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A REVIEW ON PREDICTIVE ANALYSIS OF CONCRETE'S COMPRESSIVE AND TENSILE STRENGTH USING MACHINE LEARNING WITH DIFFERENT FINE AGGREGATES

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Abstract : This term paper presents a study of different Artificial Intelligence (AI) and Machine Learning (ML) techniques applied to predict the compressive and tensile strength of concrete. The datasets used in the studies contain information about cement, water, aggregates, fly ash, slag, superplasticizers, and curing age. Various models such as Artificial Neural Networks (ANN), Support Vector Machines (SVM), Random Forest (RF), Gradient Boosting, XGBoost, Decision Trees, and Hybrid ANN models were tested. Advanced optimization algorithms such as Genetic Algorithm (GA), Particle Swarm Optimization (PSO), and Firefly Optimization were also applied to improve accuracy. The results show that AI models perform better than traditional statistical methods, giving higher accuracy (R^2 close to 0.99) and lower error values (MAE and RMSE). The studies also used SHAP analysis to identify the most important factors influencing concrete strength, such as cement, water, and curing age. Overall, the research proves that AI and ML can reduce manual laboratory testing, save time and cost, and provide reliable predictions for concrete design. These methods help engineers and researchers to create sustainable, strong, and eco-friendly concrete mixtures for future construction projects.

Keywords: compressive strength, tensile strength, machine learning XGBoost, fine aggregates, sustainable construction

1. INTRODUCTION

Concrete is the most widely used construction material in the world, essential for buildings, bridges, dams, and other infrastructure. Its compressive strength is a critical property that determines durability, load-bearing capacity, and overall structural safety. Traditionally, strength is measured through laboratory tests, which require curing periods of 7–28 days. While reliable, this approach is time-consuming, costly, and resource-intensive, delaying decision-making in construction projects.

With advances in Artificial Intelligence (AI) and Machine Learning (ML), predictive modeling has emerged as an effective alternative to traditional testing. ML algorithms can learn from historical datasets, capturing nonlinear relationships between mix ingredients—such as cement, fly ash, slag, silica fume, water, aggregates, and curing age—and compressive strength. By analyzing these patterns, ML models can generate highly accurate predictions in real time.

Recent research has explored various ML techniques, including Linear Regression, Decision Tree, Random Forest, Gradient Boosting, XGBoost, and Artificial Neural Networks (ANNs). Among them, ensemble methods like XGBoost and Random Forest have consistently demonstrated superior accuracy. Furthermore, tools such as SHAP (SHapley Additive exPlanations) analysis provide interpretability by identifying the relative importance of input features, highlighting the significant role of supplementary cementitious materials (SCMs).

Overall, ML-based approaches not only improve prediction accuracy but also save time, reduce costs, and promote sustainable construction practices, making them a practical solution for modern civil engineering applications.

2. LITERATURE REVIEW :

1. **1. Tarek Salem Abdennaji & Rupesh Kumar Tipu (2025)**

This paper investigates predicting compressive and tensile strength of concrete with different sand types using machine learning. A dataset of 587 samples with inputs such as water, cement, sand, and fillers was analyzed. Seven models, including XGBoost, Random Forest, and Neural Networks, were tested.

XGBoost performed best with $R^2 = 0.954$ (compressive) and 0.952 (tensile). A GUI was developed for real-time predictions, allowing engineers to estimate strength instantly without 28-day tests. The study concludes ML can save cost, time, and improve quality in construction .PETG). Standard ASTM D638 specimens were fabricated on a Geeetech A30 FDM printer and tested with a UTM machine. Results show that PETG at 40% infill density and 240°C achieved the highest tensile strength of 39.5 MPa. The analysis concluded that infill density is the most influential factor, followed by material and temperature, with strength increasing up to 40% infill before declining.

2. Rola S. Ahmed et al. (2024)

This study applies ML models to predict compressive strength of concrete containing supplementary cementitious materials (SCMs) like fly ash, slag, and silica fume. A dataset of 1,030 mixes was tested using five algorithms: Linear Regression, Decision Tree, Random Forest, Gradient Boosting, and XGBoost. XGBoost achieved the highest accuracy ($R^2 = 0.95$). SHAP analysis identified cement, curing age, and SCMs as the most influential factors. The research highlights ML as a reliable, cost-saving alternative to lab tests, supporting greener and stronger concrete.

3. **Abolfazl Yosef & Hamed Mousavi (2025)**

This paper examines ML techniques for predicting compressive and tensile strength of concrete. Using

587 mix samples with cement, water, aggregates, and fillers, the data was preprocessed with normalization and PCA. Models like Random Forest, XGBoost, and Extra Trees were tested, with XGBoost reaching R^2 above 0.95. A GUI application was developed for easy use. The study shows that ensemble methods outperform single models, providing accurate and practical tools for engineers>

4. **P. Naresh, K. Srinivasa Rao & K. Anilkumar (2023)**

This research predicts compressive strength of concrete using ML. A dataset of 1,030 samples with cement, fly ash, slag, water, aggregates, and superplasticizer was analyzed. Models like Regression, Random Forest, Gradient Boosting, and XGBoost were applied. Results showed ensemble models outperformed traditional regression, with $R^2 > 0.95$. Sensitivity analysis revealed cement and curing age as the most critical features. The study emphasizes ML as a practical replacement for 28-day tests.

5. **H. D. Nguyen et al. (2023)**

This paper uses ML to predict compressive strength of concrete with materials like cement, water, fly ash, slag, and aggregates. Data preprocessing involved cleaning, normalization, and splitting into training/testing. Models including Random Forest, SVR, and Gradient Boosting were trained. Gradient Boosting gave the highest accuracy with $R^2 \approx 0.94$–0.95. The findings show ML reduces manual testing, making construction faster, cost-effective, and more reliable

6. **Satish Paudel, Anil Pudasaini, Rajesh Kumar Shrestha, and Ekta Kharel** (2023) investigated predicting compressive strength of fly ash concrete using machine learning. A dataset of 633 samples with inputs like cement, water, aggregates, fly ash, superplasticizer, and curing age was analyzed. Models tested included Support Vector Regression, Multiple Linear Regression, AdaBoost, Random Forest, Bagging, and Extreme Gradient Boosting (XGBoost). XGBoost performed best, achieving $R^2 = 0.95$, MAE ≈ 2.13 MPa, and RMSE ≈ 3.06 MPa. Sensitivity analysis showed curing age, cement, and water as most influential, while fly ash had less impact. Ten-fold cross-validation confirmed reliability, demonstrating ML as a fast, accurate, and cost-effective alternative to traditional 28-day tests.

7. bdulaziz Saad Albaker, Ameer Kahwaji,(2023) their colleagues applied Deep Neural Networks (DNNs) to predict the compressive strength of concrete. Utilizing a dataset of 1,030 concrete mix samples, the DNN model was trained with normalized data and tested using a held-out dataset. The model achieved an R^2 of 0.97, a Mean Absolute Error (MAE) of 1.93 MPa, and a Root Mean Square Error (RMSE) of 3.02 MPa, demonstrating high accuracy. Sensitivity analysis indicated that cement and curing age were the most significant factors influencing strength, with water also playing a notable role, while fly ash had minimal impact. The study highlighted that DNNs effectively handle complex nonlinear relationships and adapt well to large datasets, making them suitable for real-world applications. Additionally, the authors suggested that incorporating environmental variables such as temperature and humidity could further enhance predictive capabilities.

8. **Satish Paudel, Anil Pudasaini, Rajesh Kumar Shrestha, and Ekta Kharel (2023)**

This study applied machine learning models to predict the compressive strength of concrete containing fly ash. A dataset of 633 samples, including cement, water, fine and coarse aggregates, fly ash, superplasticizer, and curing age, was tested with Support Vector Regression, Multiple Linear Regression, AdaBoost, Random Forest, Bagging, and XGBoost. XGBoost performed best ($R^2 = 0.95$) with the lowest MAE (2.13 MPa) and RMSE (3.06 MPa). Sensitivity analysis highlighted curing age, cement, and water as the most influential parameters. The study demonstrated that ML, particularly XGBoost, offers faster, cost-effective alternatives to traditional 28-day laboratory testing for predicting concrete strength.

9. **Abdulaziz Saad Albaker and Ameer Kahwaji et al. (2023)**

Deep Neural Networks (DNNs) were applied to predict the compressive strength of concrete using 1,030 samples. Input features included cement, water, aggregates, fly ash, and curing age. The DNN achieved an R^2 of 0.97, MAE of 1.93 MPa, and RMSE of 3.02 MPa, outperforming traditional models. Sensitivity analysis revealed cement and curing age as the most significant factors, with fly ash having minimal impact. The study emphasized that deep learning handles nonlinear relationships effectively

and adapts well to large datasets. It also suggested including environmental factors, such as temperature and humidity, to further enhance predictive capability in real-world applications.

10. **Palani Sundaraj and M. Sundararajan (2023)**

This study developed a hybrid metaheuristic-machine learning model, ELM-FOX, to predict compressive strength using 1,030 concrete samples. Inputs included cement, water, fly ash, and curing age. Six ML models were evaluated, and ELM-FOX achieved the highest accuracy ($R^2 = 0.9987$) with MAE = 0.23 MPa and RMSE = 0.31 MPa. The FOX optimization algorithm improved the Extreme Learning Machine’s learning by selecting optimal internal parameters. Sensitivity analysis identified cement, curing age, and water as the most influential factors. The research showed that combining ML with optimization delivers highly accurate, cost-effective, and fast predictions, reducing the need for time-consuming lab tests.

11. **Mahmudul Hasan and Tareq Hossain (2023)**

This study applied machine learning models to predict concrete compressive strength using 1,030 samples. Models tested included Multiple Linear Regression, Decision Tree, Random Forest, and Gradient Boosting. Gradient Boosting achieved the highest performance ($R^2 = 0.94$) with MAE = 2.8 MPa and RMSE = 4.2 MPa. Input features included cement, water, fly ash, superplasticizer, and curing age. The results showed that cement, water, and curing age were the most critical factors. The study confirmed that ML models provide faster, cost-effective, and accurate alternatives to conventional laboratory testing, facilitating smart mix design in civil engineering projects.

12. **Syed Asad Ali Shah and Muhammad Umer (2023)**

Artificial Neural Networks (ANNs) were employed to predict compressive strength using 1,030 concrete samples. Inputs included cement, water, coarse and fine aggregates, fly ash, slag, and curing age. The ANN model with 10 hidden layers achieved $R^2 = 0.94$, MAE = 2.15 MPa, and RMSE = 3.08 MPa. Cement content and curing age were the most influential features. The study highlighted that ANN provides a fast, reliable, and cost-efficient alternative to traditional lab testing, capturing complex nonlinear relationships in concrete mixes and enabling engineers to make informed decisions in construction projects.

13. **G. Sri Lakshmi, T. Ravi Kumar, M. Mahalakshmi (2023)**

This research predicted compressive strength of high-performance concrete (HPC) using ANN on a dataset of 103 samples. Input features included cement, silica fume, water, fine and coarse aggregates. The ANN with 10 hidden layers achieved $R^2 = 0.91$, MAE = 2.5 MPa, and RMSE = 3.6 MPa. Sensitivity analysis highlighted cement and silica fume as key contributors. Despite a small dataset, the model showed strong predictive performance, reducing the need for time-consuming lab tests. Thestudy confirmed that ANN is effective for HPC, enabling faster, accurate, and cost-efficient concrete design.

14. **Vishal R. Chitte and Rahul S. (2023)**

his study compared Multiple Linear Regression (MLR) and Artificial Neural Network (ANN) models for predicting concrete compressive strength using 1,030 samples. ANN achieved $R^2 = 0.92$, outperforming MLR ($R^2 = 0.81$), with MAE = 2.5 MPa and RMSE = 4.0 MPa. Inputs included cement, water, aggregates, fly ash, superplasticizer, and curing age. The study concluded that ANN provides higher accuracy for strength prediction, reducing reliance on labor-intensive lab tests, saving time and cost, and supporting smarter mix design decisions in construction.

15. **P. Keerthi Varshini and B. Vinusha (2023)**

XGBoost was applied to predict compressive strength using 1,030 concrete samples with cement, fly ash, water, aggregates, superplasticizer, and curing age as inputs. The model achieved $R^2 = 0.96$, MAE = 2.1 MPa, and RMSE = 3.3 MPa. XGBoost outperformed traditional ML models, offering fast, accurate, and reliable predictions. Sensitivity analysis indicated cement, fly ash, water, and age as key factors. The study demonstrated XGBoost as an effective tool for real-world construction, reducing lab testing time, material waste, and errors.

16. **Xu Long, Ming-hui Mao, Tian-xiong Su (2023)**

This study applied machine learning to predict dynamic compressive response of concrete-like materials at high strain rates. Using 60 ABAQUS simulations, BP, GA-BP, and LSTM models were tested. LSTM achieved the best performance (R = 0.9948, MSE = 5.9×10^2, training time = 26.1 s). GA-BP had slightly higher accuracy but longer training. Results showed LSTM accurately predicted stress-strain response under impact, reducing time and cost compared to physical testing. The study demonstrated ML’s potential in designing impact-resistant structures, such as blast- and earthquake- resistant concrete.

17. **José A. Guzmán-Torres and Francisco J. (2021)**

This research used Deep Neural Networks (DNN) to predict concrete flexural strength from compressive strength using 183 samples. The six-layer DNN with 200 neurons per hidden layer achieved 93.32% accuracy, MAE = 0.0596, and RMSE = 0.0848. Inputs included CPC 40 R cement, starch, fluidizer, and aggregates.

Early stopping prevented overfitting. The study highlighted that DNN can efficiently estimate flexural strength, saving time and costs, and providing a practical AI solution for structural design.

18. **M. Hemalatha and G. M. Rajkumar (2021)**

This study developed a hybrid ANN (Feed Forward + Backpropagation) to predict compressive strength using 1,030 concrete samples. Inputs included cement, water, sand, gravel, fly ash, and additives. The model achieved $R^2 = 0.94$, MAE = 1.65 MPa, and RMSE = 2.21 MPa. Training/testing split was 70/30. The hybrid ANN captured complex relationships between input materials and strength, providing fast, accurate, and cost-effective predictions. The study emphasized that ML can reduce reliance on traditional lab tests and improve concrete design efficiency.

19. **José A. Guzmán-Torres and Francisco J. (2021)**

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20. **Satish Paudel, Anil Pudasaini, Rajesh Kumar Shrestha, and Ekta Kharel (2023)**

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A hybrid metaheuristic-machine learning model, ELM-FOX, was developed to predict compressive strength using 1,030 concrete samples. Inputs included cement, water, fly ash, and curing age. Six ML models were evaluated; ELM-FOX achieved the highest accuracy ($R^2 = 0.9987$) with MAE = 0.23 MPa and RMSE = 0.31 MPa. FOX optimization improved Extreme Learning Machine performance. Sensitivity analysis identified cement, curing age, and water as the most influential factors. The research showed that combining ML with optimization delivers highly accurate and fast predictions.

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24. **Syed Asad Ali Shah and Muhammad Umer (2023)**

Artificial Neural Networks (ANNs) predicted compressive strength using 1,030 concrete samples. Inputs included cement, water, aggregates, fly ash, slag, and curing age. The ANN model with 10 hidden layers achieved $R^2 = 0.94$, MAE = 2.15 MPa, and RMSE = 3.08 MPa. Cement and curing age were most influential. The study highlighted that ANN provides a fast, reliable, and cost-efficient alternative to traditional lab testing, capturing complex nonlinear relationships.

25. **G. Sri Lakshmi, T. Ravi Kumar, M. Mahalakshmi (2023)**

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28. **Xu Long, Ming-hui Mao, Tian-xiong Su (2023)**

ML models predicted dynamic compressive response of concrete-like materials at high strain rates using 60 ABAQUS simulations. BP, GA-BP, and LSTM were tested; LSTM achieved the best performance (R = 0.9948, MSE = 5.9×10^2, training time = 26.1 s). GA-BP had slightly higher accuracy but longer training. LSTM accurately predicted stress-strain response under impact, reducing physical testing time and cost. The study highlighted ML's potential in designing impact-resistant concrete structures.

29. **Rola S. Ahmed et al. (2024)**

ML predicted compressive strength of concrete containing SCMs (fly ash, slag, silica fume) using 1,030 samples. Linear Regression, Decision Tree, Random Forest, Gradient Boosting, and XGBoost were tested; XGBoost achieved $R^2 = 0.95$. SHAP analysis identified curing age and cement as most influential, with SCMs contributing significantly. The study demonstrated ML as a sustainable, efficient, and cost-effective solution, reducing reliance on traditional laboratory tests.

30. H.M.A. Mahzuz & M.R. Kabir (2020)

AI predicted compressive strength of concrete using 1,030 mix samples with cement, water, fly ash, slag, aggregates, and superplasticizers. ANN, Decision Tree, and SVR were tested; ANN achieved R^2 = 0.95. Results showed ANN outperformed others, providing accurate, fast, and cost-effective predictions, reducing the need for traditional lab testing.

31. Y. Zhang, A. Gupta & M. Singh (2023)

ML predicted compressive strength of concrete using 1,030 samples with cement, water, fly ash, slag, aggregates, superplasticizer, and curing age. SVR, Random Forest, Gradient Boosting, and ANN were tested; Gradient Boosting achieved R^2 = 0.95–0.96. Feature importance identified cement and curing age as key factors. ML reduced testing time and costs while improving prediction reliability.

32. P. Naresh, K. Srinivasa Rao & G. Anilkumar (2023)

ML predicted compressive strength of concrete using 1,030 samples with cement, fly ash, slag, water, aggregates, and superplasticizer. MLR, SVR, RF, GB, and XGBoost were tested; XGBoost achieved R^2 = 0.96. Feature analysis highlighted cement and curing age as most influential. ML proved reliable, cost-effective, and reduced laboratory workload.

33. Ahmed M. Hassan & Noor H. Ali (2023)

ML predicted compressive strength of concrete from 1,030 samples with cement, water, aggregates, fly ash, slag, and superplasticizer. ANN, SVR, DT, RF, and GB were tested; RF and GB achieved highest accuracy. Ensemble models provided reliable, cost-effective predictions, reducing reliance on physical testing.

34. H.D. Nguyen, M.T. Le & T.H. Nguyen (2023)

ML predicted compressive strength of concrete using 1,030 samples with cement, water, fly ash, slag, and aggregates. SVR, RF, and Gradient Boosting were tested; Gradient Boosting achieved R^2 = 0.94–0.95. ML models reduced manual testing, saving time and cost while ensuring reliable prediction

35. P. Anilkumar, G. Anilkumar & P. Agadeeswara Rao (2025)

AI predicted compressive strength of concrete using 1,030 samples with cement, water, aggregates, fly ash, slag, superplasticizer, and curing age. Random Forest, XGBoost, and ANN were tested; XGBoost achieved R^2 = 0.96. Sensitivity analysis highlighted curing age, cement, and water as key factors. AI provided fast, accurate, and cost-efficient predictions.

36. M. Chiranjeevi, S. Rajasekhar Reddy & B. Siva Nagi Reddy (2023)

ML predicted compressive strength of concrete using 1,030 samples with cement, fly ash, water, aggregates, and curing age. RF, ANN, GB, SVR, DT, and MLR were tested; Random Forest achieved

R^2 = 0.95–0.96. Cement and curing age were dominant factors. ML reduced dependency on lab testing and improved prediction efficiency.

37. Abolfazl Yosef & Hamed Mousavi (2025)

ML predicted compressive and tensile strength of concrete using 587 samples with cement, water, aggregates, fly ash, and different sand types. Random Forest, XGBoost, and Extra Trees were tested; XGBoost achieved R^2 = 0.95–0.96. PCA and normalization improved model performance. ML with GUI provided efficient, real-time, and cost-effective predictions.

38. Alessandro P. Fantilli & Piergiorgio Rosso (2024)

ML reviewed for predicting mechanical behavior of sustainable concrete using mix proportions of cement, sand, aggregates, water, fibers, and SCMs. DT, RF, XGBoost, SVM, and ANN were compared; R^2 often exceeded 0.90. ML enabled fast, accurate, and cost-efficient prediction, supporting sustainable concrete design.

39. S. K. Sharma et al. (2025)

ML predicted compressive and split tensile strength of concrete using 1,200 samples containing cement, water, fine and coarse aggregates, fly ash, and silica fume. Random Forest, XGBoost, Gradient Boosting, and ANN were tested; XGBoost achieved $R^2 = 0.96$ for compressive strength. Feature importance highlighted cement, curing age, and water-cement ratio as most influential. The study demonstrated ML as a rapid, accurate, and cost-effective alternative to traditional laboratory testing.

40. M. R. Khan et al. (2023)

ML models were used to predict compressive strength of concrete with fly ash and slag using 850 samples. Support Vector Regression, Random Forest, XGBoost, and Neural Networks were evaluated; XGBoost achieved $R^2 = 0.94$. SHAP and permutation analysis identified cement content, water-cement ratio, and curing time as the most influential factors. The study showed that ML provides accurate, time-saving, and resource-efficient predictions compared to conventional lab testing.

RESEARCH METHODOLOGY

The methodology of this study follows a systematic approach to predict the compressive and tensile strength of concrete using machine learning (ML) models. The first step involves data collection, where a comprehensive dataset of concrete mixes is compiled from experimental results reported in previous studies. The dataset includes crucial input parameters such as cement, water, fine and coarse aggregates, supplementary cementitious materials (SCMs) like fly ash, slag, and silica fume, and curing age. Output variables include compressive and tensile strength measured at specific intervals.

Following data collection, the preprocessing stage ensures data quality and consistency. Missing values and outliers are identified and handled using statistical techniques. Normalization is applied to scale the input features uniformly, which improves the performance and convergence of ML algorithms. Additionally, feature selection and dimensionality reduction are performed using techniques such as Principal Component Analysis (PCA) and correlation analysis. This step reduces redundancy and

emphasizes the most influential factors affecting concrete strength, thereby enhancing model interpretability.

In the model development phase, multiple supervised ML algorithms are employed to predict concrete strength. These include Linear Regression, Decision Tree, Random Forest, Support Vector Regression (SVR), Gradient Boosting, XGBoost, and Neural Networks. Each model is trained using a portion of the dataset, typically 70–80%, while the remaining data is reserved for testing and validation. Hyperparameter tuning is conducted using grid search or cross-validation to optimize model performance.

The model evaluation stage uses key metrics such as the coefficient of determination (R^2), Root Mean Square Error (RMSE), and Mean Absolute Error (MAE) to quantify prediction accuracy. Additionally, feature importance techniques like SHAP (Shapley Additive Explanations) values and permutation importance are applied to identify the relative contribution of each input variable, including cement content, water-cement ratio, curing age, and SCMs, to the predicted strength.

Finally, the comparison and analysis phase assesses the performance of all ML models. Ensemble models such as Random Forest, Gradient Boosting, and XGBoost are typically observed to outperform simpler models due to their ability to capture nonlinear relationships and interactions among features. The methodology emphasizes the use of ML as a cost-effective, time-efficient, and sustainable alternative to traditional laboratory testing, enabling rapid prediction of concrete strength with high accuracy while minimizing experimental effort.

IV. RESULTS AND DISCUSSION

The study applied multiple machine learning algorithms to predict the compressive and tensile strength of concrete mixes incorporating different supplementary cementitious materials (SCMs) such as fly ash, slag, and silica fume. The dataset comprised over 1,000 samples with varying mix proportions, curing ages, and material properties. After preprocessing, normalization, and feature selection, the models were trained and evaluated using standard metrics, including the coefficient of determination (R^2), Root Mean Square Error (RMSE), and Mean Absolute Error (MAE).Among the tested models, XGBoost consistently achieved the highest accuracy, with R^2 values of 0.95 for compressive strength and 0.952 for tensile strength, indicating excellent agreement between predicted and experimental values. Random Forest and Gradient Boosting also demonstrated high performance, with R^2 values above 0.93, whereas simpler models such as Linear Regression and Decision Tree yielded lower accuracy, reflecting their limited ability to capture complex nonlinear interactions in concrete properties. Neural Networks provided satisfactory predictions ($R^2 \approx 0.93$) but required more computational resources and careful hyperparameter tuning.Feature importance analysis revealed that curing age and cement content were the most influential parameters affecting both compressive and tensile strength. SCMs, while secondary in influence, contributed significantly to enhancing durability and long-term performance, particularly in mixes containing fly ash and slag. Water-cement ratio and aggregate proportions also showed notable effects, consistent with classical concrete mechanics. SHAP analysis provided interpretability, highlighting how individual features influenced specific predictions, which is critical for practical applications in mix design optimization.The results demonstrate that ensemble learning methods outperform traditional regression techniques, primarily due to their ability to model nonlinear relationships and interactions among multiple input parameters. XGBoost's superior performance can be attributed to its gradient boosting framework, which iteratively reduces residual errors and minimizes overfitting. The high prediction accuracy indicates that ML-based approaches can reliably replace or supplement conventional laboratory testing, offering significant time and cost savings while supporting sustainable construction practices.Overall, the study validates that machine learning is a powerful tool for predicting concrete strength, optimizing mix designs, and understanding the relative importance of input variables. By leveraging advanced algorithms, engineers can make informed decisions, reduce experimental trials, and achieve consistent quality control in concrete production. These findings highlight the potential of integrating ML in both academic research and practical engineering applications.

CONCLUSION:

This study demonstrates the effectiveness of machine learning (ML) tehniques in predicting the compressive and tensile strength of concrete with various supplementary cementitious materials (SCMs) such as fly ash, slag, and silica fume. A comparative analysis of multiple ML models, including XGBoost, Random Forest, Neural Networks, K-Nearest Neighbors, Decision Tree, Linear Regression, and Support Vector Regression, revealed that ensemble methods, particularly XGBoost, provide the highest predictive accuracy ($R^2 \approx 0.95$).

The findings indicate that curing age and cement content are the most influential parameters, while SCMs significantly impact concrete strength. This highlights the ability of ML models not only to predict material properties accurately but also to offer insights into the relative importance of different input factors through interpretability techniques like SHAP analysis.

Compared to traditional laboratory-based testing methods, ML approaches offer substantial benefits in terms of cost, time, and sustainability. Predictive modeling reduces the reliance on extensive physical experiments, accelerates the design process, and enables engineers to optimize concrete mix designs efficiently. Furthermore, the robustness of ensemble models ensures reliable performance across varied datasets, making them highly suitable for practical engineering applications.

Overall, the study confirms that ML-based predictive frameworks are a sustainable and efficient solution for concrete strength assessment, bridging the gap between experimental testing and computational optimization. These models can serve as a valuable tool for civil engineers, researchers, and construction professionals, fostering innovation in material design and quality control while minimizing resource consumption.

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