Applied Science and Engineering Progress, Vol. 20, No. 2, 2027, 8263

Research Article

Machine Learning-Based Forecasting of Compressive Strength for Ambient-Cured GGBS Geopolymer Concrete

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Received: 13 March 2026; Revised: 17 May 2026; Accepted: 28 June 2026; Published online: 24 July 2026

Abstract

Geopolymer concrete is gaining attention as a sustainable alternative to Ordinary Portland Cement (OPC) concrete because of its lower carbon emissions and improved durability. However, predicting the compressive strength of Ground Granulated Blast Furnace Slag (GGBS)-based geopolymer concrete under ambient curing remains difficult due to the complex and non-linear effects of mix proportions and curing parameters. This study addresses that problem by developing machine learning models to predict the compressive strength of M25 grade GGBS-based geopolymer concrete using a dataset of 80 laboratory-tested samples, supplemented with published data. The input variables included NaOH molarity, aggregate proportions, activator-to-binder ratio, additional water content, activator composition, and curing age. A multi-layer feed-forward Artificial Neural Network (ANN) and Linear Regression (LR) model were developed in Python after normalizing all inputs using min-max scaling. Model performance was evaluated using Mean Absolute Error (MAE), coefficient of determination (R^2), and Root Mean Squared Error (RMSE). The ANN model outperformed LR, achieving an MAE of 2.15 N/mm², R^2 of 0.951, and RMSE of 2.89 N/mm², compared with an MAE of 3.24 N/mm², R^2 of 0.923, and RMSE of 4.18 N/mm² for LR. Sensitivity analysis showed that curing age, NaOH molarity, and activator-to-binder ratio were the most influential factors governing strength development. The results confirm that ANN-based prediction can accurately estimate compressive strength while reducing experimental effort and supporting sustainable mix design.

Keywords: Artificial Neural Network (ANN), Geopolymer concrete, Ground Granulated Blast Furnace Slag (GGBS), Linear Regression (LR)

1 Introduction

The manufacturing of Ordinary Portland Cement (OPC) accounts for 5–8% of anthropogenic CO_2 emissions, making the construction industry a major contributor to global CO_2 emissions [1]. Alkali-activated binders and geopolymer concretes that use industrial byproducts like fly ash and Ground Granulated Blast Furnace Slag (GGBS) to partially or completely replace OPC are becoming more popular [2], [3].

Alkaline activation of precursors rich in aluminosilicate produces Geopolymer Concrete (GPC), which differs from the hydration products in OPC systems by creating a three-dimensional Si-O-Al network [2]. In addition to enabling significant reductions in embodied CO_2, GGBS-based GPC can achieve high compressive strength, low permeability, and excellent chemical resistance [3], [4]. However, its mechanical properties depend on multiple interdependent variables, including precursor chemistry, activator concentration, activator-to-binder ratio, liquid-to-solid ratio, aggregate characteristics, and curing regime [5], [6].

Traditional empirical mix design approaches and simple regression models often fail to capture the complex, nonlinear relationships between these parameters and compressive strength in geopolymer systems [7]. In recent years, ML techniques such as ANN, support vector regression, decision trees, gradient boosting, and hybrid optimization-based models have shown strong performance in predicting the compressive strength of OPC and geopolymer concretes [8],[9]. Studies on fly ash, slag, and hybrid GGBS/fly ash geopolymers report high predictive accuracy (typically $R^2 > 0.9$) using ANN, adaptive boosting, and optimized ensembles [10], [11].

Despite these advances, relatively few studies have focused specifically on GGBS-based GPC under ambient curing with combined experimental and literature datasets, and systematic comparisons of simple LR with ANN for this material class remain limited [7],[9]. Moreover, many existing works emphasize model development but provide limited sensitivity analysis of input variables, which is crucial for practical mix design and parameter optimization [12], [13].

The novelty of the present study lies in the development of machine learning-based predictive models specifically for ambient-cured Ground GGBS-based geopolymer concrete using a combined experimental and literature-derived data set. Unlike many previous studies focusing on heat-cured or hybrid geopolymer systems, the present work emphasizes practical ambient curing conditions suitable for field applications. In addition, the study provides a comparative assessment between Linear Regression (LR) and Artificial Neural Network (ANN) models, along with a sensitivity analysis to identify the most influential parameters governing compressive strength development.

The present study aims to develop a curated dataset for ambient-cured GGBS-based geopolymer concrete by combining laboratory and literature data; implement and compare Linear Regression and Artificial Neural Network models for compressive strength prediction; and perform sensitivity analysis to quantify the influence of key mix parameters.

The study demonstrates how machine learning models can be integrated with experimental data to support performance-based mix design of GGBS-based geopolymer concrete, emphasizing practical applicability for structural concrete of grade M25 under realistic curing conditions.

2 Materials and Methods

2.1 *Materials*

2.1.1 Ground granulated blast furnace slag

GGBS was sourced from an integrated steel plant and conformed to IS 16714:2018 for granulated slag used in cement and concrete [14]. The Blaine fineness of 391 m^2/kg and specific gravity of 2.93 exceeded the minimum requirement of 320 m^2/kg, which promotes fast dissolution and geopolymerization under alkaline activation [2],[3],[14]. IS limits were met by magnesium oxide, loss on fire, sulfide and sulfur levels, indicating a stable chemical composition suitable for use as a principal binder [14].

2.1.2 Fine aggregate

Manufactured sand (M-sand) produced by crushing hard rock is used as fine aggregate. With a specific gravity of 2.65, a fineness module of 3.48 (Zone I), a compacted bulk density of 2056 kg/m^3, and a water absorption of 0.8%, the material met the grading and quality requirements of IS 383:2016, depicting excellent packing and low porosity properties [15], [16]. Use of M-sand as a sustainable alternative to river sand in geopolymer concretes has also been reported in recent studies [6], [17].

2.1.3 Coarse aggregate

Crushed stone coarse aggregate with a nominal maximum size of 20 mm was used. The aggregate exhibited a specific gravity of 2.71, a bulk density of 1705 kg/m^3, a Los Angeles abrasion value of 25%, an impact value of 18%, and water absorption of 0.15%, all within limits specified in IS 383 and IS 2386, confirming adequate mechanical performance and durability [15], [18]. The selected aggregate properties are similar to those used in other geopolymer concrete investigations [6], [17].

2.1.4 Alkaline activator

The alkaline activator consisted of a commercial sodium silicate solution and NaOH pellets dissolved in distilled water [2], [3]. The sodium silicate solution had a silica modulus (SiO_2/Na_2O) of approximately 3.3 and a specific gravity of 1.38, while NaOH pellets with a purity of ≥ 98% were used to prepare solutions with molarities from 2 M to 12 M [2], [3], [19]. Such combinations of Na_2SiO_3 (sodium silicate) and NaOH are widely reported for GGBS- and fly ash-based geopolymers [7], [9].

2.2 *Mix design and specimen preparation*

GGBS-based GPC mixes were proportioned for a target grade of M25, with systematic variation of NaOH molarity (2, 4, 6, 8, 10, and 12 M) while maintaining constant GGBS content of 400 kg/m³ [19]. The GGBS content was maintained at a constant of 400 kg/m³ throughout the study to isolate the influence of alkaline activator parameters, aggregate proportions, and curing age on compressive strength development. Maintaining a constant binder content also reduced variability in the dataset and enabled a more reliable comparison of machine learning model performance.

The activator-to-binder ratio and extra water content were adjusted to achieve workable mixes while maintaining a consistent total liquid content across mixtures [3], [17]. Representative proportions for 2 M and 12 M mixes are given in Table 1.

Figure 1 shows the casting of concrete and cubes in the laboratory. A total of six geopolymer concrete mixes corresponding to NaOH molarities of 2 M, 4 M, 6 M, 8 M, 10 M, and 12 M were prepared. For each mix, three cube specimens of size 150 mm × 150 mm × 150 mm were tested at curing ages of 3, 7, 28, 56, and 90 days, resulting in 90 experimental observations.

Concrete was mixed in a rotary drum mixer, placed in 150 mm cube moulds in two layers, and compacted using a vibrating table [20]. Specimens were demoulded 24 h after casting and then stored in the laboratory under ambient conditions (22 ± 2 °C and 60 ± 5% relative humidity) until testing at the specified ages, consistent with other ambient-cured geopolymer studies [6], [17], [19].

Table 1: Representative mix proportions for different NaOH molarities (kg/m³).

Material	2 M	12 M
GGBS (binder)	400	400
Fine aggregate (M-sand)	866.93	874.54
Coarse aggregate	1059.58	1068.88
NaOH solution	42.29	42.29
Na_2SiO_3 solution	105.71	105.71
Extra water	16.93	33.85

2.3 *Compressive strength testing*

Compressive strength tests were carried out in accordance with IS 516:1959 using 150 mm cubes and a 2000 kN capacity testing machine [20]. Specimens were tested at 3, 7, 28, 56, and 90 days, and the mean of three specimens was reported for each age and mix [20]. The compressive strength was obtained as f_{ck} = P/A, where P is the failure load and A is the loaded area of the cube, which is standard practice for OPC and geopolymer concretes alike [6], [7], [17].

Figure 1: The casting of concrete and samples.

2.4 *Dataset compilation*

The machine learning dataset was composed of laboratory experimental results for ambient-cured, GGBS-based geopolymer concrete (GPC) mixes, as well as published data from peer-reviewed articles focused on GGBS-rich or slag-based geopolymer concretes under ambient or near-ambient curing conditions [19], [21].

Each record consists of eight input variables (NaOH molarity, GGBS content, fine aggregate content, coarse aggregate content, Na_2SiO_3 solution quantity, NaOH solution quantity, extra water content, and curing age) and one output variable (compressive strength) [13], [22]. The dataset includes 80 observations with ranges summarized in Table 2, comparable to dataset sizes used in earlier ML-based geopolymer strength prediction studies [12], [13], [23].

Table 2: Ranges of input and output variables in the dataset.

Variable	Min	Max
NaOH molarity (M)	2	12
GGBS content (kg/m³)	400	400
Fine aggregate (kg/m³)	850	900
Coarse aggregate (kg/m³)	1000	1100
Na_2SiO_3 solution (kg/m³)	100	110
NaOH solution (kg/m³)	35	50
Extra water (kg/m³)	15	35
Curing age (days)	3	90
Compressive strength (N/mm²)	29.01	71.35

Literature data were collected from peer-reviewed journal articles related to ambient-cured slag-based or GGBS-based geopolymer concrete published between 2020 and 2025. The studies were selected based on the availability of complete mix proportions, alkaline activator composition, curing conditions, and compressive strength results. Studies involving heat curing, incomplete datasets, or insufficient experimental details were excluded from the compilation. The collected data were organized into a structured database and validated before implementation in the machine learning models. Table 3 represents the details of the dataset used in the current analysis.

Before model development, all variables were normalized between 0 and 1 using min–max scaling to improve numerical stability and convergence of the ANN

Table 3: Literature source used for dataset compilation.

Ref.	Type of Geopolymer Concrete	No. of Data Samples	Parameters Extracted
Islam *et al.*, [7]	Fly ash/GGBS GPC	15	NaOH molarity, curing age, and strength
Xiong *et al.*, [9]	Alkali-activated slag concrete	12	Activator ratio, aggregate content
Al-Qutaifi *et al.*, [13]	GGBS/FA geopolymer concrete	10	Binder content, strength
Cao *et al.*, [19]	GGBS-based geopolymer concrete	20	Mix proportions and curing age.
Present experimental work	Ambient-cured GGBS GPC	23	All parameters

[13], [19]. Feature scaling is standard in ANN-based and ensemble ML models for concrete strength prediction [13], [22].

2.5 *Machine learning models*

In the current study, the models are implemented in Python 3.x using Keras/TensorFlow (multi-layer perceptron: 8-64-32-16-1 neurons, ReLU, Adam optimizer). Normalization was applied using min-max scaling to all variables prior to the 80/20 train-test split.

Linear Regression (LR) and Artificial Neural Network (ANN) models were selected in the present study to compare the performance of conventional statistical and nonlinear machine learning approaches for predicting the compressive strength of geopolymer concrete. LR was adopted as a baseline model because of its simplicity, interpretability, low computational cost, and widespread application in concrete strength prediction studies. In contrast, ANN was selected due to its strong capability to capture complex nonlinear relationships among geopolymer concrete mix parameters, curing conditions, and compressive strength development. Unlike traditional regression techniques, ANN can effectively learn hidden patterns and interactions from relatively small experimental datasets without requiring explicit assumptions regarding parameter relationships. Previous studies have also demonstrated that ANN models provide high prediction accuracy for concrete and geopolymer systems containing multiple interacting variables. Furthermore, the widespread adoption of ANN in geopolymer concrete prediction studies enables meaningful comparison of the obtained results with existing literature.

2.5.1 Linear regression

Multiple LR was used as a baseline model relating compressive strength to the eight input variables.

$$y = w_0 + \sum_{i=1}^{n} w_i \, x_i \tag{1}$$

where y is the predicted compressive strength, x_i are input variables, and w_i are regression coefficients estimated by least squares [6], [8]. Model training minimized MSE on the training set, and the final model was evaluated on an unseen test set [8], [13]. LR is widely adopted as a benchmark in concrete and geopolymer strength studies due to its interpretability and low computational cost [19], [24].

2.5.2 Artificial neural network

A feed-forward ANN with multilayer perceptron architecture was implemented using Python and a standard deep learning library [13], [22]. The ANN architecture was selected based on trial-and-error optimization and recommendations from previous geopolymer concrete prediction studies. Multiple network configurations with varying hidden layers and neuron combinations were evaluated to obtain minimum validation loss and stable convergence. The network comprised eight input neurons, three hidden layers with 64, 32, and 16 neurons, respectively (ReLU activation), and a single linear output neuron for compressive strength [19]. Training employed the Adam optimizer with a learning rate of 0.001, batch size 8, and a maximum of 500 epochs, with early stopping based on validation loss stagnation for 20 epochs to mitigate over fitting [13], [22]. Similar ANN architectures and training strategies have been successfully used for predicting the compressive strength of geopolymers and alkali-activated slag concretes [22], [23].

2.5.3 Data splitting and evaluation metrics

The dataset was randomly partitioned into 80% training (64 observations) and 20% test (16 observations), ensuring that the test set remained unseen during model training [13], [19]. MAE, RMSE, and R^2 were used to evaluate performance, which are widely applied metrics in ML-based strength prediction and allow direct comparison with recent literature [5], [12], [25].

3 Results and Discussion

3.1 *Linear regression performance*

For a representative 4M mix, LR predictions at different ages are shown in Table 4 [23]. Across the entire test set, LR achieved MAE = 3.24 N/mm², RMSE = 4.18 N/mm², and R^2 = 0.923, indicating that the model explains about 92.3% of the variance in compressive strength but tends to over-predict strengths at longer ages [19]. The comparatively higher prediction error observed in the LR model indicates that compressive strength development in geopolymer concrete is governed by nonlinear interactions among activator concentration, curing age, and mixture proportions, which cannot be fully represented using linear relationships. Similar limitations of LR in capturing nonlinear strength development trends have been reported for fly ash and slag-based geopolymers [5], [12], [23].

Table 4: LR predictions for 4M mix at different ages.

Age (days)	**Actual (N/mm²)**	**LR predicted (N/mm²)**	**Error (%)**
3	30.75	32.54	+5.8
7	35.44	33.48	-5.5
28	36.78	38.40	+4.4
56	42.66	44.97	+5.4
90	47.35	52.94	+11.8

3.2 *ANN performance*

The ANN converged after 347 epochs when validation loss plateaued, and its predictions for the 4 M mix are presented in Table 5 [19]. On the test set, the ANN achieved MAE = 2.15 N/mm², RMSE = 2.89 N/mm², and R^2 = 0.951, corresponding to significantly lower errors and a higher explained variance than LR [19]. Scatter plots of predicted versus experimental strengths showed data points closely clustered around the 45° line for the ANN, with reduced dispersion at both low and high strengths compared to LR, consistent with other ANN-based GPC prediction studies [19], [22]. The improved prediction capability of the ANN model can be attributed to its ability to learn complex nonlinear relationships among the input parameters and identify hidden interactions affecting geopolymerization and strength development.

Table 5: ANN predictions for 4M mix at different ages.

Age (days)	Actual (N/mm^2)	ANN predicted (N/mm^2)	Error (%)
3	30.75	32.62	+5.7
7	35.44	33.51	-5.5
28	36.78	38.18	+3.8
56	42.66	44.40	+4.1
90	47.35	51.96	+9.7

3.3 *Direct comparison between LR and ANN*

A direct comparison of LR and ANN performance is summarized in Table 6 [19]. The ANN reduced MAE by 33.6% and RMSE by 30.9% and increased R^2 by 0.028 compared to LR, confirming the benefit of capturing nonlinear dependencies among mixture and curing variables [5], [13]. Comparable or higher gains have been reported when replacing LR with ANN or ensemble models in other geopolymer and alkali-activated concrete datasets [12], [23], [25].

Table 6: Performance comparison of LR and ANN on test data.

Metric	LR	ANN	Improvement (ANN vs. LR)
MAE (N/mm^2)	3.24	2.15	−33.6%
RMSE (N/mm^2)	4.18	2.89	−30.9%
R^2	0.923	0.951	+0.028
Average error (%)	6.6%	4.2%	−2.4 percentage points

3.4 *Sensitivity analysis*

Sensitivity analysis using the trained ANN quantified the relative importance of each input variable, summarized in Table 7 [19]. The analysis confirms that curing age is the most influential parameter, followed by NaOH molarity and activator-to-binder ratio, which control the extent and rate of geopolymerization [5], [9], [25]. Similar importance rankings for curing age and activator-related variables have been reported in GGBS/fly ash GPC and alkali-activated slag concrete studies using ANN, XGBoost, and SHAP-based feature analysis [5], [12], [13]. Aggregate contents show negative sensitivity within the examined range, reflecting that higher aggregate volumes at fixed binder content are associated with lower strength in the compiled dataset, a trend consistent with paste-rich geopolymer mixes used to achieve higher strengths [6], [17].

Table 7: Sensitivity analysis of ANN inputs.

Input variable	Sensitivity coefficient	Relative importance (%)
Curing age	0.487	24.2
NaOH molarity	0.412	20.4
Activator-to-binder ratio	0.368	18.3
Extra water content	0.295	14.6
Na_2SiO_3 solution	0.201	10.0
NaOH solution	0.134	6.7
Fine aggregate content	−0.082	−4.1
Coarse aggregate content	−0.126	−6.3

3.5 *Failure behavior of compression-tested specimens*

The compression-tested geopolymer concrete cubes exhibited typical brittle failure characterized by diagonal cracking and edge spalling near the loaded surfaces. Specimens with higher NaOH molarity showed comparatively denser microstructure and more confined crack propagation, indicating improved bonding and geopolymerization. The observed failure patterns were generally similar to those reported for conventional OPC concrete and other GGBS-based geopolymer concretes.

3.6 *Implications for mix design*

While designing GGBS-based GPC mixes for targeted compressive strengths, the dominance of curing age, NaOH molarity, and activator-to-binder ratio indicates that such factors shall be prioritized [5], [13]. Moderate to high NaOH molarity, along with an appropriate activator-to-binder ratio and curing period, can be used to achieve performance on par with or exceeding OPC concrete for structural applications requiring greater strengths [6], [17].

To find promising combinations of molarity, activator content, and additional water while adhering to practical limitations like workability and cost implications, practitioners can use the ANN model as a computational tool to explore the design space prior to laboratory trials [19], [24]. For a given target strength and curing age, the model allows rapid estimation of acceptable ranges for activator composition and binder–aggregate proportions, thereby reducing the number of trial mixes required [13], [22].

3.7 *Comparison with literature*

The ANN performance achieved in this study ($R^2 \approx 0.95$, MAE ≈ 2.15 N/mm²) is comparable to or slightly lower than some studies that employed larger datasets and additional input variables, which often report R^2 values above 0.95 for fly ash or hybrid GPC systems [12], [23], [25]. However, those works typically include wider curing regimes and a broader spectrum of mix designs, while the present study focuses on GGBS-based GPC under ambient curing using a relatively modest dataset supplemented from literature [6], [19].

Recent research on slag-based and alkali-activated concretes using advanced ML techniques (e.g., gradient boosting, optimized ensembles, and deep learning) also indicates that feature importance analysis consistently highlights curing age and activator-related variables as dominant factors, aligning with the sensitivity results of this study [26], [27]. This agreement supports the robustness of the identified relationships and underscores the relevance of the selected input set for practical mix design [5], [13].

3.8 *Limitations and future work*

The main limitations are the relatively small dataset size (80 observations), restriction to ambient curing, and the use of a single activator system (Na_2SiO_3–NaOH) with fixed GGBS content [19]. Larger datasets covering broader ranges of binder contents, aggregate gradations, and curing regimes (including elevated-temperature curing) would enable more generalizable models and deeper exploration of nonlinear interactions [6], [17].

Future work should evaluate additional ML algorithms such as random forests, XGBoost, and deep learning architectures (e.g., LSTM) for compressive strength prediction in GGBS-based GPC to determine whether they provide further accuracy gains over ANNs [26], [27]. Integrating durability-related outputs (e.g., sorptivity, chloride penetration, and chemical attack resistance) into a multi-output prediction framework would also support holistic performance-based design of geopolymer concretes [6].

4 Conclusions

GGBS-based GPC under ambient curing achieved compressive strengths in the range of 29–71 N/mm² across the studied combinations of NaOH molarity, activator-to-binder ratio, aggregate content, and curing age [19]. The LR model produced reasonable predictions (R^2=0.923) but systematically overpredicted long-term strengths, indicating that linear relationships cannot fully capture the strength development behavior of GGBS-based GPC [19], [25]. The ANN model significantly outperformed LR, reducing MAE and RMSE by 33.6% and 30.9%, respectively, and increasing R^2 to 0.951, demonstrating strong capability to capture nonlinear interactions among input variables [7], [8], [19].

Sensitivity analysis identified curing age (24.2% relative importance), NaOH molarity (20.4%), and activator-to-binder ratio (18.3%) as the most influential parameters governing compressive strength, followed by extra water and activator component doses, consistent with other GGBS/FA geopolymer and alkali-activated slag studies [5], [12], [13]. The developed ANN model offers a practical instrument to assist performance-based mix design of GGBS-based GPC, minimizing experimental effort and promoting the broader utilization of geopolymer binders as sustainable substitutes for OPC in structural applications [27].

Acknowledgments

The authors acknowledge the support of their respective institutions for providing laboratory facilities and materials used in this research. The authors would like to express their sincere gratitude to Visvesvaraya Technological University (VTU) Belagavi-590018, Karnataka, India, for its encouragement and supporting our research work.

Author Contributions

D.R.: Investigation, methodology, writing, and editing; M.K.: Reviewing, editing, and presenting; A.R.: Conceptualization, modelling, and analysing; H.H.N.: Methodology and reviewing; C.B.A.: Research design and data analysis. G.M.H.: Project administration, data curation, and modeling. All authors have read and agreed to the published version of the manuscript.

Conflicts of Interest

The authors declare no conflict of interest.

Declaration of generative AI and AI-assisted technologies in the writing process

The authors utilized the ChatGPT tool to enhance the language and readability of the manuscript.

References

[1] U. N. Environment, K. L. Scrivener, V. M. John, and E. M. Gartner, "Eco-efficient cements: Potential economically viable solutions for a low-CO2 cement-based materials industry," *Cement and Concrete Research*, vol. 114, pp. 2–26, 2018, doi:10.1016/j.cemconres.2018.03.015.

[2] J. L. Provis, "Alkali-activated materials," *Cement and Concrete Research*, vol. 114, pp. 40–48, 2018, doi: 10.1016/j.cemconres.2017.02 .009.

[3] C. Shi, D. Roy, and P. Krivenko, *Alkali-Activated Cements and Concretes*. Boca Raton, FL, USA: CRC Press, 2003.

[4] H. Khosravi and M. Bahram, "Prediction of geopolymer concrete compressive strength using artificial neural network and genetic algorithm," *Results in Engineering*, vol. 27, Art. no. 105537, 2025, doi:10.1016/j.rineng.2025.105537.

[5] M. Abuhussain, A. Ahmad, M. Amin, F. Althoey, Y. Gamil, and T. Najeh, "Data-driven approaches for strength prediction of alkali-activated composites," *Case Studies in Construction Materials,* vol. 20, Art. no. e02920, Feb. 2024, doi: 10.1016/j.cscm.2024.e02920.

[6] I.-C. Yeh, "Modeling of strength of high-performance concrete using artificial neural networks," *Cement and Concrete Research*, vol. 28, no. 12, pp. 1797–1808, 1998, doi:10.1016/ S0008-8846(98)00165-3.

[7] M. M. Islam, M. A.-M. Provath, G. M. Sadiqul Islam, and M. T. Islam, "Strength prediction of geopolymer concrete with wide-ranged binders and properties using artificial neural network," *Advances in Civil Engineering*, vol. 2024, no. 1, Art. no. 8534390, 2024, doi: 10.1155/adce/853 4390.

[8] F. Rehman, S. A. Khokhar, and R. A. Khushnood, "ANN based predictive mimicker for mechanical and rheological properties of eco-friendly geopolymer concrete," *Case Studies in Construction Materials*, vol. 17, Art. no. e01536, 2022, doi:10.1016/j.cscm.2022. e01536.

[9] X. Qin, Q. Ma, R. Guo, Z. Song, Z. Lin, and H. Zhou, "Compressive strength prediction of alkali-activated slag concretes by using artificial neural network (ANN) and alternating conditional expectation (ACE)," *Advances in Civil Engineering*, vol. 2022, no. 1, Art. no. 8214859, 2022, doi: 10.1155/2022/ 8214859.

[10] H. Tanyildizi, "Deep learning–based prediction of compressive strength of eco-friendly geopolymer concrete," *Environmental Science and Pollution Research*, vol. 31, no. 28, pp. 41246–41266, 2024.

[11] G.-H. Fang, Z.-M. Lin, C.-Z. Xie, Q.-Z. Han, M.-Y. Hong, and X.-Y. Zhao, "Optimized machine learning model for predicting compressive strength of alkali-activated concrete through multi-faceted comparative analysis," *Materials*, vol. 17, no. 20, Art. no. 5086, 2024, doi: 10.3390/ma17205086.

[12] S. Philip and N. Marakkath, "Compressive strength prediction and feature analysis for GGBS-Based geopolymer concrete using optimized XGBoost and SHAP: A comparative study of optimization algorithms and experimental validation," *Journal of Building Engineering*, vol. 108, Art. no. 112879, 2025, doi: 10.1016/j.jobe.2025.112879.

[13] H. U. Ahmed, A. A. Mohammed, and A. Mohammed, "Soft computing models to predict the compressive strength of GGBS/FA-geopolymer concrete," *PLoS One*, vol. 17, no. 5, Art. no. e0265846, 2022, doi: 10.1371/journal. pone.0265846.

[14] *Ground Granulated Blast Furnace Slag for Use in Cement, Mortar and Concrete – Specification*, IS 16714, Bureau of Indian Standards, New Delhi, India, 2018.

[15] *Coarse and Fine Aggregate for Concrete – Specification*, IS 383, Bureau of Indian Standards, New Delhi, India, 2016.

[16] *Methods of Testing Aggregates for Concrete – Part 3: Specific Gravity, Density, Voids, Absorption, and Bulking*, IS 2386 (Part 3), Bureau of Indian Standards, New Delhi, India, 1963.

[17] M. A. M. Morsy, S. A. Saleh, A. H. Shalan, "Experimental verification for machine-learning approaches in compressive strength prediction of alkali-activated concrete," *Journal of Structural Design and Construction Practice*, vol. 30, no. 1, Art. no. 04023058, 2024, doi: 10.1061/JSDCCC.SCENG-1565.

[18] *Methods of Test for Aggregates for Concrete – Part 4: Mechanical Properties*, IS 2386 (Part 4), Bureau of Indian Standards, New Delhi, India, 1963.

[19] R. Cao, Z. Fang, M. Jin, and Y. Shang, "Application of machine learning approaches to predict the strength property of geopolymer concrete," *Materials*, vol. 15, no. 7, Art. no. 2400, 2022, doi: 10.3390/ma15072400.

[20] *Methods of Tests for Strength of Concrete*, IS 516, Bureau of Indian Standards, New Delhi, India, 1959.

[21] Y. Dodo, K. Arif, M. Alyami, M. Ali, T. Najeh, and Y. Gamil, "Estimation of compressive strength of waste concrete utilizing fly ash/slag in concrete with interpretable approaches: optimization and graphical user interface (GUI)," *Scientific Reports*, vol. 14, no. 1, Art. no. 4598, 2024, doi: 10.1038/s41598-024-54513-y.

[22] G. K. Arunvivek, S. Anandaraj, P. Kumar, B. Pratap, and R. Y. Sembeta, "Compressive strength modelling of cenosphere and copper slag-based geopolymer concrete using deep learning model," *Scientific Reports*, vol. 15, no. 1, Art. no. 27849, 2025, doi:10.1038/s41598-025-13176-z.

[23] T. Gupta and M. C. Rao, "Prediction of compressive strength of geopolymer concrete using machine learning techniques," *Structural Concrete*, vol. 23, no. 5, pp. 3073–3090, 2022, doi: 10.1002/suco.202100354.

[24] H. Taghavizade Zahiri and H. Tanyildizi, "Application of ANN & ANFIS models in determining compressive strength of concrete," *Journal of Soft Computing in Civil Engineering*, vol. 2, no. 1, pp. 62–70, 2018, doi: 10.22115/scce.2018.51114.

[25] H. X. Mohammed, A. S. Mohammed, and A. M. T. Hassan, "Soft computing models to evaluate the effect of fly ash and ground granulated blast furnace slag (GGBS) on the compressive strength of concrete in normal and high strength ranges," *Structures*, vol. 58, Art. no. 105459, 2023, doi:10.1016/j.istruc.2023.105459.

[26] A. M. Alnadish, M. Hamza, S. Ali, N. Murad, and S. M. K. Durrani, "Machine learning–driven optimization of compressive and tensile strength in concrete with GGBS, eggshell powder, and waste glass powder," *Scientific Reports*, vol. 15, no. 1, Art. no. 40499, 2025, doi:10.1038/s41598-025-24438-1.

[27] G. X. K. Ramujee and P. Sadula, "Prediction of geopolymer concrete compressive strength using convolutional neural networks," *Computer Modeling in Engineering & Sciences*, vol. 139, no. 2, pp. 1921–1940, 2024, doi: 10.32604/cmes.2023.043384.