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AI-Based prediction of fine-aggregate geopolymer concrete strength using machine learning algorithms

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KEYWORDS

Fine-aggregate geopolymer concrete
Fly ash
Ground granulated blast-furnace slag
Flexural strength
Compressive strength
Machine learning algorithms

ABSTRACT

This study presents a machine learning framework implemented in WEKA to predict the compressive and flexural strengths of fine-aggregate geopolymer concrete (FAGPC). Utilizing two experimental datasets (90 instances for compressive strength and 45 instances for flexural strength), the study investigated the non-linear relationships between fly ash/ ground granulated blast-furnace slag contents, curing age and strength. Four classical regression algorithms – M5P, REP Tree, Random Forest and Random Tree – were systematically evaluated using an 80/20 train-test split. Model performance was evaluated by using several statistical performance indicators, including the Correlation Coefficient (R), mean absolute error (MAE), relative absolute error (RAE), mean squared error (MSE), and root mean squared error (RMSE). The results demonstrate reliable predictive performance for both mechanical properties. For compressive strength, the Random Tree model achieved the highest correlation (R = 0.7628), while the REP Tree model yielded the lowest error (RMSE = 7.02 MPa) on the test set. For flexural strength, the Random Forest model emerged as the superior predictor, achieving an outstanding correlation coefficient (R = 0.8833) and a low RMSE of 1.00 MPa. These findings indicate that the selected input variables (precursor content, curing age) are sufficient to capture the complex behavior of FAGPC.

1. Introduction

Geopolymer concrete, as an alternative to traditional cement concrete, has been studied for several decades and has recently been increasingly applied as a construction material. This type of concrete is produced from industrial waste materials (such as fly ash, ground granulated blast furnace slag, silica fume, and rice husk ash) with the support of an alkaline activator solution (AAS). The activator solution plays an important role in the polymerization reaction process. The selection of aluminosilicate source materials depends on cost and the specific intended application [1]. Studies on the production of geopolymer concrete using curing methods under natural environmental conditions (ambient temperature) are considered more economical compared with other curing methods, such as heat curing.

Fine-aggregate geopolymer concrete (FAGPC) has gained significant attention as a sustainable alternative to traditional Portland cement-based concrete, offering superior mechanical properties, enhanced durability, and a substantially lower environmental impact [2-4]. FAGPC is formed through the alkali activation of aluminosilicate-rich industrial by-products, such as fly ash (FA) and ground granulated blast-furnace slag (GGBFS), creating a three-dimensional polymeric structure with excellent resistance to chemical attack and thermal stress [2, 5, 6].Recent advancements, including the incorporation of nano-materials and optimized binder systems, have further improved its performance, making it suitable for applications in high-strength infrastructure [7, 8].

Despite these benefits, predicting the mechanical strength of FAGPC remains challenging due to the nonlinear relationships between mix proportions – such as precursor ratios and curing conditions [9, 10]. Traditional empirical models often fall short, requiring extensive trial-and-error experimentation that is time-intensive and resource-heavy [11, 12]. The variability in precursor chemistry and activation processes further exacerbates these issues, limiting scalability in practical mix design.

The emergence of artificial intelligence (AI) and machine learning (ML) has revolutionized materials engineering by enabling data-driven predictions of complex behaviors [13-15]. ML algorithms, such as artificial neural networks (ANNs), decision trees, and ensembles, excel at modeling intricate interactions in construction materials [16-18]. For instance, recent studies have applied ML to optimize geopolymer formulations, achieving high predictive accuracy. However, many existing works rely on large or synthetic datasets, which are not representative of typical laboratory-scale experiments [19, 20]. Real-world laboratory data is often limited and sparse. Consequently, there is a clear need for data-efficient and interpretable models that can function effectively with small datasets [19, 21].

This study utilizes two refined experimental datasets: one with 90 instances for compressive strength and another with 45 instances for flexural strength Both datasets cover three curing ages (3, 7, and 28 days) and are processed using the WEKA platform [22, 23]. WEKA's intuitive interface facilitates a rapid and robust comparison of algorithms without the need for extensive coding expertise [22]. This

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study investigated the non-linear relationships between fly ash/ ground granulated blast-furnace slag contents, curing age and strength. Four classical regression algorithms – M5P, REP Tree, Random Forest and Random Tree – were systematically evaluated using an 80/20 train-test split. Model performance was evaluated by using several statistical performance indicators, including the Correlation Coefficient (R), mean absolute error (MAE), relative absolute error (RAE), mean squared error (MSE), and root mean squared error (RMSE).

2. Data and Methodology

2.1. Materials and mix Proportions

2.1.1. Materials

The fine-aggregate geopolymer concrete (FAGPC) mixtures in this study were developed using industrial by-products and locally sourced materials to maximize sustainability while ensuring superior mechanical performance [2, 3]. The primary binder system consisted of Class F fly ash (FA) from the Pha Lai thermal power plant and Grade S95 ground granulated blast-furnace slag (GGBFS) from Hoa Phat, Vietnam.

A "one-part" geopolymer approach was adopted by utilizing a solid dry powder activator, primarily sodium metasilicate (Na_2O $SiO_2.nH_2O$). This solid activator was pre-mixed with the precursors (FA and GGBFS), significantly enhancing operational safety and simplifying material handling compared to conventional liquid alkali solutions like NaOH or Na_2SiO_3 [6, 24]. To ensure adequate workability and low water demand, a polycarboxylate ether (PCE)-based superplasticizer was incorporated at dosages ranging from 0.5 % to 1.5 % by binder weight.

The aggregate phase included coarse sand (0.3–0.6 mm) and fine sand (0.1–0.3 mm), both of which were dried and sieved to achieve a uniform particle size distribution.

2.1.2. Mixture proportions

The mixture proportions of UHPGC in this study were developed with a binder (FA + GGBFS) content of 950 kg/m^3 and a water-to-binder ratio (W/B) ranging from 0.20 to 0.25. The dosage of the superplasticizer (as a percentage of binder mass) was determined to achieve the minimum flow time (lowest viscosity) and the maximum flow spread of the concrete mixture.The mixture proportions are presented in Table 1.

2.2. Sample preparation and Data Setup

Sample preparation followed a standardized procedure to ensure the consistency and reproducibility of FAGPC specimens. The mixing sequence began with the dry blending of FA, GGBFS, and the solid sodium metasilicate activator for 2 minutes in a laboratory planetary mixer. Fine and coarse sands were then added and mixed for an additional 3 minutes. The superplasticizer, pre-dissolved in 20 % of the mixing water, was introduced gradually, followed by the remaining water. The total mixing time ranged from 8 to 10 minutes – longer than conventional Portland cement concrete – to ensure the full dissolution of the solid activator and a homogeneous dispersion of the aluminosilicate precursors [6].

Fresh FAGPC was evaluated for workability using a modified slump flow test adapted for high-viscosity alkali-activated mixtures. The concrete was placed in a truncated conical mold (top diameter 70 mm, bottom diameter 100 mm, height 60 mm) in two layers, each compacted by 15 strokes of a tamping rod. Average slump flow values exceeded 220 mm for all mixtures, indicating excellent self-compacting behavior suitable for intricate precast components.

Specimens were cast in prismatic molds (40 × 40 × 160 mm) and subjected to an ambient curing regime (22 ± 3 °C, RH ≥ 95 %). Mechanical testing was conducted at 3, 7, and 28 days in accordance with TCVN 3121-11:2003. According to the testing protocol, each prismatic specimen was first subjected to a three-point bending test to determine its flexural strength. Subsequently, the two resulting halves of the broken prism were used for compressive strength testing. This procedure yielded a refined dataset consisting of 45 flexural strength instances and 90 compressive strength instances.

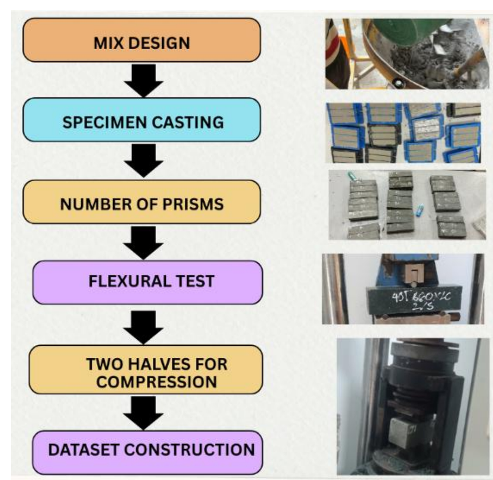

Figure 1. Experimental data pipeline: From laboratory mix design and specimen testing to the construction of the machine learning dataset.

2.3. Data Acquisition and Model Configuration

The experimental results were systematically compiled into two primary datasets to facilitate predictive modeling within the Waikato Environment for Knowledge Analysis (WEKA) platform [22, 23]. These datasets represent the mechanical performance of various geopolymer binders across multiple curing durations. The configuration and statistical distribution of these datasets are summarized in Table 2.

To provide a representative overview of the experimental campaign, Table 3 presents the measured strength values for the various mix designs. This data serves as the foundation for the non-linear relationship mapping performed by the ML algorithms.

2.3.1. Feature Selection and Engineering

The predictive capacity of the models was evaluated based on three primary independent input variables (X_1–X_3):

X_1: Fly ash content (g) – range [285, 665].

X_2: GGBFS content (g) – range [285, 665].

X_3: Curing age (days) – [3, 28].

Certain parameters were intentionally excluded from the feature set to prevent multicollinearity and overfitting [19, 20]. The "FA/GGBFS ratio" was omitted as it is a dependent function of X_1 and X_2. Furthermore, environmental and chemical factors such as "Curing temperature" were removed from the input matrix because they remained constant throughout all experimental batches, offering no variance for the algorithms to learn from [12, 19]. The finalized datasets were formatted in Comma-Separated Values (CSV) to ensure seamless processing during the training phase in WEKA.

2.4. Machine Learning Algorithms and WEKA Platform

2.4.1. Introduction to WEKA and Model Configuration

The Waikato Environment for Knowledge Analysis (WEKA), version 3.9.6, was utilized as the primary computational framework for strength prediction [22, 23]. Developed by the University of Waikato, New Zealand, this open-source platform provides a robust suite of tools for data preprocessing, regression, and visualization. WEKA was selected for its high efficiency with small-to-medium datasets, such as the refined experimental records used in this study (90 instances for compressive and 45 for flexural strength).

To ensure the statistical stability and robustness of the predictive models, a 10-fold cross-validation procedure was conducted during the initial training and hyperparameter tuning phase [19]. This validation step confirms that the models maintain consistent performance regardless of data partitioning. However, for the purpose of assessing the final generalization capability on completely unseen data, the performance metrics reported in the Results section are derived from the independent 80/20 train–test split [20].

To ensure the reproducibility of the machine learning results, specific global configurations were applied:

- Data Partitioning: An 80/20 train–test split was employed, where 80 % of the data was used for model training and 20 % reserved for independent performance evaluation.
- Reproducibility: A fixed random seed of 42(S = 42) was implemented during the randomization process to ensure consistent data splitting and result stability across different runs.
- Validation Mode: During the tuning phase, 10-fold cross-validation was utilized to minimize bias and evaluate the robustness of the regression models.

Figure 2. Weka Interface.

2.3.2. Predictive Models and Hyperparameters

Four classical regression algorithms were implemented to predict compressive strength (Y_1) and flexural strength (Y_2). The specific mechanisms and hyperparameters for each model are detailed below:

- M5P (Model Tree): This algorithm generatzes a decision tree structure but replaces constant leaf values with multivariate linear regression models [25]. For this study, the model was configured with a minimum number of instances per leaf of 4.0 (M = 4.0). This hybrid design allows the capturing of complex nonlinear interactions through a set of piecewise linear functions.
- Random Forest (RF): RF is an ensemble learning method that constructs a collection of unpruned Random Trees using bootstrap aggregation (bagging) and random feature selection at each split [16]. By averaging the predictions of 100 independent trees, the model significantly reduces variance and mitigates the risk of overfitting.
- REP Tree (Reduced-Error Pruning Tree): This algorithm builds a regression tree based on variance reduction and applies reduced-error pruning to simplify the model. One-third of the training data is held out as a validation set to guide the pruning process, iteratively removing subtrees that increase validation error to enhance generalization.
- Random Tree (RT): RT is a single-tree algorithm that recursively partitions the input space by randomly selecting $\sqrt{p}$ attributes (where p is the number of input variables) at each split. Unlike RF, RT grows the tree to its full depth without pruning or ensemble averaging, which allows for fast training and high precision on the training set, though it requires careful monitoring for overfitting.

All models were executed natively in the WEKA Classify interface, with output metrics calculated to four decimal places to maintain statistical granularity.

Figure **3** represents the system architecture for concrete strength prediction.

2.3.3. Model Evaluation Metrics

Model performance was rigorously assessed using a comprehensive set of statistical metrics, drawing from established practices in machine learning applications for concrete strength prediction. These metrics provide a multifaceted evaluation of predictive accuracy, capturing aspects such as linear correlation, error magnitude, relative efficiency, and variance explanation. The primary metrics – Correlation Coefficient (R) and Root Mean Squared Error (RMSE) – were prioritized for consistency with prior FAGPC studies, while additional indicators ensured robust validation against overfitting and bias. All computations were performed natively in WEKA, supplemented by external sensitivity analysis to quantify input-output relationships [10, 12, 26].

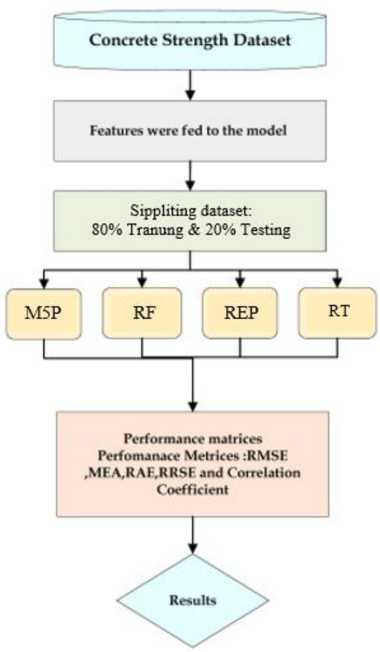

Figure 3. System architecture for concrete strength systems prediction [27].

Table 4 summarizes the key evaluation metrics, including their formulas, interpretations, and relevance to this study.
These metrics were computed separately for training (TR) and testing (TS) phases using 10-fold cross-validation and an 80/20 hold-out split [19, 20]. Sensitivity analysis, inspired by UHPC modeling approaches [e.g., ablation studies on input variables like FA/GGBFS ratio], was conducted via WEKA's attribute evaluator to rank feature importance. External validation involved comparing predicted strengths against an independent subset of 6 held-out samples, ensuring generalizability. Scatter plots of actual vs. predicted values, residual plots, and radar charts of normalized metrics (e.g., scaled R, RMSE, and R^2) were generated to visually diagnose model fit, heteroscedasticity, and bias, aligning with best practices for interpretable AI in sustainable materials [18]. This multi-metric framework not only validates the models' efficacy but also supports their deployment as decision tools for reducing experimental iterations in FAGPC development.

3. Results and discussion

This section presents a detailed performance evaluation and comparative analysis of four machine learning algorithms – M5P, Random Forest (RF), Random Tree (RT), and REP Tree – in predicting the compressive and flexural strengths of fine-aggregate geopolymer concrete (FA-GPC). To rigorously assess the generalization capability and predictive reliability of each model, all performance results are reported based on the independent test datasets, which represent 20 % of the total instances (specifically 18 instances for compressive strength and 9 instances for flexural strength).

3.1. M5P Model

The M5P algorithm, a model tree that combines a decision tree structure with multivariate linear regression models at the leaf nodes, was evaluated for its predictive accuracy. The detailed performance of the M5P model on both the training and test datasets is presented in Table 5.
For Compressive Strength (Y_1):

The M5P algorithm exhibited acceptable predictive performance, achieving a correlation coefficient of R = 0.7186 and a RMSE of 7.52 MPa on the test dataset. While the model successfully captured the general trend of strength development, it showed the lowest predictive accuracy among the four evaluated models for this property. The Relative Root Squared Error (RRSE) of 88.65 % on the test set suggests that while the model is valid, it is less efficient at capturing the highly non-linear interactions within the compressive dataset compared to ensemble-based methods.

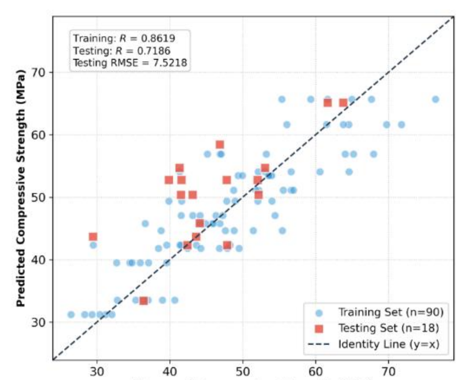

Figure 4. Actual vs. Predicted Compressive Strength Scatter Plot for M5P.

For Flexural Strength (Y_2):

In contrast, the M5P model demonstrated a significantly higher predictive capability for flexural strength. It achieved a high correlation coefficient of R = 0.8158 and a low RMSE of 1.26 MPa on the test set. The model displayed notable stability, with the test R-value remaining competitive with the training R-value (0.8847). The RRSE was 56.15 %, indicating a reliable predictive model that effectively utilizes the piecewise linear functions at its leaf nodes to forecast the flexural capacity of fine-aggregate geopolymer concrete.

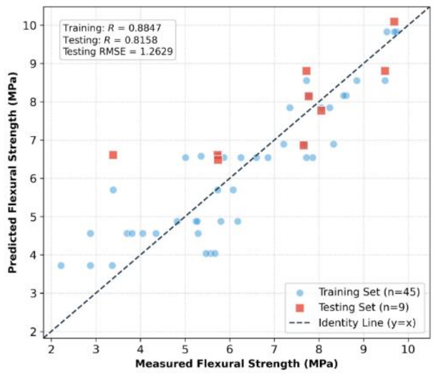

Figure 5. Actual vs. Predicted Flexural Strength Scatter Plot for M5P.

3.2. REP Tree Model

REP Tree is a decision tree algorithm that utilizes variance reduction to construct a regression tree and employs reduced-error pruning to mitigate overfitting. The performance of this model was evaluated on both training and test datasets for the 90/45 experimental instances, with the detailed results presented in Table 6.

For Compressive Strength (Y1):

The REP Tree algorithm demonstrated significant error-minimization capabilities on the test dataset. While achieving a correlation coefficient of R = 0.7504, it yielded the lowest RMSE = 7.0247 MPa among all tested algorithms for compressive strength prediction. This performance highlights the effectiveness of the model's pruning mechanism in simplifying the tree structure and enhancing generalization by removing subtrees that do not contribute to accuracy on held-out validation data.

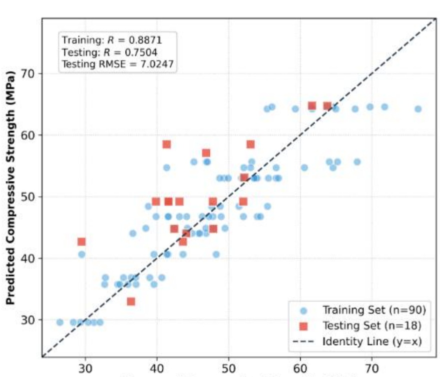

Figure 6. Actual vs. Predicted Compressive Strength Scatter Plot for REP Tree.

For Flexural Strength (Y_2):

The REP Tree model also provided a statistically valid prediction for flexural strength, with a test correlation coefficient of R = 0.7225 and an RMSE of 1.32 MPa. Although its predictive efficiency, as indicated by the RRSE (58.87 %), was lower than that of ensemble methods like Random Forest, the results remain within acceptable bounds for experimental laboratory data. This outcome confirms that the model successfully captured the underlying patterns between the precursor materials (FA, GGBFS), and the resulting flexural capacity of the fine-aggregate geopolymer matrix.

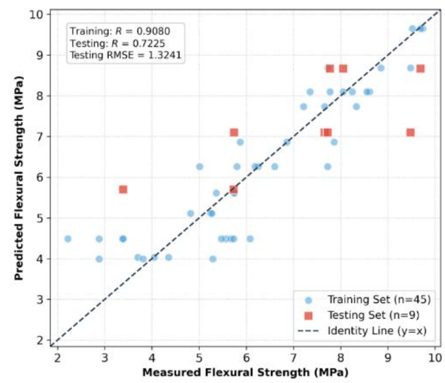

Figure 7. Actual vs. Predicted Flexural Strength Scatter Plot for REP Tree.

3.3. Random Forest

Random Forest is an ensemble learning algorithm that constructs a multitude of decision trees during training and outputs the average prediction of the individual trees to enhance predictive accuracy and control overfitting. This method utilizes bootstrap aggregation (bagging) and random feature selection at each split to ensure model diversity and robustness. The detailed results for this model on the 90/45 experimental instances are presented in Table 7.

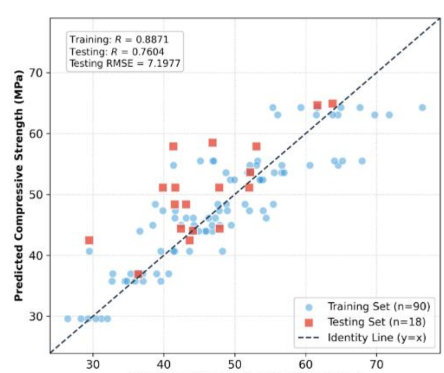

Figure 8. Actual vs. Predicted Compressive Strength Scatter Plot for Random Forest.

For Compressive Strength (Y_1):

The Random Forest algorithm produced competitive results on the test dataset, achieving a correlation coefficient of R = 0.7604 and an RMSE of 7.20 MPa. This performance ranks it as one of the most reliable models for compressive strength prediction. The model demonstrated good stability between the training (R = 0.8871) and test phases, indicating that the ensemble mechanism effectively mitigated the variance typically associated with individual decision trees.

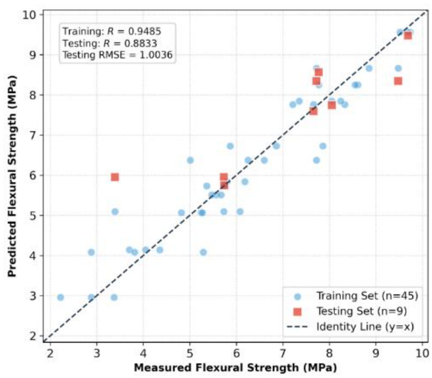

Figure 9. Actual vs. Predicted Flexural Strength Scatter Plot for Random Forest.

For Flexural Strength (Y_2):

The Random Forest model emerged as the superior predictor for flexural strength in this study, delivering the highest predictive accuracy among all evaluated algorithms. It achieved an outstanding correlation coefficient of R = 0.8833 on the test set, accompanied by the lowest error rates (MAE = 0.66 MPa and RMSE = 1.00 MPa). With a Relative Root Squared Error (RRSE) of only 44.62 %, the RF model proves highly efficient at capturing the complex, non-linear contributions of precursor materials, curing age to the flexural capacity of the geopolymer matrix.

3.4. Random Tree Model

Random Tree is a single decision tree algorithm that constructs a predictive model without pruning and incorporates randomization in attribute selection at each split. For this study, the model was grown to its full depth to capture the complex, non-linear relationships within the 90/45 experimental instances. The detailed performance metrics for the RT model are presented in Table 8.

For Compressive Strength (Y_1):

The Random Tree model emerged as the top-performing algorithm for compressive strength prediction on the updated dataset. It achieved the highest test correlation coefficient of R = 0.7628. While single-tree models without pruning often risk overfitting, the RT model in this study demonstrated a well-balanced performance, with the training R (0.8876) translating effectively to the test set. This indicates that the randomization of features during splitting successfully captured the dominant influence of precursor ratios and curing age on the mechanical properties of the fine-aggregate matrix.

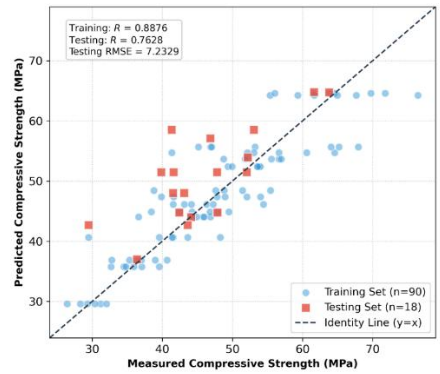

Figure 10. Actual vs. Predicted Compressive Strength Scatter Plot for Random Tree.

For Flexural Strength (Y_2):

The Random Tree model demonstrated exceptionally high predictive accuracy, achieving a test correlation of R = 0.8752 and a low RMSE of 1.04 MPa. These results are nearly identical to those achieved by the ensemble-based Random Forest, confirming that the input variables –specifically the interaction between the geopolymer precursors (fly ash and slag) and the curing age – are highly sufficient for the model to learn the governing mechanisms of flexural behavior. The low RRSE of 46.41 % on the test set further validates the high suitability of this algorithm for modeling the strength characteristics of sustainable fine-aggregate materials targeted for precast applications.

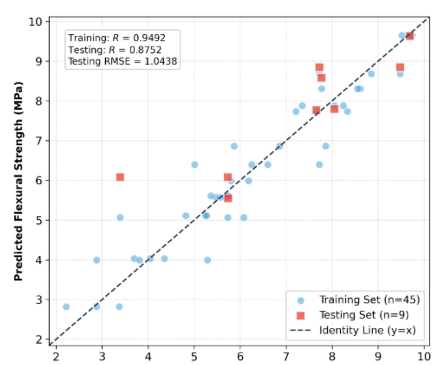

Figure 11. Actual vs. Predicted Flexural Strength Scatter Plot for Random Tree.

3.5. Comparative Summary

To provide a holistic overview, the performance of all four models on both the training and test datasets is summarized in Table 9. This comparison highlights the generalization capability and predictive precision of the implemented algorithms across the refined 90/45 instance datasets.

Table 1. Mixture proportions of Geopolymer concrete with w/b ratio 0.22.

Mixtures	Metalsilicate (kg)	Fly ash (kg)	GBFS (kg)	SP (kg)	Fine sand (kg)	Coarse sand (kg)	Water (kg)
70FA.30GBFS	142.5	665	285	47.5	935	401	215
60FA.40GBFS	142.5	570	380	47.5	935	401	215
50FA.50GBFS	142.5	475	475	47.5	935	401	215
40FA.60GBFS	142.5	380	570	47.5	935	401	215
30FA.70GBFS	142.5	285	665	47.5	935	401	215

Table 2. Machine Learning Dataset Configuration.

Property	Total Instances	Test Set (20 %)	Curing Ages (days)	Output Variable
Compressive	90	18	3, 7, 28	(Y_1): Compressive Strength (MPa)
Flexural	45	9	3, 7, 28	(Y_2): Flexural Strength (MPa)

Table 3. Summary of Averagre Representative Experimental Results.

Mixture ID	Age (days)	Flexural Strength (MPa)	Compressive Strength (MPa)
70FA.30GBFS	3	7.89	53.65
	7	8.32	52.41
	28	5.08	44.04
60FA.40GBFS	3	5.62	46.14
	7	7.74	47.39
	28	6.88	54.73
50FA.50GBFS	3	4.04	40.65
	7	6.09	48.17
	28	6.45	57.11
40FA.60GBFS	3	4.00	35.76
	7	5.12	44.89
	28	8.70	64.57
30FA.70GBFS	3	2.83	29.62
	7	5.58	36.87
	28	9.66	63.79

Table 4. Summary table of formula data.

Metric	Formula	Interpretation
Correlation Coefficient (R)	$R = \frac{\sum(y_i - \bar{y})(\hat{y}_i - \bar{\hat{y}})}{\sqrt{\sum(y_i - \bar{y})^2 \sum(\hat{y}_i - \bar{\hat{y}})^2}}$	Measures the linear correlation between actual (y) and predicted ($\hat{y}$) values. Values closer to 1.0 indicate strong positive correlation and reliable predictions. Higher is better (ideal: 1.0). Used as the primary indicator of model fit in FA-GPC literature [9, 10].
Root Mean Squared Error (RMSE)	$\mathrm{RMSE} = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2}$	Quantifies the average magnitude of prediction errors in MPa, penalizing larger deviations more heavily. Lower is better (ideal: 0). Essential for assessing practical accuracy in strength forecasting [9, 12, 26].
Mean Absolute Error (MAE)	$MAE = \frac{1}{N}\sum_{i=1}^{N}\lvert\hat{y}_i - y_i\rvert$	(Interpretation for MAE): "Quantifies the average error magnitude in MPa, robust to outliers. Lower is better (ideal: 0)."
Relative Absolute Error (RAE)	$RAE = \frac{\sum\lvert y_i - \hat{y}_i\rvert}{\sum\lvert y_i - \bar{y}\rvert} \times 100\%$	Measures the ratio of the model's absolute error to the error of a simple mean predictor. Values below 100% indicate that the model

Metric	Formula	Interpretation
		performs better than a baseline prediction using the average of actual values. Lower values denote higher predictive efficiency.
Root Relative Squared Error (RRSE)	$RRSE = \sqrt{\frac{\sum(y_i - \hat{y}_i)^2}{\sum(y_i - \bar{y})^2}} \times 100\%$	Represents the square root of the ratio between the model's mean squared error and that of a mean predictor. It penalizes large deviations more heavily than RAE. RRSE values below 100% signify a model with superior generalization capability.

Table 5. Detailed Performance Results for the M5P Model (90/45 Dataset).

Strength Property	Dataset Type	R	MAE (MPa)	RMSE (MPa)	RAE (%)	RRSE (%)
Compressive Strength Y_1	Training	0.8619	4.2753	5.5163	48.96	50.71
	Test	0.7186	5.7416	7.5218	82.92	88.65
Flexural Strength Y_2	Training	0.8847	0.7438	0.9175	45.31	46.62
	Test	0.8158	0.9401	1.2629	48.39	56.15

Table 6. Detailed Performance Results for the REP Tree Model.

Strength Property	Dataset Type	R	MAE (MPa)	RMSE (MPa)	RAE (%)	RRSE (%)
Compressive Strength	Training	0.8871	3.7648	5.0203	43.11	46.15
	Test	0.7504	5.3071	7.0247	76.64	82.8
Flexural Strength	Training	0.908	0.6161	0.8246	37.53	41.9
	Test	0.7225	1.0891	1.3241	56.07	58.87

Table 7. Detailed Performance Results for the Random Forest (RF) Model.

Strength Property	Dataset Type	R	MAE (MPa)	RMSE (MPa)	RAE (%)	RRSE (%)
Compressive Strength	Training	0.8871	3.7721	5.025	43.19	46.19
	Test	0.7604	5.3191	7.1977	76.82	84.83
Flexural Strength	Training	0.9485	0.4567	0.6251	27.82	31.76
	Test	0.8833	0.6585	1.0036	33.9	44.62

Table 8. Detailed Performance Results for the Random Tree Model.

Strength Property	Dataset Type	R	MAE (MPa)	RMSE (MPa)	RAE (%)	RRSE (%)
Compressive Strength	Training	0.8876	3.7546	5.01	42.99	46.06
	Test	0.7628	5.3228	7.2329	76.87	85.25
Flexural Strength	Training	0.9492	0.4458	0.6196	27.16	31.48
	Test	0.8752	0.6917	1.0438	35.61	46.41

Table 9. Summary of Model Performance on Updated 90/45 Dataset.

Strength	Model	Dataset Type	R	MAE (MPa)	RMSE (MPa)	RAE (%)	RRSE (%)
Compressive Strength	M5P	Training	0.8619	4.2753	5.5163	48.96	50.71
		Test	0.7186	5.7416	7.5218	82.92	88.65
	RandomForest	Training	0.8871	3.7721	5.025	43.19	46.19
		Test	0.7604	5.3191	7.1977	76.82	84.83
	RandomTree	Training	0.8876	3.7546	5.01	42.99	46.06
		Test	0.7628	5.3228	7.2329	76.87	85.25
	REPTree	Training	0.8871	3.7648	5.0203	43.11	46.15
		Test	0.7504	5.3071	7.0247	76.64	82.8

Strength	Model	Dataset Type	R	MAE (MPa)	RMSE (MPa)	RAE (%)	RRSE (%)
Flexural Strength	M5P	Training	0.8847	0.7438	0.9175	45.31	46.62
		Test	0.8158	0.9401	1.2629	48.39	56.15
	RandomForest	Training	0.9485	0.4567	0.6251	27.82	31.76
		Test	0.8833	0.6585	1.0036	33.9	44.62
	RandomTree	Training	0.9492	0.4458	0.6196	27.16	31.48
		Test	0.8752	0.6917	1.0438	35.61	46.41
	REPTree	Training	0.908	0.6161	0.8246	37.53	41.9
		Test	0.7225	1.0891	1.3241	56.07	58.87

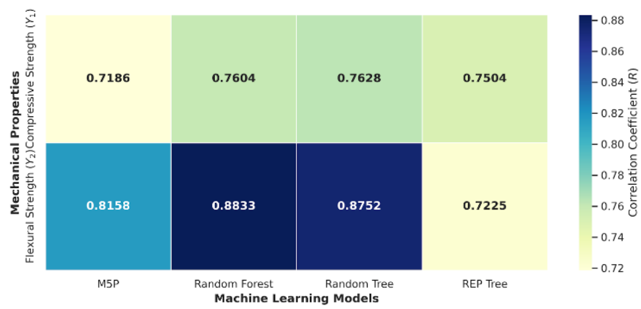

Figure 12. Heat Map of Model Performance (R_values on Test Set).

On Compressive Strength: The analysis confirms that Random Tree and Random Forest achieved the highest linear correlation on the test set, with R values of 0.7628 and 0.7604, respectively. However, REP Tree demonstrated the most effective error minimization, securing the lowest RMSE (7.02 MPa) and RRSE (82.80 %). These results indicate that for the compressive properties of fine-aggregate systems, tree-based models offer a robust balance between capturing non-linear trends and maintaining generalization stability.

On Flexural Strength (The Key Finding): A significant scientific contribution of this study is the high predictive accuracy achieved for flexural strength. Historically regarded as a difficult property to model due to its sensitivity to microstructural defects, flexural strength in this dataset proved highly predictable. Random Forest was the top-performing model, achieving a correlation of R = 0.8833 and a very low RMSE of 1.00 MPa. Even the least accurate model, REP Tree (R = 0.7225), maintained a valid prediction. The relatively low RRSE values (44.6 % – 58.9 %) confirm that these models are highly reliable for practical forecasting.

Hypothesis: The high accuracy achieved in forecasting flexural strength indicates that for this specific FAGPC system, the primary input variables – precursor proportions (FA and GGBFS) and curing duration – are sufficient to characterize the dominant mechanisms governing flexural capacity. These findings suggest that the experimental dataset is characterized by high internal consistency and that the machine learning models successfully captured the complex, non-linear interactions within the material. Specifically, the models effectively mapped the synergy between the chemically activated geopolymer matrix and the optimized fine-aggregate packing system tailored for high-performance precast applications.

4. Conclusions and future works

This study successfully demonstrates the application of machine learning techniques implemented via the WEKA platform for predicting the compressive and flexural strengths of FAGPC. By utilizing refined laboratory-scale datasets – comprising 90 instances for compressive strength and 45 instances for flexural strength – and optimizing the mix design for high-strength precast applications through a "one-part" geopolymer binder system, the following conclusions are drawn:

Predictive Modeling of Compressive Strength: The Random Tree model was identified as the most effective algorithm for capturing linear correlations, achieving the highest test R-value of 0.7628. Conversely, the REP Tree model demonstrated superior robustness in error minimization, yielding the lowest Root Mean Squared Error (RMSE = 7.02 MPa). These results confirm that tree-based algorithms are highly capable of mapping the non-linear interactions between precursor content and curing age within sustainable concrete matrices

High Predictability of Flexural Strength: A significant scientific finding of this work is the outstanding predictive performance achieved for flexural strength. The Random Forest model emerged as the superior predictor, achieving a high correlation of R = 0.8833 and a low RMSE of 1.00 MPa on the test set. These results strongly indicate that the primary input features – specifically the fly ash/slag ratios and curing age – are sufficient to characterize the mechanical mechanisms governing flexural behavior. This finding challenges previous assumptions regarding the inherent unpredictability of flexural strength in alkali-activated materials and confirms its stability within optimized fine-aggregate systems.

Future Work: While the current models provide high reliability, future research should expand the datasets to include more diverse chemical compositions of precursors and varying curing temperatures. Such expansions will further enhance the models' generalization capability across different environmental conditions. Additionally, the integration of these predictive models into real-time quality control systems for precast manufacturing processes warrants further exploration to ensure industrial-scale consistency.

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