SSRG International Journal of Civil Engineering
ISSN: 2348-8352/ https://doi.org/10.14445/23488352/IJCE-V13I4P105

Volume 13 Issue 4, 63-72, April 2026

Original Article

Prediction of Fly Ash Concrete Compressive Strength using Machine Learning: A Data-Driven Study based on Indonesian Mix Designs

Riza Suwondo[1], Nunung Nurul Qomariyah[2], Militia Keintjem[3], Chee Fui Wong[4]

[1]*Civil Engineering Department, Faculty of Engineering, Bina Nusantara University, Jakarta, Indonesia.*
[2]*Department of Computer Science, School of Computing and Creative Arts, Bina Nusantara University, Jakarta, Indonesia.*
[3]*Karbonara Research Institute, Jakarta, Indonesia.*
[4]*Department of Civil Engineering, Lee Kong Chien Faculty of Engineering, Universiti Tunku Abdul Rahman, Selangor, Malaysia.*

[1]*Corresponding Author : riza.suwondo@binus.ac.id*

Received: 06 January 2026 Revised: 07 February 2026 Accepted: 06 March 2026 Published: 28 April 2026

Abstract - *Predicting the compressive strength of fly ash concrete plays a crucial role in achieving sustainable mix design and efficient feedback control. Unfortunately, conventional empirical approaches often limit the accuracy of nonlinear interactions between the material proportions and curing age. To address this challenge, this study developed a machine learning-based framework to predict the compressive strength of fly ash concrete using concrete mix data from Indonesia. A total of 250 mix compositions with varying material proportions and curing ages were used as datasets to train and deploy four models: Linear Regression (LR), Artificial Neural Network (ANN), Random Forest (RF), and Gradient Boosting (GB). The model performance was evaluated based on the coefficient of determination (R^2), Root Mean Square Error (RMSE), Mean Absolute Error (MAE), and Mean Absolute Percentage Error (MAPE) using cross-validation and independent testing. The study findings indicate that the nonlinear machine learning-based model significantly outperforms linear regression, confirming that nonlinearity dominates the strength-development process in fly ash concrete. Among the four models tested, gradient boosting performed the best in terms of overall prediction accuracy and generalisability across the strength range of the data. Residual analysis further indicated the absence of a systematic prediction bias. The findings highlight the potential of ensemble-based machine learning models to support preliminary mix design optimisation and construction quality control through reliable estimates of compressive strength.*

Keywords - *Fly ash concrete, Compressive strength prediction, Machine learning, Gradient boosting, Data-driven modelling.*

1. Introduction

The fact that the cost of concrete as a construction material is low, and the fact that concrete can be constructed into almost any shape as a construction material, make concrete highly valued. One of the most important properties of concrete is its sufficient compressive strength. To achieve compressive strength with concrete, there must be adequate quantities of cement, water, aggregates, and Supplementary Cementitious Materials (SCMs). In most conventional methods for determining the compressive strength of concrete, the concrete is analysed in a laboratory. This is not only a lengthy process but also an expensive process that makes it impractical to check the quality of concrete as it is being constructed. They provide an almost real-time quality analysis of concrete [1–3]. Over the past few decades, fly ash has been increasingly used as a supplementary cementitious material in concrete production [4–6]. Fly ash contributes to the sustainability of concrete by reducing the amount of cement required, and therefore the carbon dioxide emissions associated with cement production, while also improving the workability and long-term durability of concrete. However, concrete made with fly ash develops strength over time in a more complicated manner than conventional concrete. This is mainly because of the pozzolanic reactions that occur with fly ash and the complicated interrelations between the water content, degree of cement replacement, and age of the concrete. These factors greatly complicate the construction of traditional empirical models for predicting strength.

As one of the largest construction markets in Southeast Asia, Indonesia has embraced fly ash concrete construction owing to its sustainability, material availability, and cost [7–9]. However, concrete mix designs in Indonesia are characterised by insufficient data, with varying construction practices, fly ash replacement ratios, and sources of materials. Therefore, this exemplifies the necessity of predictive models in analysing and effectively articulating the intricate relationships between compressive strength and fly ash concrete within construction frameworks.

The use of Machine Learning (ML) and Artificial Intelligence (AI) methods in civil engineering and construction materials research is rapidly growing. This is driven by their ability to model and explain a variety of nonlinear entities with varying ranges and levels of complexity [10,11]. In concrete engineering, ML has been applied to predict and understand various material characteristics, such as compressive strength, rheological behaviour, creep response, durability, and other performance indicators [12–16]. Various studies have shown that these data-driven approaches are not only superior to conventional regression models but also capable of achieving a level of predictive accuracy that is difficult to match, particularly when the concrete behaviour is strongly influenced by the complex interactions among the binder composition, water content, and curing conditions. ML-based methods have also been optimised recently to better predict and utilise resources in concrete mix design [17–20].

Many researchers have applied these AI-based methods to concrete with SCMs, including fly ash, and have claimed better prediction accuracy compared to empirical strength models [21–23]. More recent studies have begun to investigate ensemble learning and hybrid AI models, which further improve the predictive performance. However, most of these studies appear to be based on either relatively small experimental datasets or large, often used benchmark datasets, such as the UCI concrete compressive strength dataset, which likely do not depict the regional construction practices of Indonesia sufficiently.

Recent studies have reported coefficient of determination (R^2) values typically ranging between 0.85 and 0.98 for compressive strength prediction using ANN, support vector machines, random forests, and gradient boosting models, depending on dataset size and variability[24, 25]. Ensemble-based approaches, such as random forests and gradient boosting, have generally demonstrated improved robustness and generalisation compared to single learners, particularly when nonlinear interactions among input variables are significant.

Furthermore, while numerous studies have demonstrated the reliability of machine learning models in predicting concrete compressive strength, most of these studies tend to focus solely on improving accuracy metrics. Other important aspects, such as the representativeness of the dataset and its practical relevance in real-world construction scenarios, often receive insufficient attention in the literature. This gap is even more pronounced in developing countries, where material variability tends to be high owing to differences in raw material sources and local production practices. However, research specifically addressing the challenges in this regional context remains limited.

Most existing studies rely on generic datasets or laboratory experiments, whereas studies based on data from actual construction practices, particularly for fly ash concrete, are still very limited. Furthermore, systematic comparisons between various machine learning algorithms, especially ensemble-based methods, within a consistent validation framework have been limited. Consequently, understanding the generalisability of these models across varying concrete strengths remains limited.

Based on the identified gaps, this study developed a data-driven framework for predicting the compressive strength of fly ash concrete using a dataset sourced from construction practices in Indonesia. The main research question was whether ensemble-based machine learning models could reliably predict the strength of fly ash concrete in a region-specific context, particularly across a range of strength levels. This study tests the hypotheses that (i) nonlinear models demonstrate superior predictive performance compared to linear regression, and (ii) ensemble methods have better generalisation capabilities in capturing the complexity of material behaviour owing to local variability.

The four models implemented in this study—Linear Regression (LR), Artificial Neural Network (ANN), Random Forest (RF), and Gradient Boosting (GB)—were systematically evaluated through cross-validation and independent testing. The novelty of this study lies in three key aspects: (i) the utilisation of actual, region-specific construction data; (ii) the application of a consistent comparative validation framework across models; and (iii) an in-depth evaluation of the reliability of predictions across a spectrum of strength ranges. The scope of this study was limited to compressive strength prediction based on the mix composition and curing age variables. Therefore, the generalisation of the findings to other regional contexts requires further study, considering local material characteristics and construction practices.

2. Methodology

Figure 1 presents an overview of the methodology used in this study. The first step involved the sequential collection and filtering of fly ash concrete mixture data sourced from construction practices in Indonesia. After preprocessing, the data were checked for quality and consistency to ensure their reliability before further use. The validated dataset was divided into two parts: the training and testing sets. Several machine learning models were built and trained using the training data, followed by hyperparameter tuning and cross-validation to improve their robustness and avoid overfitting.

The statistical performance of each model was calculated using predetermined metrics, followed by a comprehensive comparison to objectively evaluate the predictive capabilities.

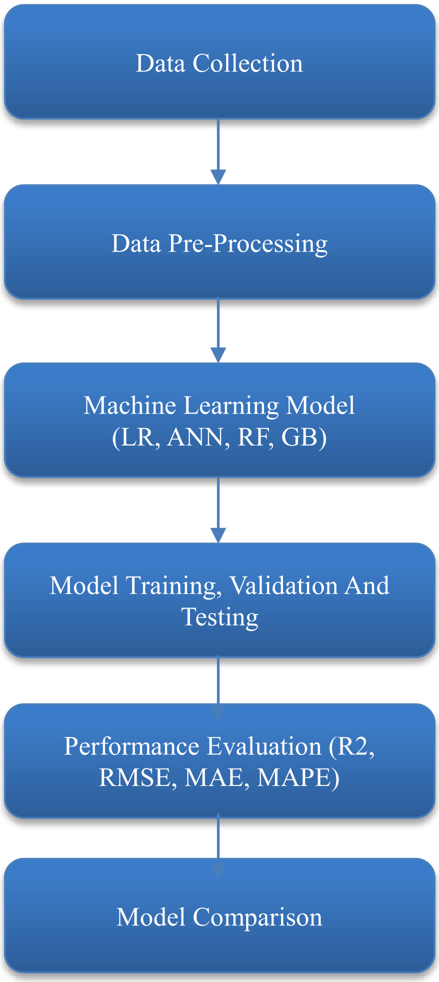


Fig. 1 Methodological framework

2.1. Data Set Description

The data used in this study were fly ash concrete mix compositions derived from construction practices in Indonesia. To build a comprehensive and representative database for machine learning analysis, a search and synthesis of various published literature was conducted [26–44]. This approach allows for a wider range of mix variations and enriches the data diversity according to the material conditions and field practices. Each record in the database reflects a concrete mix design incorporating fly ash as a substitute for Portland cement. The predictors were the constituents of the mix, such as cement, fly ash, and water; fine and coarse aggregates; admixture; and the age at which the concrete was cured. The only response variable was the compressive strength of the concrete. The dataset captures the typical proportions used in Indonesian Construction projects to enhance the predictive potential of the developed models.

2.2. Data Pre-Processing

Prior to model development, the dataset underwent data preprocessing to increase the reliability and performance of the model. Data integrity was maintained by removing incomplete or missing records from the dataset. The outlier input variables, unreasonable values, and engineering extremes were adjusted.

All input features were standardised to a numerical range to eliminate bias, especially for distance- and gradient-based machine learning model training. The dataset was randomly split into training and testing subsets to assess the generalisation ability of the developed models.

2.3. Machine Learning Models

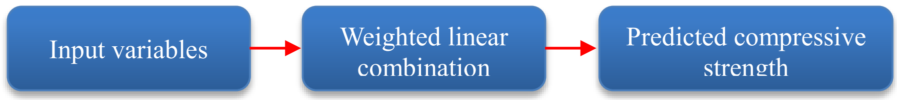
Four Machine Learning models with different complexity levels were used to forecast the compressive strength of fly ash concrete and to facilitate a linear and nonlinear modelling comparison. Figure 2 presents the conceived frameworks of the chosen models and the primary distinctions among the approaches of linear regression, neural network-based learning, and ensemble-based learning.

The baseline model is represented by Linear Regression (LR), which denotes a traditional statistical prediction model. This model assesses the users' input variables and the linearity of the compressive strength and provides a basis for evaluating the advantages of higher-order machine-learning methods (Figure 2(a)).

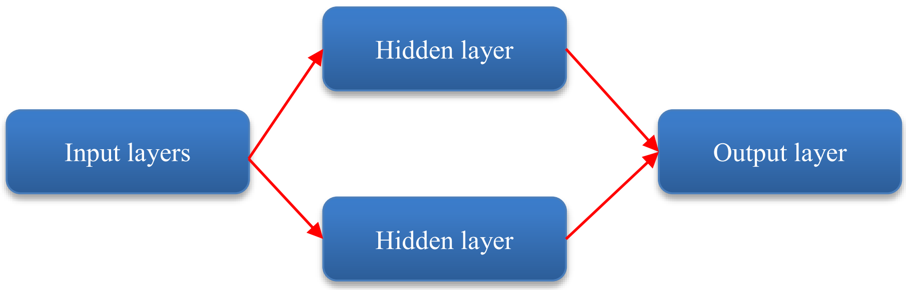
The nonlinear relationships in the behaviour of fly ash concrete were captured using three different nonlinear models. An example of this is the Artificial Neural Network (ANN) model shown in Figure 2(b), which is helpful in modelling complex relationships for any given input or output using interlayer connections and nonlinear activation functions. Although ANN models can approximate complex nonlinear functions, they are sensitive to several attributes, such as data heterogeneity and parameters, given their application in field-based datasets.

An example of such an approach is Random Forest (RF) modelling, as illustrated in Figure 2(c). In RF, several decision trees are constructed over random subsets of the data and feature space for ensemble prediction. In addition, RF is a powerful model in the domain of concrete strength modelling, particularly for complex and non-additive relationships.

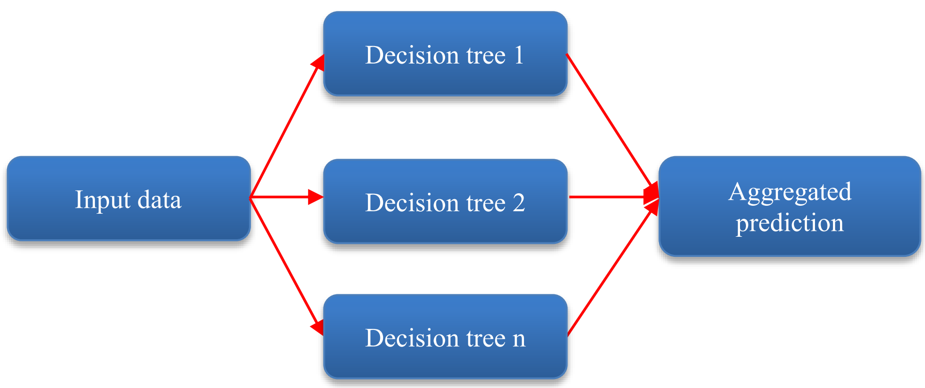
Finally, a Gradient Boosting (GB) model, an advanced ensemble technique, was employed, where decision trees were built sequentially, with each tree adjusting the errors made by its predecessors (Figure 2(d)). Owing to its iterative mechanism for minimising errors, gradient boosting works well for capturing more intricate nonlinear relationships and interactions among the mix design variables, which are inherent in the development of fly ash concrete strength.



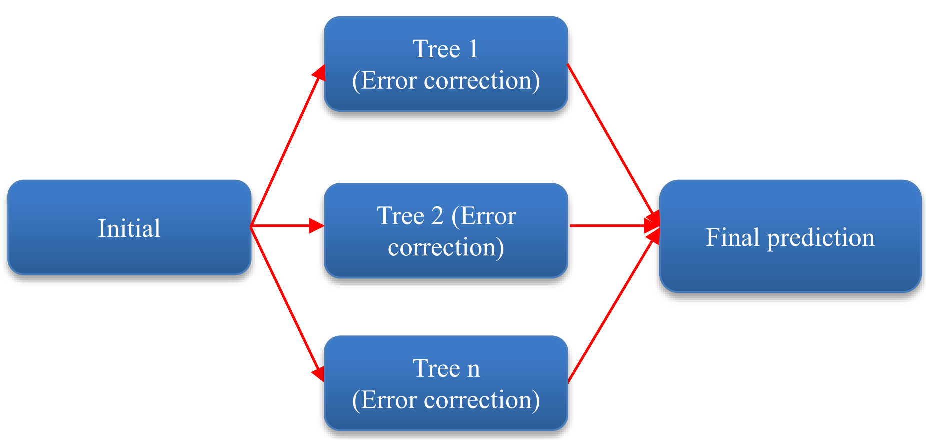
(a) Linear Regression (LR)



(b) Artificial Neural Network (ANN)



(c) Random Forest (RF)



(d) Gradient Boosting (GB)

Fig. 2 Conceptual schematics of machine learning models

This study used the Scikit-learn and TensorFlow/Keras libraries in Python to implement all machine learning models. Hyperparameter optimisation was performed using cross-validation on the training dataset, whereas the independent testing dataset was kept separate for the final model evaluation to provide an unbiased performance assessment.

The application of gradient boosting, random forest, and artificial neural network models provided an even comparison between ensemble and neural-based learning approaches for predictive performance and interpretative analysis.

2.4. Model Training and Validation

The dataset training subset was used to train the models. A systematic tuning approach was used to optimise the hyperparameters for each ML model to achieve the best predictive performance while minimising overfitting. K-fold cross-validation was used to increase the robustness of the model and guarantee reliable performance across varying data splits. The models were tested after training on a separate testing subset that was not used during any of the training or tuning phases of the study. This method provides the most unbiased evaluation of each model's generalisation ability.

2.5. Performance Evaluation

The models were assessed for predictive performance using the most widely utilised regression-based machine learning techniques and their corresponding evaluation metrics: R-squared (R^2), Root Mean Square Error (RMSE), and Mean Absolute Error (MAE). These metrics are used to evaluate the predictive performance, error magnitude, and reliability, and provide different insights into the prediction accuracy and overall model reliability, evaluating different dimensions of the model's reliability.

To determine the most suitable machine learning model for predicting the compressive strength of fly ash concrete, the machine learning models were evaluated using these metrics.

The calculation method for the evaluation metric is as follows:

$$R^2 = 1 - \frac{\sum_{i=1}^{N}(y_i - \hat{y}_i)^2}{\sum_{i=1}^{N}(y_i - \bar{y}_i)^2} \tag{1}$$

$$RMSE = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(y_i - \hat{y}_i)^2} \tag{2}$$

$$MAE = \frac{1}{N}\sum_{i=1}^{N}|y_i - \hat{y}_i| \tag{3}$$

$$MAPE = \frac{100}{N}\sum_{i=1}^{N}\left|\frac{y_i - \hat{y}_i}{y_i}\right| \tag{4}$$

where y_i is the observed compressive strength, $\hat{y}_i$ is the predicted value, $\bar{y}_i$ is the mean of observed values, and N is the number of data samples.

3. Results and Discussion

3.1. Dataset Characteristics and Exploratory Insights

The dataset included 250 fly ash concrete mixes from a total of 318 records, which represented realistic mix designs from Indonesian building sites. The mixes listed in Table 1 were extracted from a large database with a wide variation in the proportions of materials and curing ages. These are useful for building robust data models.

The cement content ranged from 53 to 751 kg/m^3, and the fly ash varied from 17 to 746 kg/m^3. This shows a mix of both conventional and high-volume fly ash concrete. The water content ranged from 66 to 236 kg/m^3, indicating a wide variation in the water/binder ratios which control the strength.

Table 1. Summary statistics of the fly ash concrete dataset used in this study

Variables	mean	std	min	max
Cement (kg/m^3)	317	116	53	751
Fly Ash (kg/m^3)	178	161	17	746
Water (kg/m^3)	168	43	66	236
Coarse Aggregate (kg/m^3)	962	196	628	1335
Fine Aggregate (kg/m^3)	716	204	0	1045
Superplasticizer (kg/m^3)	6	9	0	28
Age (days)	22	17	1	90
Compressive strength (Mpa)	34	19	4	88

The aggregate contents demonstrated substantial dispersion, which illustrated the differences in the mixing processes. The superplasticiser ranged from 0 to 28 kg/m^{3,} which means that some samples were admixture-free and some were chemically modified mixes. The curing age ranged from 1 to 90 days. This captured both the early age and long-term strength development of fly ash concrete. The compressive strength ranged from 4.2 to 88 MPa, with an average of 34 MPa.

The variability in both the input parameters and compressive strength reflects the complexity of fly ash concrete behaviour, which is the reason for developing machine learning models to understand the interrelations of the mix components.

3.2. Model Performance Comparison

The selected machine learning models were evaluated using training data cross-validation and independent testing to check their generalisation ability. The results showed that the models exhibited different performances, highlighting the need for nonlinear learning methods to predict the compressive strength of fly ash concrete.

From the cross-validation results in Table 2, the gradient boosting (GB) model achieved the best performance and had the highest coefficient of determination and the lowest error metrics compared to all models evaluated. The random forest (RF) model exhibited a slightly higher error rate than the best model, although its overall predictive ability remained competitive. Meanwhile, the Artificial Neural Network (ANN) model ranked in the middle with an average performance. Conversely, Linear Regression (LR) performed below average, indicating that this model could not adequately capture the nonlinear relationships underlying the strength development process in fly ash concrete.

The results in Table 3 reiterate the trends observed in the cross-validation phase. Once more, the GB model stands out as the most precise in forecasting unseen datasets, followed by the RF model, with all ensemble-based techniques exhibiting positive R^2 scores and low metrics on the errors. Among the models, the ANN model exhibited a dip in the predictive accuracy of the testing dataset. This model may be more sensitive to data variability and overfitting. The testing results of the LR model were the weakest, with greater values for the errors and the highest mean absolute percentage error. This confirms that linear assumptions regarding the modelling of fly ash concrete behaviour are inappropriate.

Table 2. Cross-validation performance of machine learning models for predicting the compressive strength of fly ash concrete

Model	R^2	RMSE	MAE
GB	0.911	5.437	4.017
RF	0.897	5.893	4.472
ANN	0.846	7.281	4.902
LR	0.565	12.199	9.218

Table 3. Testing performance metrics of the evaluated machine learning models for fly ash concrete compressive strength prediction

Model	R^2	RMSE	MAE	MAPE (%)
GB	0.876	6.630	4.413	15.586
RF	0.846	7.395	5.046	19.455
ANN	0.746	9.483	6.410	19.838
LR	0.607	11.812	9.368	37.432

Further analysis of the results from the training and testing still shows that the ensemble learning models have the most robust results. With GB and RF having small performance degradation, it shows that they have consistently learned and been able to process the challenges of the complex interactions among the parameters of the mix design. In contrast, the larger performance discrepancies in ANN and LR show that they seem to have a greater loss when faced with more varied and unstructured data from the field.

From an engineering perspective, these results confirm that the compressive strength of fly ash concrete is governed by strongly nonlinear interactions among the water content, binder composition, aggregate proportions, and curing age. The performance advantages demonstrated by ensemble-based models, particularly gradient boosting, underscore their ability to effectively capture complex relationships without sacrificing the generalisability of the model. This makes them not only accurate but also reliable for predicting material behaviour in diverse contexts.

The predictive performance achieved in this study—with R^2 values comparable to recent international studies (generally ranging from 0.90 to 0.98 for ensemble models)—demonstrates that high accuracy can be maintained even when using data sourced from region-specific construction practices. Unlike many previous studies that rely on benchmark datasets, such as the UCI concrete dataset, the dataset used in this study reflects the true variability of construction practices in Indonesia. The fact that comparable performance can still be achieved confirms that the ensemble learning approach is not only technically robust but also adaptive to the local material conditions. This finding strengthens the argument that the method is feasible for application in real-world construction scenarios that are far from ideal laboratory conditions.

3.3. Predicted vs. Measured Compressive Strength

The relationship between predicted and actual compressive strength values generated by the gradient boosting model is presented in Figure 3. It can be seen that the data points are densely distributed along the 45° reference line, indicating a good agreement between the model predictions and the actual measured values. This pattern confirms that the model can accurately capture the strength development trend of fly ash concrete across almost the entire strength range studied. This visual agreement correlates with the high value of the coefficient of determination paired with low values of the prediction error in the test results.

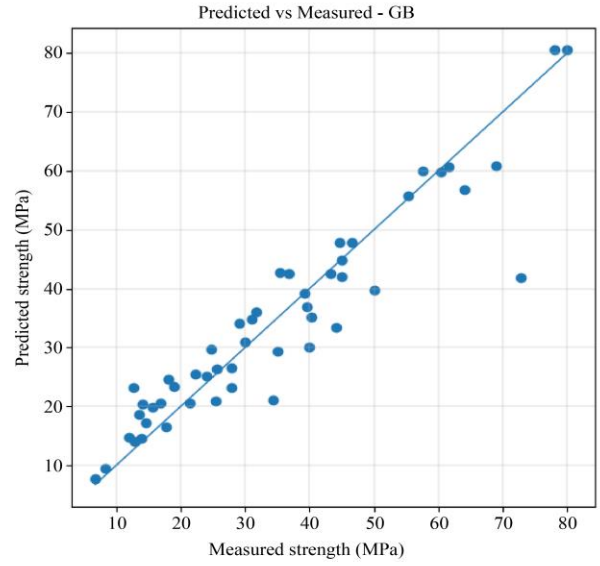


Fig. 3 Predicted versus measured compressive strength of fly ash concrete obtained using the gradient boosting model

The prediction scatter at low-to-moderate strength levels was very low, suggesting that the model streamlined the effects of the mix composition parameters that control the rate of strength gain at early and medium levels. At higher strength levels, the scatter increased slightly, and there was some localised under-prediction. This is likely due to the aggressive behaviour of higher-strength fly ash concrete to several factors that were excluded from the model, such as fly ash reactivity, curing temperature, and microstructural development, which tend to play an increasingly critical role as the strength level increases.

Figure 4 provides more evidence of the confidence we can have in the gradient boosting model. The residuals were generally equally spread around zero. This shows that there is no bias in the model. In the important strength range of the model, that is, low-moderate strength, the residuals were small and evenly spread. This shows that the model performed reliably in that range. A slight increase in the spread of the residuals was observed at high predicted strength values. However, there was no evidence of increasing or decreasing residual bias. This confirmed that no residual bias was present at high values, nor was there any heteroscedasticity.

The analyses of the residuals and predicted versus measured values justify the robust compressive strength estimating capabilities of the gradient boosting model. The analyses also justify the estimation capabilities of a wide variety of fly ash concrete mix designs. In the concrete mix design context, this study demonstrates the value of a data-driven approach for the preliminary assessment and ongoing monitoring of construction quality, especially in variable material conditions that are present in most construction situations.

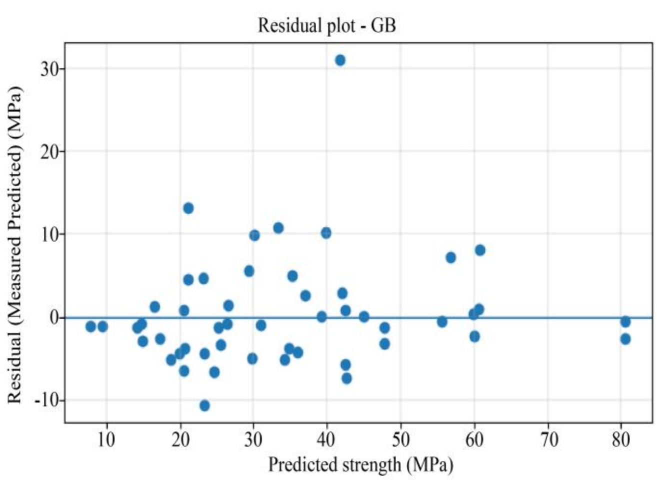


Fig. 4 Residual distribution of the gradient boosting model as a function of predicted compressive strength for fly ash concrete

3.4. Limitations and Future Works

Although the suggested ML framework performs well, some limitations must be considered. First, the dataset is limited to the mix design parameters of the construction practice and does not include material-specific details such as the fly ash chemical composition, particle size distribution, and temperature during curing. Such details can affect the development of strength, especially higher strength levels, and their absence may be a factor in the prediction dispersion being greater in that range.

Second, although the dataset used is site-specific and representative of construction practices in Indonesia—a major strength of this study—it also limits the generalisability of the findings to other regional contexts with different material characteristics, standards, and construction practices. Furthermore, the developed model only considers a static time point (curing age) when predicting compressive strength, without accounting for temporal dynamics beyond the available concrete age range. Consequently, this study cannot describe the continuous evolution of concrete strength or predict material behaviour at ages not covered by the dataset.

Future research should expand the dataset coverage by integrating a wider variety of material properties, varying curing conditions, and data from different geographic regions to improve the generalisability of the findings. Modelling approaches that consider temporal aspects, such as modelling strength evolution over time, also need to be developed so that predictions can reflect the behaviour of fly ash concrete throughout its life cycle. Furthermore, the application of advanced model interpretation techniques, such as feature attribution analysis or partial dependence plots, is highly recommended to improve model transparency and support more informed and accountable technical decision-making in engineering practice.

4. Conclusion

This study developed a machine learning framework to predict the compressive strength of fly ash concrete using mix composition data sourced from construction practices in Indonesia. A total of 250 mixed datasets with varying material proportions and curing periods were used to train and deploy four models: Linear Regression (LR), Artificial Neural Network (ANN), Random Forest (RF), and Gradient Boosting (GB).

The results confirmed that the nonlinear model significantly outperformed the linear regression, demonstrating that complex and nonlinear interactions play a crucial role in the strength development of fly ash concrete. Among the four models tested, gradient boosting achieved the highest predictive accuracy and lowest error rate in both cross-validation and independent testing, indicating its superior ability to generalise data patterns. The random forest model also demonstrated competitive predictive performance, whereas the Artificial Neural Network (ANN) exhibited relatively lower stability when exposed to varying conditions. Further residual analysis indicated that the model predictions remained reliable across the strength range studied, although a slight increase in the variance was observed in the high-strength region.

Unlike previous studies that generally relied on global benchmarks or controlled laboratory experimental data, this study emphasises the importance of region-specific validation. Local material variability and field construction practices have been shown to influence the model behaviour and generalisability. The key findings of this study demonstrate that ensemble-based models maintain high predictive accuracy even when exposed to variability reflecting actual construction practices. This underscores the potential application of this method in real-world scenarios that are far from being ideal.

From a practical perspective, the framework developed in this study offers potential benefits for screening mix proportions at an early stage, reducing the reliance on extensive trial mixing, and assisting quality control engineers in rapidly estimating strength using readily available mix parameters. However, it should be noted that the dataset used is region-specific and limited in available mix design variables; therefore, the direct application of the model to other geographic contexts or different material systems requires caution. Therefore, further research is recommended to expand the diversity of the dataset, integrate additional materials and curing parameters, and conduct more extensive external validation to improve the transferability and generalisability of the model.

Acknowledgements

The authors express their sincere gratitude to the Karbonara Research Institute for the invaluable support and resources provided throughout this study.

Ethical Considerations

This study did not require ethical approval because it did not involve human participants or animal subjects. The dataset consists solely of concrete mix composition and compressive strength records derived from construction practices. No personal, confidential, or sensitive information was collected or used in this study.

Funding Statement

This work was supported by Bina Nusantara University.

Author Contribution

Riza Suwondo: Conceptualization, Methodology, Writing – original draft, Supervision. Nunung Nurul Qomariyah: Validation, Writing – review & editing, Supervision. Militia Keintjem: Data curation, Resources, Writing – review and editing. Chee Fui Wong: Writing – review & editing, Supervision.

Data Availability

Data analysis https://zenodo.org/records/18169628

References

[1] Yutao Bu et al., "Data-Driven Compressive Strength Estimation and Mix Optimization for Ultra-High-Performance Concrete," *Journal of Building Engineering*, vol. 114, 2025. [CrossRef] [Google Scholar] [Publisher Link]

[2] Qingqing Chen et al., "Compressive Strength Prediction of High-Performance Concrete: Integrating Multi-Ingredient Influences and Mix Proportion Insights," *Construction and Building Materials*, vol. 451, 2024. [CrossRef] [Google Scholar] [Publisher Link]

[3] Hai-Bang Ly, and Thuy-Anh Nguyen, "Enhancing Compressive Strength and Sustainability: A Machine Learning Approach to Recycled Brick and Tile Concrete Mix Design," *Materials Today Communication*, vol. 40, 2024. [CrossRef] [Google Scholar] [Publisher Link]

[4] Aslıhan Nida Derinpinar, Mehmet Burhan Karakoç, and Ahmet Özcan, "Performance of Glass Powder Substituted Slag based Geopolymer Concretes Under High Temperature," *Construction and Building Materials*, vol. 331, 2022. [CrossRef] [Google Scholar] [Publisher Link]

[5] Alaa M. Rashad, "A Brief on High-Volume Class F Fly Ash as Cement Replacement-A Guide for Civil Engineer," *International Journal of Sustainable Built Environment*, vol. 4, no. 2, pp. 278-306, 2015. [CrossRef] [Google Scholar] [Publisher Link]

[6] A. Fernández-Jiménez, A. Palomo, and M. Criado, "Microstructure Development of Alkali-Activated Fly Ash Cement: A Descriptive Model," *Cement and Concrete Research*, vol. 35, no. 6, pp. 1204-1209, 2005. [CrossRef] [Google Scholar] [Publisher Link]

[7] Meiri Triani, Kania Dewi, and Addina Shafiyya Ediansjah, "Prediction of Carbon Dioxide Emission from Electricity Generation in ASEAN," *Indonesian Journal of Urban and Environmental Technology*, vol. 6, no. 1, pp. 20-35, 2023. [CrossRef] [Google Scholar] [Publisher Link]

[8] Muhammad Sigit Darmawan et al., "Shear Strength of Geopolymer Concrete Beams using High Calcium Content Fly Ash in a Marine Environment," *Buildings*, vol. 9, no. 4, pp. 1-13, 2019. [CrossRef] [Google Scholar] [Publisher Link]

[9] M. Sigit Darmawan et al., "A Case Study of Low Compressive Strength of Concrete Containing Fly Ash in East Java Indonesia," *Procedia Engineering*, vol. 125, pp. 579-586, 2015. [CrossRef] [Google Scholar] [Publisher Link]

[10] Olivia P. Pfeiffer et al., "Bayesian Design of Concrete with Amortized Gaussian Processes and Multi-Objective Optimization," *Cement and Concrete Research*, vol. 177, 2024. [CrossRef] [Google Scholar] [Publisher Link]

[11] Xianlin Wang et al., "Machine Learning for Design, Optimization and Assessment of Steel-Concrete Composite Structures: A Review," *Engineering Structures*, vol. 328, 2025. [CrossRef] [Google Scholar] [Publisher Link]

[12] Shiqi Wang et al., "Multi Objective Optimization of Recycled Aggregate Concrete based on Explainable Machine Learning," *Journal of Cleaner Production*, vol. 445, 2024. [CrossRef] [Google Scholar] [Publisher Link]

[13] Oğulcan Canbek et al., "Predicting the Rheology of Limestone Calcined Clay Cements (LC^3): Linking Composition and Hydration Kinetics to Yield Stress Through Machine Learning," *Cement and Concrete Research*, vol. 160, pp. 1-37, 2022. [CrossRef] [Google Scholar] [Publisher Link]

[14] Chang Gao et al., "Creep Behavior Evaluation of Recycled Aggregate Concrete using Machine Learning Technology," *Journal of Building Engineering*, vol. 99, 2025. [CrossRef] [Google Scholar] [Publisher Link]

[15] Afshin Marani, Timileyin Oyinkanola, and Daman K. Panesar, "Probabilistic Deep Learning Prediction of Natural Carbonation of Low-Carbon Concrete Incorporating SCMs," *Cement and Concrete Composites*, vol. 152, 2024. [CrossRef] [Google Scholar] [Publisher Link]

[16] Pranjal Tamuly, and Vincenzo Naval, "Machine Learning based Conformal Predictors for Uncertainty-Aware Compressive Strength Estimation of Concrete," *Construction and Building Materials*, vol. 487, pp. 1-13, 2025. [CrossRef] [Google Scholar] [Publisher Link]

[17] Bin Chen et al., "Optimization of High-Performance Concrete Mix Ratio Design using Machine Learning," *Engineering Applications of Artificial Intelligence*, vol. 122, 2023. [CrossRef] [Google Scholar] [Publisher Link]

[18] Vuong Nguyen-Van et al., "Modelling of 3D Concrete Printing Process: A Perspective on Material and Structural Simulations," *Additive Manufacturing*, vol. 61, 2023. [CrossRef] [Google Scholar] [Publisher Link]

[19] Sai Yang et al., "Intelligent Multiobjective Optimization for High-Performance Concrete Mix Proportion Design: A Hybrid Machine Learning Approach," *Engineering Applications of Artificial Intelligence*, vol. 126, 2023. [CrossRef] [Google Scholar] [Publisher Link]

[20] Ahmed A. Alawi Al-Naghi et al., "Sustainable Optimisation of GGBS-based Concrete: De-Risking Mix Design Through Predictive Machine Learning Models," *Case Studies in Construction Materials*, vol. 23, pp. 1-23, 2025. [CrossRef] [Google Scholar] [Publisher Link]

[21] De-Cheng Feng et al., "Machine Learning-based Compressive Strength Prediction for Concrete: An Adaptive Boosting Approach," *Construction and Building Materials*, vol. 230, pp. 1-20, 2020. [CrossRef] [Google Scholar] [Publisher Link]

[22] Mulusew Aderaw Getahun, Stanley Muse Shitote, and Zachary C. Abiero Gariy, "Artificial Neural Network based Modelling Approach for Strength Prediction of Concrete Incorporating Agricultural and Construction Wastes," *Construction and Building Materials*, vol. 190, pp. 517-525, 2018. [CrossRef] [Google Scholar] [Publisher Link]

[23] Mohsin Ali Khan et al., "Compressive Strength of Fly-Ash-based Geopolymer Concrete by Gene Expression Programming and Random Forest," *Advances in Civil Engineering*, vol. 2021, no. 1, pp. 1-17, 2021. [CrossRef] [Google Scholar] [Publisher Link]

[24] Asad S. Albostami, Rwayda Kh. S. Al-Hamd, and Ali Ammar Al-Matwari, "Data-Driven Predictive Modeling of Steel Slag Concrete Strength for Sustainable Construction," *Buildings*, vol. 14, no. 8, pp. 1-25, 2024. [CrossRef] [Google Scholar] [Publisher Link]

[25] Yassir M. Abbas, and Abdulaziz Alsaif, "Explainable Data-Driven Modeling for Optimized Mix Design of 3D-Printed Concrete: Interpreting Nonlinear Synergies among Binder Components and Proportions," *CMES - Computer Modeling in Engineering and Sciences*, vol. 145, no. 2, pp. 1789-1819, 2025. [CrossRef] [Google Scholar] [Publisher Link]

[26] M. Solikin, and T. Mulyanto, "Mechanical Properties of Self-Compacting Concrete Incorporated with High Volume Fly Ash," *IOP Conference Series: Materials Science and Engineering*, vol. 821, no. 1, pp. 1-8, 2020. [CrossRef] [Google Scholar] [Publisher Link]

[27] Y. Sunarno et al., "Effect of Accelerators on High Early Strength Concrete (HESC) using High Volume Fly Ash," *IOP Conference Series: Earth and Environmental Science*, vol. 1272, no. 1, pp. 1-7, 2023. [CrossRef] [Google Scholar] [Publisher Link]

[28] Eva Arifi, Achfas Zacoeb, and Mitsuhiro Shigeishi, "Effect of Fly Ash on the Strength of Concrete Made from Recycle Aggregate by Pulsed Power," *International Journal of GEOMATE*, vol. 7, no. 13, pp. 1009-1016, 2014. [Google Scholar] [Publisher Link]

[29] Stefanus A. Kristiawan, Agus Setiya Budi, and Andreas Nur Hadi, "Uniaxial Compressive Stress-Strain Behavior of Self-Compacting Concrete with High-Volume Fly Ash," *International Journal of GEOMATE*, vol. 14, no. 41, pp. 77-85, 2018. [Google Scholar] [Publisher Link]

[30] Fahrizal Zulkarnain, Satrio Wibowo, and Mohd Zailan Sulieman, "Evaluating the Elastic Modulus of Geopolymer Concrete: The Impact of Fly Ash as a Cement Substitute using a No-Soaking Method for Sustainable Construction," *Journal of Advanced Research Design*, vol. 126, no. 1, pp. 53-68, 2025. [CrossRef] [Google Scholar] [Publisher Link]

[31] Y. Sunarno, "The Influence of Fly Ash Characteristics as a Supplementary Cementitious Material (SCM) on Concrete's Mechanical Properties," *Materials Research Proceedings*, vol. 48, pp. 587-596, 2025. [CrossRef] [Google Scholar] [Publisher Link]

[32] Faroq Ali Ali Hussein Qazwan, "*The Effect of Using Fly Ash as Supplementary Material on Conventional Concrete*," Diss, Universitas Islam Indonesia, 2024. [Google Scholar] [Publisher Link]

[33] Afippullah et al., "Comparison of the Use of Type V and Type I Cement with Fly Ash as Cementitious in Concrete Against Chloride Ion Penetration using the Accelerated Method," *Journal of Global Engineering Research and Science*, vol. 2, no. 1, pp. 8-15, 2023. [CrossRef] [Google Scholar] [Publisher Link]

[34] Fadhilah Muslim, and Rachmat Hermawan, "Mechanical Properties and Durability of Concrete Containing Indonesian Coal Fly Ash," *Civil Engineering and Architecture*, vol. 13, no. 1, pp. 331-348, 2025. [CrossRef] [Google Scholar] [Publisher Link]

[35] Yohans Sunarno, M. Wihardi Tjaronge, and A. Bakri Muhiddin, "Mechanical Properties of High-Volume Fly Ash Concrete with Varying Fly Ash Content," *ARPN Journal of Engineering and Applied Sciences*, vol. 19, no. 16, pp. 1-7, 2024. [CrossRef] [Google Scholar] [Publisher Link]

[36] D. Rantung, S.W.M. Supit, and S. Nicolaas, "Effects of Different Size of Fly Ash as Cement Replacement on Self-Compacting Concrete Properties," *Journal of Sustainable Engineering: Proceedings Series*, pp. 180-186, 2019. [CrossRef] [Google Scholar]

[37] Yohans Sunarno et al., "Strength and Sustainability in Concrete: The Dual Role of Fly Ash and Accelerators in Reducing Environmental Impacts," *Engineering, Technology and Applied Science Research*, vol. 15, no. 3, pp. 23260-23267, 2025. [CrossRef] [Google Scholar] [Publisher Link]

[38] Yohans Sunarno et al., "Utilization of High-Volume Fly Ash as A Supplementary Cementitious Material in Environmentally Friendly Concrete," *Indonesian Journal of Urban and Environmental Technology*, vol. 7, no. 1, pp. 106-118, 2024. [CrossRef] [Google Scholar] [Publisher Link]

[39] Wahyuniarsih Sutrisno et al., "A Case Study of Concrete Incorporating High Volume Fly Ash and Bottom Ash for Sustainable Housing," *Civil Engineering and Architecture*, vol. 12, no. 5, pp. 3179-3192, 2024. [CrossRef] [Google Scholar] [Publisher Link]

[40] M. Mujiburrakhman, and S. Widodo, "Study on Partial Replacement of Sand with Fly Ash in Concrete Mixes based on Pozzolanic Cementing Efficiency to the Strength-Weight and Cost-Strength Ratio," *Journal of Physics: Conference Series*, vol. 1625, no. 1, pp. 1-11, 2020. [CrossRef] [Google Scholar] [Publisher Link]

[41] Maizuar et al., "Effect of Graphene Oxide on the Performance of Fly Ash Concrete Exposed to Ambient Temperature," *Civil Engineering Journal (Iran)*, vol. 11, no. 7, pp. 2736-2750, 2025. [CrossRef] [Google Scholar] [Publisher Link]

[42] Ni Nyoman Kencanawati et al., "Properties of Concrete Containing Type-C Fly Ash Under Elevated Temperature," *Semesta Teknika*, vol. 26, no. 2, pp. 194-202, 2023. [CrossRef] [Google Scholar] [Publisher Link]

[43] Mochamad Solikin et al., "Analysis of the use of Fly Ash Variations as a Partial Cement Substitute for Roller Compacted Concrete (RCC) Mixtures †," *Engineering Proceedings*, vol. 84, no. 1, pp. 1-11, 2025. [CrossRef] [Google Scholar] [Publisher Link]

[44] Muhammad Iqbal Alfaroji et al., "The Effect of using Coal Fly Ash as a Fine Aggregate Substitute on the Compressive Strength of Concrete," *The South East Asian Journal of Advance Engineering and Technology*, vol. 2, no. 2, pp. 43-47, 2025. [CrossRef] [Google Scholar] [Publisher Link]