete. With an RMSE of 3.87 and an R^2 value of 0.955, the ensemble/stacked regressor model outperformed the other three models, explaining 95.5 percent of the variation in the compressive strength. The ensemble decreased individual model biases and enhanced generalization capacity by combining predictions from CatBoost, XGBoost, and LightGBM. These findings demonstrate that ensemble learning outperforms solo models in providing a dependable and accurate framework for compressive strength prediction.

According to the performance evaluation, the nonlinear interactions governing concrete compressive strength were successfully represented by all four models. CatBoost outperformed XGBoost and LightGBM in terms of predicting accuracy among individual models, as evidenced by a greater R^2 and lower error values. CatBoost's tolerance to correlated input characteristics and its ordered boosting technique are responsible for this gain. The results of the evaluation metrics are shown in Table 2.

Results of evaluation metrics

Table 2.

Model	R^2	RMSE (MPa)	MAE (MPa)
XGBoost	0.947	4.28	3.12
CatBoost	0.953	4.01	2.94
LightGBM	0.949	4.19	3.05
Ensemble / Stacked	0.955	3.87	2.81

Figures 6 and 7 reveal additional evidence of the ensemble model robustness. The residual plot in Figure 6 shows that there is no apparent pattern and that the residuals are randomly distributed about zero, suggesting that there is no systematic bias and that the variance is fairly constant. The near symmetric distribution confirms the stacked ensemble approach applicability for accurate compressive strength prediction and supports the accuracy. The actual vs predicted plot of the stacked ensemble model in Figure 7 demonstrates an effective agreement between the experimental and predicted compressive strength values, with data points closely aligned along the 45 degrees reference line. This demonstrates the strong prediction accuracy of the model and its ability to capture the non-linear interactions between curing age and concrete mix factors over the whole strength range.

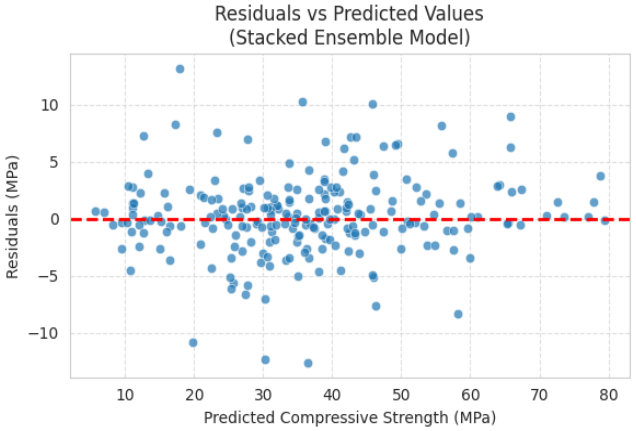


Figure 6. Plot for residuals vs predicted values (Ensemble model)

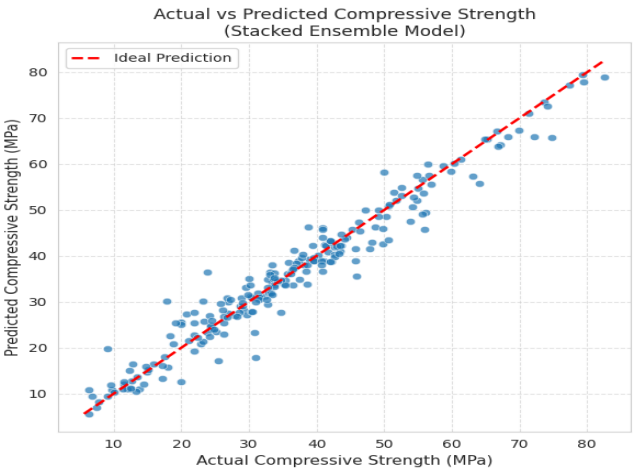


Figure 7. Plot of actual vs predicted compressive strength (Ensemble model)

The findings show that gradient boosting method s are superior for tabular, non-linear datasets. CatBoost in particular demonstrated exceptional

generalization capacity because of its strong regularization and efficient handling of feature interactions. Ensemble model enhanced predictive performance by lowering the model variance. The findings imply that the majority of the underlying input-output relations has been captured by the CatBoost regressor. On the other hand, stacking allowed a meta-learner to aggregate model predictions from many feature space areas in the best possible way. This resulted in the highest R^2 value (0.955), confirming that localized error correction is more effective than global averaging when performance is already near optimal. Statistical testing confirms that the stacked ensemble model significantly outperforms individual learners with both statistically and practically meaningful improvements.

3.1. Statistical validation of results of models

The prediction errors (cross-validated RMSE) of each model were compared to the ensemble/stacked model, which serves as the reference, in order to perform the statistical validation. To ensure that each model was evaluated on the same data, paired statistical tests were used, allowing for an impartial and balanced comparison. When compared to XGBoost, CatBoost, and LightGBM, the ensemble model produces a statistically significant reduction in RMSE ($p < 0.05$), according to the paired t-test findings. The Wilcoxon signed-rank test was used as a non-parametric alternative to account for any non-normality of error distributions, and it corroborated the same findings. These results show that the ensemble model's better performance represents a real gain in predicted accuracy rather than the result of random variance. The results of the statistical validation of errors are presented in Table 3.

Results of statistical validation

Table 3.

Models	**Statistical Test**	**Test Statistic**	***p*-value**	**Significance**
Ensemble vs XGBoost	Paired *t*-test	$t = -4.32$	< 0.01	Significant
Ensemble vs XGBoost	Wilcoxon signed-rank	$Z = -3.21$	< 0.01	Significant
Ensemble vs CatBoost	Paired *t*-test	$t = -3.85$	< 0.01	Significant
Ensemble vs CatBoost	Wilcoxon signed-rank	$Z = -2.87$	< 0.01	Significant
Ensemble vs LightGBM	Paired *t*-test	$t = -4.91$	< 0.001	Significant
Ensemble vs LightGBM	Wilcoxon signed-rank	$Z = -3.64$	< 0.001	Significant

3.2. Compressive strength prediction interface

To offer a precise, comprehensible, and user-friendly decision-support tool for mix design, a web based concrete compressive strength prediction interface was created. A stacked ensemble ML architecture that combines the three effective regression models forms the basis of the predictor. Cement content, blast furnace slag, fly ash, water content, superplasticizer dose, fine aggregate, coarse aggregate, and curing age were the important mix factors included in the multivariate dataset. The web-based prediction interface is shown in Figure 8.

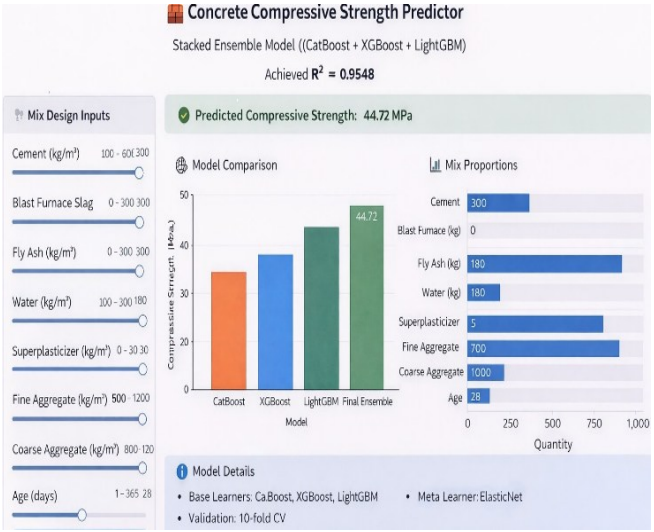


Figure 8. Web based compressive strength predictor

The trained model was included into an interactive web application created using the streamlit framework in order to facilitate practical deployment. Through simple slider controls, the application's user interface enables users to enter concrete mix quantities. Following submission, the system produces real time compressive strength estimates and visualizations that show the input mix composition and model wise predictions.

Additionally, the program was included as a standalone Windows executable, allowing offline use without requiring a Python environment. This distribution strategy guarantees accessibility for both industry professionals and scholarly academics. All things considered, the produced concrete compressive strength predictor shows how ensemble machine learning techniques may be effectively applied in conjunction with contemporary online technologies to produce a precise, comprehensible, and deployable prediction tool for civil engineering applications.

4. Discussion

The findings of the current study were compared with earlier research outcomes regarding the prediction of concrete's compressive strength. The gradient boosting regressor demonstrated the highest level of predictive accuracy, achieving a R2 value of 0.94. An analysis of feature importance indicated that the water cement ratio and the age of the concrete are the most significant factors influencing the compressive strength [15]. The results of our research support previous research showing boosted trees or hybrid techniques outperforming traditional regressors and highlight the efficacy of ensemble methods for compressive strength prediction [23-24]. The bagging algorithm shows high accuracy towards the predicting the compressive strength of concrete with fly ash admixture as indicated by its high coefficient correlation (R2) value equals to 0.95 [25]. While predicting the compressive strength of concrete produced from recycled concrete aggregates, gradient boosting with particle swarm optimization shows the best prediction accuracy, with R = 0.9356, RMSE = 5.5604 MPa, and MAE = 4.2882 MPa [26]. The support vector regressor demonstrated superior prediction accuracy of 88.18%, owing to its adeptness in managing continuous target variables and the complex interactions between the input parameters and the compressive strength [27]. The results obtained from the present study, as evidenced by the ensemble/stacked model's R2 for strength categories, validate the powerful ensemble techniques can handle the heterogeneous aspects of concrete composites and deliver superior predictive performance.

5. Conclusions

This study provided a thorough ML framework for forecasting concrete's compressive strength based on mix proportions and curing age. Prior to model development, the input datasets stability and dependability were ensured by comprehensive data preparation, which included multicollinearity evaluation, feature scaling, and outlier removal. CatBoost regressor outperformed other individual models because of its capacity to manage the correlated characteristics and non-linear interactions. Nevertheless, the stacked ensemble model which included XGBoost,CatBoost, and LightGBM achieved the best prediction accuracy , producing the lowest error metrics and the highest R2 value. This illustrates the way ensemble learning improves generalization and lessens the bias of individual models.

Concrete compressive strength is primarily affected by cement content, curing age, water contentand othercementitious elements, according to feature important analysis. The interpretability of the results supported the physical validity of the model predictions by being in line with accepted tangible technological principles. Residual analysis and actual versus predicted plots further validated the robustness of the proposed ensemble model, showing unbiased predictions, homoscedastic residuals, and strong agreement with experimental values across the full-strength range. Statistical validation using cross-validation and non-parametric testing confirmed the reliability of the obtained results.

Overall, the developed stacked ensemble-based predictor provides a robust, accurate, and interpretable tool for estimating concrete compressive strength. The framework can be effectively extended for practical applications such as decision-support systems, mix design optimization, and deployment as a web-based or desktop prediction tool in real-world construction engineering practice.

6. Patents

Author Contributions: "Conceptualization, Author 1 and Author 2; methodology, Author 3; software, Author 1; validation, Author 2, 3 and 4; formal analysis, Author 1; investigation, Author 2,3 and 4; resources, Author 1; data curation, Author 2.; writing—original draft preparation, Author 4; writing—review and editing, Author 1. All authors have read and agreed to the published version of the manuscript."

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Conflicts of Interest: Declare conflicts of interest or state "The authors declare no conflict of interest."

References

1. Prakash, M., Manikandan, S., Surenther, I., Aswin Kumar. M.N., Ilakkiya, S., & Menaka, D. Speculation of compressive strength of concrete in real-time. Int. j. recent technol. eng 2019, Vol. 7, pp. 988–992.
2. Wu, X., Han, J., Cui, H., Li, T., Bai, X., He, Y., & Liu, N. A Comparative Review of Recent Research Progress in Prefabricated Buildings in China and Other Countries. Buildings 2024, Vol.14, pp. 1-21.
3. Ali-Benyahia, K., Kenai, S., Ghrici, M., Sbartai, Z.M., & Elachachi, S.M. Analysis of the accuracy of in-situ concrete characteristic compressive strength assessment in real structures using destructive and non-destructive

testing methods. Constr. Build. Mater 2023, Vol.366, pp. 1-27.
4. Mouawad, F., Homsi, F., Geara, F., & Mina, R. Predicting Compressive Strength of Sustainable Concrete Using Machine Learning and Artificial Neural Networks. Constr.Mater. 2025, Vol. 5, pp.1-15.
5. Asteris, P.G., & Mokos, V.G. Concrete compressive strength using artificial neural networks. Neural Comput. Appl. 2020, Vol.32, pp.11807–11826.
6. Loureiro, A.A.B., & Stefani, R. Comparing the performance of machine learning models for predicting the compressive strength of concrete. Discov. Civ. Eng. 2024, Vol.1, pp. 1-19.
7. Alghamdi, S.J. Prediction of Concrete's Compressive Strength via Artificial Neural Network Trained on Synthetic Data. ETASR 2023, Vol.13, pp.12404–12408.
8. Asteris, P.G., Ashrafian, A., & Rezaie-Balf, M. Predicting the compressive strength of self-compacting concrete using surrogate models. COMPUT CONCRETE 2019, Vol.24, pp.137–150.
9. Inqiad, W.B., Siddique, M.S., Alarifi, S.S., Butt, M.J., Najeh, T., & Gamil, Y. Comparative analysis of various machine learning algorithms to predict 28-day compressive strength of Self-compacting concrete. Heliyon 2023, Vol.9, pp. 1-16.
10. Paudel, S., Pudasaini, A., Shrestha, R.K., & Kharel, E. Compressive Strength of Concrete Material Using Machine Learning Techniques. Cleaner Eng. Technol. 2023, Vol.15, pp. 1-17.
11. Chou, J.S., & Pham, A.D. Enhanced artificial intelligence for ensemble approach to predicting high performance concrete compressive strength. Construction and Building Materials 2013, Vol. 49, pp. 554–563.
12. Prasad, B.K.R., Eskandari, H., & Reddy, B.V.V. Prediction of compressive strength of SCC and HPC with high volume fly ash using ANN, Construction and Building Materials, 2009, Vol. 23, pp.117–128.
13. Ali, B., Venous, B., Mahsa, M. G., & Kursat, E.A. Prediction of the compressive strength of normal and high-performance concretes using M5P model tree algorithm. Construction and Building Materials 2017, Vol.142, pp. 199-207,
14. Fu, H., Zhou, X., Xu, P., & Sun, D. Prediction of Compressive Strength of Concrete Using Explainable Machine Learning Models. Materials 2025, Vol.18, pp. 1-25.
15. Nikoopayan Tak, M.S., Feng, Y., & Mahgoub, M. Advanced Machine Learning Techniques for Predicting Concrete Compressive Strength. Infrastructures 2025, Vol.10, pp.1-26.
16. Dac-Khuong, B., Tuan, N., Jui-Sheng, C., Nguyen-Xuan, H., Tuan, D. N. A modified firefly algorithm-artificial neural network expert system for predicting compressive and tensile strength of high-performance concrete. Construction and Building Materials 2018, Vol.180, pp. 320–333.
17. Vinutha, H.P., Poornima, B., Sagar, B.M. Detection of Outliers Using Interquartile Range Technique from Intrusion Dataset. In Information and Decision Sciences, Proceedings of the 6th International Conference on FICTA 2017, Bhubaneswar, India.
18. Hover, K.C. The Influence of Water on the Performance of Concrete. Construction and Building Materials 2011, Vol.25, pp.3003–3013.
19. Hashemi, M., Shafigh, P., Karim, M.R.B., & Atis, C.D. The Effect of Coarse to Fine Aggregate Ratio on the Fresh and Hardened Properties of Roller-Compacted Concrete Pavement. Construction and Building Material 2018, Vol. 169, pp. 553–566.
20. Iqbal Khan, M., Abbass, W., Alrubaidi, M., & Alqahtani, F.K. Optimization of the Fine to Coarse Aggregate Ratio for the Workability and Mechanical Properties of High Strength Steel Fiber Reinforced Concretes. Materials 2020, Vo. 13, pp. 1-17.
21. Goodfellow, I., Bengio, Y., Courville, A. Deep Learning., MIT Press: Cambridge, USA, 2016; pp. 1-801.
22. Pedregosa, F., Varoquaux, G., Gramfort, A., Michel, V., Thirion, B., Grisel, O., Blondel, M., Prettenhofer, P., Weiss, R., & Dubourg, V. Scikit-Learn: Machine Learning in Python. J. Mach. Learn. Res. 2011, Vol. 12, pp. 2825–2830.
23. Alghrairi, N.S., Aziz, F.N., Rashid, S.A., Mohamed, M.Z., & Ibrahim, A.M. Machine Learning-Based Compressive Strength Estimation in Nanomaterial-Modified Lightweight Concrete. Open Eng. 2024, Vol. 14, pp. 1-20.
24. Ding, Y., Wei,W., Wang, J., Wang, Y., Shi, Y., & Mei, Z. Prediction of Compressive Strength and Feature Importance Analysis of Solid Waste Alkali-Activated Cementitious Materials Based on Machine Learning. Construction and Building Materials 2023, Vol. 407, pp.1-22.
25. Song, H., Ahmad, A., Farooq, F., Ostrowski, K.A., Ma´slak, M., Czarnecki, S., & Aslam, F. Predicting the Compressive Strength of Concrete with Fly Ash Admixture Using Machine Learning Algorithms. Construction and Building Materials 2021, Vol. 308, pp. 1-18.
26. Quan Tran, V., Quoc Dang, V., Si Ho, L. Evaluating Compressive Strength of Concrete Made with Recycled Concrete Aggregates Using Machine Learning Approach. Construction and Building Materiasl 2022, Vol.323, pp. 1-20.
27. Keshav, M., Dhaneshwar, M., & Charanjeet Singh, T. Prediction of concrete compressive strength employing machine learning techniques, Materials Today: Proceedings 2023 (in press).