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Predictive modeling of precast concrete compressive strength using artificial neural networks in a data-driven engineering framework: enhancing structural durability and sustainable construction

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Abstract: This study addresses the critical need for sustainable construction by developing a predictive model for the compressive strength of Grade C40 precast concrete using Artificial Neural Networks (ANN). The purpose of the research is to enhance construction efficiency, reduce material waste, and promote sustainability. Employing a dataset of 1503 entries, the methodology involved analyzing 16 variables—such as water-to-cement ratio, aggregate properties, and curing conditions—to account for the complex interactions affecting concrete strength. The ANN model was chosen for its superior ability to uncover intricate, nonlinear relationships between input parameters and outputs, outperforming other machine learning models like XGBoost and Gradient Boosting in capturing these complexities. Key findings highlight the significant influence of factors like ambient and curing temperatures, water content, and mix proportions, with Gradient Boosting achieving the highest prediction accuracy for both 7- and 28-day compressive strengths (R^2 scores of 0.92 and 0.90, respectively). The ANN model contributed nuanced insights into these interactions, making it indispensable for understanding concrete behavior under varying conditions. Practical implications of the research are profound: by minimizing reliance on trial-and-error methods, this approach not only reduces costs and time but also supports the development of optimized concrete mixes, thereby decreasing carbon emissions and material waste. The findings align with the goals of sustainable construction and climate resilience, enabling a shift toward data-driven, resource-efficient practices. Furthermore, this model empowers local construction industries to adopt autonomous, AI-driven frameworks, fostering both technological self-reliance and sustainable infrastructure development.

Keywords: *AI - Artificial intelligence, ANN - Artificial neural network, Climate change, Deep learning, Environmental sustainability, ML - Machine learning, NDT - Non-destructive testing, Precast concrete, Sustainable construction.*

1. Introduction

The construction industry stands at the crossroads of technological innovation and traditional methods, facing an increasing demand for sustainable construction, this study explores the use of advanced machine learning models to accurately predict the compressive strength of Grade C40 concrete. By validating with real-world environmental factors, such as temperature and curing conditions, this research seeks to optimize material use and reduce carbon emissions, aligning with SDG 11 (Sustainable Cities and Communities). AI-driven solutions that enable construction companies to maintain control over their data and technology infrastructure. This framework not only enhances resource efficiency but also promotes resilient and sustainable infrastructure, advancing global sustainability goals, cost-efficient, and structurally sound practices. As the urgency for climate-resilient infrastructure grows, it is vital for conventional construction techniques in Nigeria to evolve through the integration of modern technology. Leveraging advanced tools can improve construction quality, optimize resource usages such as time, cost, labour, and materials—and support environmentally sustainable outcomes. This research delves into predictive modeling of precast concrete's compressive

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strength using machine learning, highlighting the associated challenges, significance, purpose, scope, limitations, and key terminology [1].

Concrete, a cornerstone of global construction for nearly two centuries, remains indispensable due to its cost-effectiveness, abundant raw materials, environmental adaptability, and strength. Its widespread use—second only to water—reflects its critical role in infrastructure, with global concrete consumption surpassing that of steel, wood, plastics, and aluminum combined [2]. Concrete mix designs continue to evolve, especially as new materials and sustainability-driven innovations emerge. However, the traditional trial-and-error approach to developing and testing concrete mixes is both time-intensive and resource-draining. This calls for the development of predictive models that can estimate concrete strength based on mixed designs. These models minimize the need for extensive physical testing, reducing material waste and energy consumption, thereby contributing to the economic and environmental sustainability of construction projects.

The integration of machine learning into concrete mix design has opened new avenues for enhancing construction efficiency and accuracy. Machine learning's ability to predict the compressive strength of concrete, based on a variety of factors, can revolutionize the construction industry by offering faster, more precise, and economically viable solutions. By analysing complex datasets, these models can identify patterns that influence concrete strength, accounting for variables such as aggregate quality, cement composition, curing temperatures, and water-to-cement ratios—factors increasingly impacted by climate change. This data-driven approach allows for more refined concrete mixtures, optimizing material use while lowering the carbon footprint of construction.

In practice, concrete strength is typically assessed at intervals of 7, 14, and 28 days. Machine learning models can predict strength at these intervals based on initial mix parameters, reducing the risk of overdesign, material wastage, and project delays. Waste reduction is especially critical for sustainable construction, as excessive use of resources not only increases costs but also contributes to environmental degradation. By accumulating large datasets and refining these predictive models, construction companies can customize their concrete mix designs based on local material availability, such as stone dust, sand, and aggregates, rather than relying solely on standardized formulas. This flexibility promotes the efficient use of materials, minimizing the environmental impact associated with cement production, which is one of the largest contributors to global CO_2 emissions.

Precast concrete offers a range of sustainability benefits, including reduced construction times, improved quality control, and environmentally friendly production methods. However, to fully leverage these advantages, accurately predicting the compressive strength of precast concrete is essential. A reliable predictive model aids in the development of optimized mix designs that reduce raw material usage, enhance structural resilience, and contribute to sustainable building practices. Such models also support the broader goals of mitigating the construction industry's environmental impact, addressing climate change, and advancing sustainable infrastructure development [3].

As the construction industry adapts to technological advancements, this research aligns with the trend of embracing digital transformation and data-driven decision-making. It serves as a bridge between traditional construction methods and the rapidly emerging field of construction informatics, which integrates computational techniques and sustainability principles into modern building processes. By adopting these predictive models, the construction sector can move towards more sustainable, economically viable, and climate-resilient practices, ensuring a better balance between technological progress and environmental stewardship.

This rewrite emphasizes sustainability, economic factors, and the impact of climate change while maintaining the technical details and objectives of your original text. It integrates themes of resource optimization, waste reduction, and environmental impact to enhance the relevance of machine learning in sustainable construction.

1.1. Statement of the Research Problem

Research problems and questions that were investigated.

- A need to address critical construction uncertainty.
- To enhance construction sustainability and safety.

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- To bridge the gap to a data driven construction era.

Addressing Critical Construction Uncertainty: This study aims to resolve the longstanding challenge of accurately predicting the compressive strength of precast concrete. Variability in concrete mixes, curing conditions, and design parameters introduces uncertainty that this predictive model will address.

Bridge to a Data-Driven Construction Era: This research underscores the transformation of construction practices, merging tradition with technology. It holds the potential to set a new industry standard by leveraging data and simulations to meet the demands of modern construction.

1.2. Aim

To develop a comprehensive predictive modeling of compressive strength of precast concrete using machine learning (ANN) in a data-driven engineering framework to enhance structural durability and sustainable construction.

1.3. Significance of the Study

This work on predictive modeling of precast concrete features strength using machine learning has Profound and wide-ranging consequences, embracing numerous elements of the construction industry and beyond. The significance of this study lies in its mission to address the longstanding challenge in construction by accurately predicting the compressive strength of precast concrete. This challenge stems from the inherent variability in concrete mixes, curing conditions, and design parameters, which introduce uncertainty into construction processes. By deploying an innovative methodology that uses machine learning, this research offers a forward-thinking approach to predictive modeling, custom-tailored to the unique complexities of precast concrete. The commitment to data-driven precision not only enhances construction efficiency but also promotes sustainability by reducing over-design and material waste. Furthermore, this project signifies a pivotal bridge to a data-driven era in construction. It reflects the transformation of construction practices, blending tradition with technology, and has the potential to set a new industry standard. By leveraging data analysis, this study is poised to meet the demands of modern construction, ensuring structural safety, and fostering more efficient, sustainable, and precise construction practices.

1.4. Review

Attempts at predicting concrete strength in pre-cast concrete using machine learning approaches have faced difficulties, owing largely to the delicate interaction of components (sand, cement, gravel and water), and these components may have different physical or chemical properties and complex manufacturing procedures inherent in pre-cast concrete manufacture. Even though there are only a few academics working in this field, present studies mostly focus on plain concrete, ignoring the examination of unknown data sources for estimating concrete compressive strength. To fill this need, this study will examine the effectiveness of using data from precisely specified sources (primary dataset), including the compressive strength of plain, with the goal of authenticating and refining the prediction output.

Artificial intelligence algorithms to accurately estimate the strength of concrete. Recently, a boost in machine-learning algorithm involvement has been witnessed in various civil engineering applications, such as smart cities, green buildings, high-performance concrete, etc. The high volume of the experimental databank in structural engineering helps the structural engineers to build sophisticated algorithms that learn from the experimental database, while satisfying a certain statistical performance to predict the desired outputs for certain problem input parameters accurately [4].

[5] ML (Machine Learning) techniques have often been used to model structural engineering problems. They also extend to assessments in the structural reliability realm, such as downscaling the computing effort of stochastic simulations and performance evaluating of structural systems of high complexity. Some of these studies have delivered interesting results on the application of ML and other soft computing techniques to model concrete engineering problems.

Below are the diverse Machine Learning Models (MLD), where algorithms and data converge to empower systems with the ability to learn and make predictions or decisions

- Linear Regression: Linear regression is a supervised learning algorithm used for regression tasks. Its objective is to predict a continuous output variable based on one or more input features. The algorithm assumes a linear relationship between the input features and the output variable. It finds the best-fitting line that minimizes the sum of squared differences between the predicted and actual values [6].
- Decision trees are versatile models applicable to both classification and regression tasks. They represent a tree-like structure where each internal node signifies a decision based on an attribute, branches represent decision outcomes, and leaves denote final predicted outputs. Decision trees are known for their interpretability and ability to handle non-linear relationships [7].
- Random Forest is an ensemble learning method that builds multiple decision trees and combines their predictions. Each tree is trained on a random subset of the training data, providing diversity. The final prediction is obtained by aggregating the outputs of individual trees. Random Forests enhance accuracy and robustness and are resilient to overfitting [8].
- K-Nearest Neighbours (KNN): KNN is an instance-based learning algorithm for classification and regression tasks. It makes predictions based on the majority class or average value of the k-nearest data points in the feature space. While simple and intuitive, KNN can be computationally expensive for large datasets due to its lazy learning approach.

Neural networks, a core component of deep learning, consist of layers of interconnected nodes capable of learning complex patterns. They excel in various tasks, including image recognition and natural language processing. Deep neural networks, with multiple layers, have proven successful in solving intricate problems by automatically extracting hierarchical features.

Gradient Boosting Machines (e.g., XGBoost, LightGBM): Gradient Boosting is an ensemble learning method that builds a series of weak learners (typically decision trees) sequentially. Each tree corrects errors of the previous one, and their predictions are combined to form a robust model. Algorithms like XGBoost and LightGBM are popular implementations known for their high predictive accuracy and efficiency.

This in-depth review focuses on the important topic of predicting concrete compressive strength for industrial applications, putting light on this domain's critical relevance. It highlights the limits of previous investigations, which were mostly due to their dependence on small-scale, laboratory-derived datasets. To overcome these constraints, this paper suggests and promotes the use of statistical and machine learning models, with a focus on compressive strength prediction using significantly bigger datasets, frequently reaching 10,000 observations derived from job-site data. This transition to large-scale, real-world data intends to address the drawbacks of previous studies, highlighting the potential gains feasible through this new technique in the field of concrete compressive strength prediction.[9].

The study addresses the difficult challenge of estimating concrete compressive strength by considering variables such as aggregate size, water-cement ratio, and the addition of industrial waste such as fly ash. It describes how to use machine learning algorithms to estimate compressive strength using critical input factors like as cement, fine aggregate, coarse aggregates, fly ash, water content, superplasticizer %, and curing days.[10].

The argument over concrete mixture design optimization falls into its inspiration, which is motivated by the need to achieve a wide range of performance requirements, including cost-effectiveness, workability, mechanical properties, durability, and sustainability. It explains how design decision-making has shifted from obtaining certain tangible attributes to the more complex skill of modifying and enhancing these properties using computer tools and methodologies [11].

Investigate the use of Machine Learning (ML) models to forecast the compressive strength of Self-Compacting Concrete (SCC) with Supplementary Cementitious Materials (SCMs) and Recycled Coarse Aggregate (RCA). Traditional experimental techniques to forecasting concrete strength are inefficient, time-consuming, and expensive, according to the study. The research provides a core understanding of SCC properties critical for predictive modeling by building a complete database of 337 samples with 10 attributes, including varied material compositions and curing ages. This technique is consistent with the conceptual framework in that it investigates ML's capacity to overcome limits in forecasting concrete strength in the context of complex material interactions inside SCC.[12].

The research focuses on the transition from traditional empirical and statistical models to the examination of Machine Learning (ML) models for predicting concrete mechanical characteristics. The constraints of previous models, which require substantial experimental labour and might yield erroneous findings for complicated concrete mixtures, have spurred this transition. The study serves as a conceptual foundation by emphasizing the necessity for different techniques to properly estimate concrete strength [13].

The paper develops a conceptual framework by questioning the widespread reliance on laboratory data to predict concrete performance. The study advocates a move toward leveraging industrial data for ML model development, highlighting the uncertainties in industrial contexts and significant differences between laboratory and industrial concrete. This conceptual change reflects the study's primary goal of investigating the use of ML models specifically on industrially produced concrete, while admitting the limits of previous research that relied mostly on laboratory-derived models [14].

[15] The conceptual framework of the study combines NDT methods with ML algorithms to forecast concrete strength, challenging the conventional dependence on time-consuming and costly laboratory procedures. The study proposes a paradigm shift toward time-efficient and cost-effective prediction models for concrete strength evaluation by highlighting the utilization of NDT data—Schmidt hardness, ultrasonic velocities—along with curing durations and moisture conditions.

Conceptually, the study focuses on leveraging machine learning, specifically ANN, to establish a predictive model for concrete compressive strength. It emphasizes the utilization of previously published data and the selection of key input variables to accurately predict the 28-day compressive strength of concrete [16].

To verify the machine learning models, the study uses a dataset of 638 RAC combinations. It focuses on the actual use and efficacy of ensemble machine learning algorithms in estimating RAC compressive and flexural strengths. The empirical component emphasizes the models' precision and accuracy in estimating RAC strengths [17].

[18] This paper focuses on the impact of training data amount on the accuracy of Machine Learning (ML) models, proposing a unique strategy for decreasing bias and improving predictions. It underlines the critical relevance of training data size in improving the precision of ML models by promoting the use of separate datasets for training and testing.

After an extensive review of multiple papers exploring the intersection of machine learning for determining the characteristic compressive strength of precast concrete, the research findings are notably positive. While the literature generally showcases encouraging results in predicting concrete strength, there are discernible gaps. Many papers rely on datasets from external sources, posing uncertainties about real-world applicability. Some utilize industrial datasets but face limitations in training due to a restricted amount of input data, while others with extensive datasets fail to adequately represent the diverse range of concrete grades.

Notably, authors like [19] and [20] employ various machine learning models, including ANN, XGBoost, and KNN, yet often draw data from multiple external sources. On the other hand, contributions from [21].

In contrast to existing studies, the study emphasis remains on a controlled environment, concentrating on precast concrete where vigilant monitoring and proper curing are ensured post-production before delivery. A significant observation from the literature is the frequent use and promising results of Artificial Neural Networks (ANN), which plan to adapt in this study. Ultimately, to enhance the robustness of the algorithm, I intend to validate the ML predicted result with real life concrete test. This holistic approach aims to contribute comprehensively to the field, offering insights into both theoretical predictions and practical applications in the realm of concrete strength determination.

1.5. Research Design and Methodology

This study employs a predictive modeling approach to assess precast concrete's compressive strength using machine learning. Data is gathered from a VIP company specializing in concrete production. Essential parameters such as sand and water content, aggregate compositions, cube sample weight, water-cement ratio, and additives are collected, focusing on 7- and 28-day strength values.

Machine learning algorithms, notably Artificial Neural Networks (ANN), analyse this dataset to predict compressive strength. The methodology includes data cleaning with a customized Excel template, filtering incomplete or erroneous entries to ensure a robust dataset. Site observations and consultations with industry experts provide qualitative insights.

ANN's strength lies in its ability to learn from empirical data, refining predictions over time. Validation involves testing the model against actual data. The study integrates both quantitative (algorithm analysis) and qualitative (industry observations) methods for comprehensive research into precast concrete characteristics.

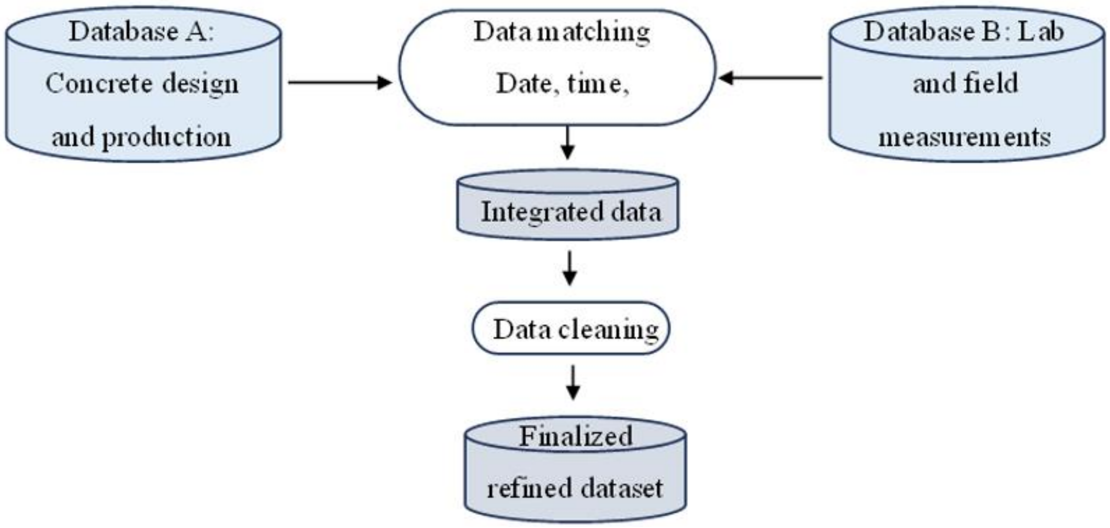

Figure 1.
Flowchart of data collection and processing.

2. Results

The dataset collected has several missing values, in columns of high correspondence to the output, which was then fixed using K-Nearest Neighbours (KNN) imputation, to fill in the gaps within the dataset. KNN is a non-parametric algorithm used or classification and regression tasks, and its prediction is based on the similarity of data points. For a given data point xq, find its K nearest neighbours from the training set based on a distance metric

$$d\,(x_i, x_q,)\ (2.1)$$

For regression: y1, y2, …, yk are the output values of the K nearest neighbours, then the predicted output yq for xq was calculated as the mean and weighted mean of

$$y_1,\ y_2, \dots ,\ y_k.\ (2.2).$$

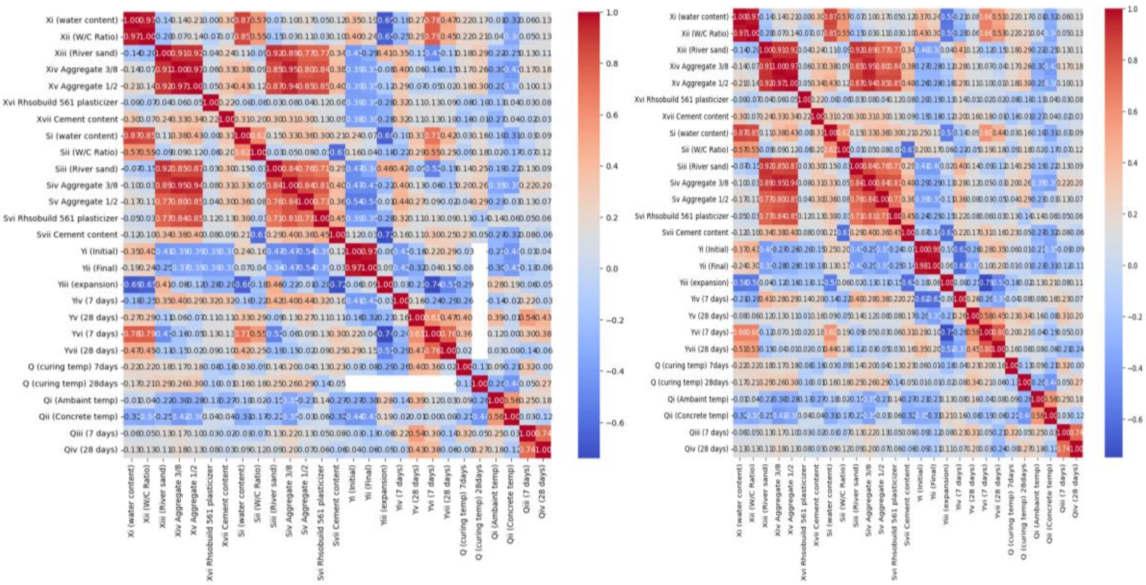

Figure 2.
Correlation matrix using heat map of independent variables and dependent variables before and after filling in missing values.

After using KNN model to input missing, a check was done for the correlation again to make sure there was no risk having collinearity or multi-collinearity.

Table 1.
Statical analysis of 1503 dataset.

	Unit	Mean	Std.	Min.	25%	50%	75%	Max.
Water	(Kg/m^3)	148.76	12.21	122.00	142.64	149.17	157.79	169.96
W/C ratio		0.35	0.03	0.28	0.33	0.35	0.37	0.40
River sand	(Kg/m^3)	840.43	23.63	801.89	829.79	840.31	848.87	998.22
Aggregate 3/8”	(Kg/m^3)	464.72	12.87	451.00	457.47	465.42	469.72	557.11
Aggregate ½”	(Kg/m^3)	553.62	15.34	540.57	542.96	554.53	558.86	665.33
Plasticizer	(Kg/m^3)	4.00	0.01	4.00	4.00	4.00	4.00	4.13
Cement	(Kg/m^3)	428.32	8.28	375.56	428.09	430.00	431.75	444.40
7-day curing	($°C$)	18.55	0.92	17.00	18.00	18.00	19.20	20.00
28-day curing	($°C$)	18.77	0.97	17.00	18.00	18.70	20.00	22.00
Ambient	($°C$)	29.23	3.09	24.00	26.75	29.10	31.80	35.00
Concrete	($°C$)	30.48	1.31	28.00	30.00	30.00	31.00	34.00
f_c 7 days	N/mm^2	42.59	3.11	31.00	40.00	43.00	44.20	50.00
f_c 28 days	N/mm^2	50.91	3.60	39.00	49.00	52.00	53.00	60.00

2.1. Model Selection

We evaluated several models and utilized comparative analysis to identify the most optimal model architecture, XGBoost, Support Vector Machine (SVM), Gradient Boosting, Linear Regression, and Random Forest. Using cross-validation and performance metrics such as Mean Absolute Error (MAE) and root mean square error (RMSE), evaluate each candidate model's ability to accurately predict 7-day and 28-day compressive strength,

- Mean Absolute Error – Mean Absolute Error (MAE) is the mean of the distance between the target variable and predicted value. MAE can be computed by
  $$\text{MAE} = \frac{\sum_{i=1}^{n} \quad |y_i - x_i|}{n}$$
  where y^i is the predicted value for training example i, yi is the target variable for training example i.
- Root-mean-square (RMSE) - The sum of the squared differences between the predicted and observed values is divided by the number of observations, and the square root of the result is taken to yield the RMSE.

$$RMSE \ = \sqrt{\sum_{i=1}^{n} \quad \frac{(\, \widehat{y_\iota} \ - \ y_i)^2}{n}}$$

where $\widehat{y_\iota}$ are predicted values, y_i are observed values, and n is the number of observations

2.1.1. XGBoost (Extreme Gradient Boosting):

$$\text{Obj} = \sum_{i=1}^{n} \quad L(x_i, y_i) + \sum_{k=1}^{K} \quad \Omega(f_k) \ (4.3)$$

Where Lxi,yi is the loss function measuring the difference between the true label xi and the predicted label yi, Ω (fk) is the regularization term, which penalizes the complexity of individual trees to prevent overfitting, fk represents the k-th tree in the ensemble.

Model prediction is the sum of predictions from all trees

$$\text{y} = \sum_{k=1}^{K} \quad \eta \ \cdot f_k(x) \ (4.4)$$

2.1.2. Support Vector Machine (SVM):

Given training data (x_i, y_i) where $(x_i,)$ is the feature vector and $(y_i,)$ is the class label

$$(y_i \ \in \{-1, 1\}) \ (4.5)$$

$$min_{w,b} \ \frac{1}{2} \ ||w||^2 \ (4.6)$$

Subject to: $y_i \ (w \ \cdot \ x_i + b) \ \geq 1$ for i = 1,2, …, n

The decision function is

$$\text{f(x)} = \text{w} \cdot \text{x} + \text{b} \ (4.7)$$

2.1.3. Gradient Boosting

At each iteration m, the model fits a weak learner to the negative gradient of the loss function:

$$h_m(x) = \arg min_h \sum_{m=1}^{M} \quad \left(\frac{\eth L(xi, yi)}{\eth yi}\right)]^2 \ (4.8)$$

Final prediction:

$$\text{y} = \sum_{m=1}^{M} \quad \eta \ \cdot h_m(x) \ (4.9)$$

2.1.4. Linear Regression

Model equation:

$$\text{y} = \beta_0 + \ \beta_1 x_1 + \ \epsilon \ (4.10)$$

Where y is the dependent variable, x_1 is the independent variable, β_0 is the intercept, β_1 is the coefficient for x_1, and ϵ is the error term.

Table 2.
Average results of performance evaluation of ML of 7-day f_c.

	Model	R^2	MAE	RMSE	MSE
0	GradientBoosingRegressor	0.920	0.53	0.93	0.87
1	SVR	-0.061	2.31	3.39	11.52
2	XGBRFRegressor	0.855	0.84	1.26	1.58
3	LinearRegression	0.643	1.56	1.97	3.88
4	RandomForestRegressor	0.897	0.72	1.06	1.12
5	ANN	0.795	1.64	2.35	5.52

Table 3.
Average results of performance evaluation of ML of 28-day f_c.

	Model	R^2	MAE	RMSE	MSE
0	GradientBoosingRegressor	0.908	0.76	1.18	1.39
1	SVR	-0.165	3.10	4.20	17.66
2	XGBRFRegressor	0.903	0.86	1.21	1.46
3	LinearRegression	0.766	1.41	1.88	3.55
4	RandomForestRegressor	0.891	0.83	1.29	1.65
5	ANN	0.198	1.37	1.78	3.19

2.1.5. Neural Network

Neural networks can implicitly detect complex nonlinear relationships between dependent and independent variables and the ability to detect all possible interactions between predictor variables. The machine learning models above performed quite alright, but to extract more nuanced relationships of each of the dependent variables, a neural network with 8 hidden layers, and 2 output layers was used to predict 7 days and 28 days and was trained over 1000 epochs.

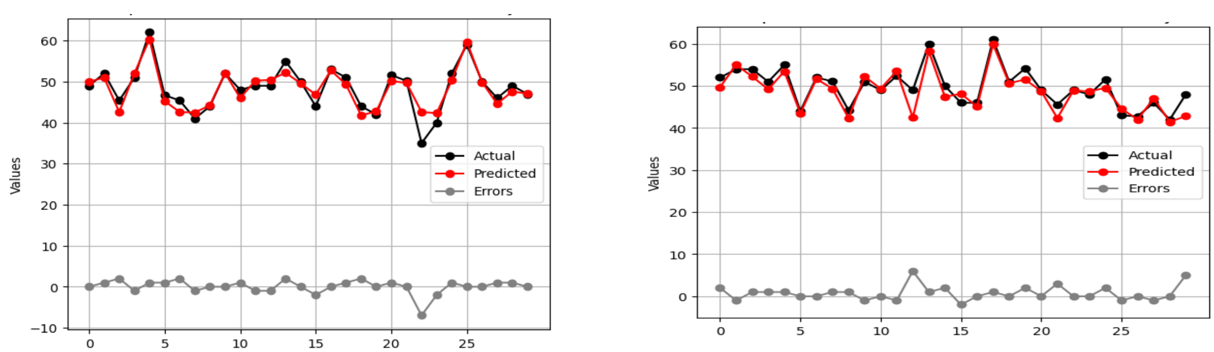

Figure 3.
ANN model of 8 hidden layers comparison of predicted and actual value for 28 days in relation to 7 days.

3. Conclusion

This study employed the development of a predictive model using Machine Learning with the findings offer valuable insights into the critical role of curing conditions and temperature on the performance of concrete, and to simulate real-world conditions, curing took place in a curing tank at a controlled temperature of 12–18°C. To verify accuracy, the study matched the FEA results with experimental data on crushed concrete cubes. Beyond improving accuracy in predicting concrete performance, this research has important implications for environmental sustainability. By providing reliable predictions of compressive strength, it minimizes the need for trial-and-error in concrete mix designs, thereby reducing material waste, lowering carbon emissions, and optimizing resource use [23]. This aligns with SDG 11 (Sustainable Cities and Communities), as it supports the development of more resilient infrastructure while promoting sustainable construction practices [24]. By utilizing locally developed AI-driven predictive models, construction companies can reduce their reliance on external technologies, enhancing self-reliance in managing and optimizing their resources [25]. This promotes a more autonomous digital framework, where local contractors can maintain control over their data and simulation tools, advancing both technological independence and environmental sustainability in the industry. Future research should explore the inclusion of additional material properties and expanded simulation scenarios, particularly focusing on the impacts of climate change on curing conditions. By integrating more advanced predictive models with digitally sovereign technologies, the construction industry can continue to advance toward more sustainable and resilient infrastructure, contributing to the broader goals of global sustainability.

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References

[1] K. Ibrahim, "Assessment of Sustainable Construction Practices in Nigerian Construction industry (Abuja)," International journal of advances in engineering and management (IJAEM), vol. 3, no. 6, p. 1675, 2021, doi: 10.35629/5252-030616751684.
[2] Cement: Background and Low-Carbon Production," 2023. [Online]. Available: https://crsreports.congress.gov
[3] R. W. M. Wong and B. P. Y. Loo, "Sustainability implications of using precast concrete in construction: An in-depth project-level analysis spanning two decades," J Clean Prod, vol. 378, Dec. 2022, doi: 10.1016/j.jclepro.2022.134486
[4] O. Alshboul, G. Almasabha, A. Shehadeh, R. E. Al Mamlook, A. S. Almuflih, and N. Almakayeel, "Machine Learning-Based Model for Predicting the Shear Strength of Slender Reinforced Concrete Beams without Stirrups," Buildings, vol. 12, no. 8, Aug. 2022, doi: 10.3390/buildings12081166.
[5] P. Spyridis and O. B. Olalusi, "Predictive modelling for concrete failure at anchorages using machine learning techniques," Materials, vol. 14, no. 1, pp. 1–22, Jan. 2021, doi: 10.3390/ma14010062.
[6] A. Schneider, G. Hommel, and M. Blettner, "Lineare regressionsanalyse - Teil 14 der serie zur bewertung wissenschaftlicher publikationen," Nov. 05, 2010. doi: 10.3238/arztebl.2010.0776.
[7] Y. Y. Song and Y. Lu, "Decision tree methods: applications for classification and prediction," Shanghai Arch Psychiatry, vol. 27, no. 2, pp. 130–135, Apr. 2015, doi: 10.11919/j.issn.1002-0829.215044.
[8] L. Breiman, "Random Forests," 2001.
[9] B. A. Young, A. Hall, L. Pilon, P. Gupta, and G. Sant, "Can the compressive strength of concrete be estimated from knowledge of the mixture proportions: New insights from statistical analysis and machine learning methods," Cem Concr Res, vol. 115, pp. 379–388, Jan. 2019, doi: 10.1016/j.cemconres.2018.09.006.
[10] S. Paudel, A. Pudasaini, R. K. Shrestha, and E. Kharel, "Compressive strength of concrete material using machine learning techniques," Eng Technol, vol. 15, Aug. 2023, doi: 10.1016/j.clet.2023.100661.
[11] M. A. DeRousseau, J. R. Kasprzyk, and W. V. Srubar, "Computational design optimization of concrete mixtures: A review," Jul. 01, 2018, Elsevier Ltd. doi: 10.1016/j.cemconres.2018.04.007.
[12] P. Huang, K. Dai, and X. Yu, "Machine learning approach for investigating compressive strength of self-compacting concrete containing supplementary cementitious materials and recycled aggregate," Journal of Building Engineering, vol. 79, Nov. 2023, doi: 10.1016/j.jobe.2023.107904.
[13] W. Ben Chaabene, M. Flah, and M. L. Nehdi, "Machine learning prediction of mechanical properties of concrete: Critical review," Constr Build Mater, vol. 260, Nov. 2020, doi: 10.1016/j.conbuildmat.2020.119889.
[14] X. Zhang, M. Zeshan Akber, C. S. Poon, and W. Zheng, "Predicting the 28-day compressive strength by mix proportions: Insights from a large number of observations of industrially produced concrete," Constr Build Mater, vol. 400, Oct. 2023, doi: 10.1016/j.conbuildmat.2023.132754.
[15] O. Günaydın, E. Akbaş, A. Özbeyaz, and K. Güçlüer, "Machine learning based evaluation of concrete strength from saturated to dry by nondestructive methods," Journal of Building Engineering, vol. 76, Oct. 2023, doi: 10.1016/j.jobe.2023.107174.
[16] T. T. Nguyen, L. T. Ngoc, H. H. Vu, and T. P. Thanh, "Machine Learning-Based Model for Predicting Concrete Compressive Strength," International Journal of GEOMATE, vol. 20, no. 77, pp. 197–204, 2020, doi: 10.21660/2020.77.j2019.
[17] X. Yuan et al., "Machine Learning Prediction Models to Evaluate the Strength of Recycled Aggregate Concrete," Materials, vol. 15, no. 8, Apr. 2022, doi: 10.3390/ma15082823.
[18] S. A. Alavi, M. Noel, F. Moradi, and H. Layssi, "Development of a machine learning model for on-site evaluation of concrete compressive strength by SonReb," Journal of Building Engineering, vol. 82, p. 108328, Apr. 2024, doi: 10.1016/j.jobe.2023.108328.
[19] Z. T. Hong, W. Da Wang, L. Zheng, and Y. L. Shi, "Machine learning models for predicting axial compressive capacity of circular CFDST columns," Structures, vol. 57, Nov. 2023, doi: 10.1016/j.istruc.2023.105285.

[20] H. Zhang, Q. Q. Guo, and L. Y. Xu, "Prediction of long-term prestress loss for prestressed concrete cylinder structures using machine learning," Eng Struct, vol. 279, Mar. 2023, doi: 10.1016/j.engstruct.2022.115577.
[21] M. Mirrashid and H. Naderpour, "Recent Trends in Prediction of Concrete Elements Behavior Using Soft Computing (2010–2020)," Archives of Computational Methods in Engineering, vol. 28, no. 4, pp. 3307–3327, Jun. 2021, doi: 10.1007/s11831-020-09500-7.
[22] H. I. Erdal, O. Karakurt, and E. Namli, "High performance concrete compressive strength forecasting using ensemble models based on discrete wavelet transform," Eng Appl Artif Intell, vol. 26, no. 4, pp. 1246–1254, Apr. 2013, doi: 10.1016/j.engappai.2012.10.014.
[23] O. Samuelson and L. Stehn, "Digital Transformation in Construction – A Review," Journal of Information Technology in Construction, vol. 28, pp. 385–404, 2023, doi: 10.36680/j.itcon.2023.020.
[24] L. B. Fundação and G. Vargas, "Community Networks: Building Digital Sovereignty and Environmental Sustainability Official Outcome of the UN IGF Dynamic Coalition on Community Connectivity," 2023. [Online]. Available: https://www.researchgate.net/publication/375989662
[25] G. Falkner, S. Heidebrecht, A. Obendiek, and T. Seidl, "Digital sovereignty - Rhetoric and reality," 2024, Routledge. doi: 10.1080/13501763.2024.2358984