AI-Based Predictive Modeling of Sustainable Geopolymer Concrete Using Agricultural Waste Materials.

Abstract

The construction industry is one of the largest contributors to global carbon emissions due to the extensive use of cement in conventional concrete production. Sustainable alternatives such as geopolymer concrete have gained significant attention because they incorporate agricultural and industrial waste materials while reducing environmental impact. This research presents an Artificial Intelligence (AI)-based predictive modeling framework for sustainable geopolymer concrete utilizing agricultural waste materials including Sugarcane Bagasse Ash (SBA), Banana Peel Ash (BPA), and Fly Ash Type C polymer. The proposed framework integrates machine learning algorithms with a lightweight web-based application to predict key concrete performance metrics including compressive strength, flexural strength, and initial and final setting times. Four regression-based machine learning modelsRidge Regression, Elastic Net Regression, Partial Least Squares Regression (PLS), and Support Vector Regression (SVR)were trained and evaluated using experimental geopolymer concrete datasets. Results demonstrated that SVR significantly outperformed the other models, achieving high predictive accuracy with R2 values reaching 0.979 for certain output variables. Feature analysis revealed that Sugarcane Bagasse Ash positively influenced compressive and flexural strength, while Banana Peel Ash reduced concrete setting times. Fly Ash Type C demonstrated predominantly negative effects on overall concrete performance. The developed system provides researchers and material scientists with a rapid, cost-effective, and user-friendly decision-support platform capable of accelerating sustainable concrete research and minimizing the need for extensive laboratory experimentation. Concrete is one of the most widely used construction materials worldwide; however, conventional cement production contributes significantly to global carbon emissions and environmental degradation. The incorporation of agricultural and industrial waste materials into geopolymer concrete presents a sustainable alternative capable of reducing environmental impact while maintaining structural integrity. This study proposes an Artificial Intelligence (AI)-based predictive modeling framework for sustainable geopolymer concrete using agricultural waste materials including Sugarcane Bagasse Ash (SBA), Banana Peel Ash (BPA), and Fly Ash Type C polymer. Machine learning techniques were utilized to predict compressive strength, flexural strength, and initial and final setting times of geopolymer concrete mixtures. Four regression models including Ridge Regression, Elastic Net Regression, Partial Least Squares (PLS), and Support Vector Regression (SVR) were trained and evaluated using experimental concrete composition data. The developed framework also includes a lightweight web-based interface for user interaction and predictive analysis. Results demonstrate that SVR achieved the highest predictive performance across most output variables, with R2 scores ranging from 0.73 to 0.98 and low prediction error rates. Feature analysis revealed that Sugarcane Bagasse Ash positively influenced compressive and flexural strength, while Banana Peel Ash significantly reduced setting times. Fly Ash Type C showed predominantly negative effects on concrete performance. The proposed AI-driven system provides material scientists and researchers with a rapid and

cost-effective decision-support tool for evaluating sustainable geopolymer concrete compositions.

Keywords

Artificial Intelligence, Machine Learning, Sustainable Concrete, Geopolymer Concrete, Agricultural Waste, Support Vector Regression, Fly Ash, Banana Peel Ash, Sugarcane Bagasse Ash

1. Introduction

Concrete is the most widely used construction material in the world and plays a critical role in the development of roads, bridges, residential buildings, commercial infrastructure, and industrial facilities [1], [10], [18]. Despite its importance, conventional concrete production contributes significantly to global environmental degradation due to the carbon-intensive manufacturing process associated with Portland cement production [1], [18], [31]. Current studies estimate that cement manufacturing alone contributes nearly 7–8% of total global carbon dioxide emissions, making the construction industry one of the largest contributors to climate change and environmental pollution [1], [31], [33]. As concerns regarding sustainability and greenhouse gas emissions continue to increase, researchers have focused on identifying environmentally friendly alternatives capable of reducing the ecological footprint of modern infrastructure development [12], [14], [15].

One promising solution involves the development of geopolymer concrete utilizing agricultural and industrial waste materials [12], [14]. Geopolymers are inorganic aluminosilicate materials formed through chemical activation processes that can partially or completely replace conventional cementitious binders [12], [15]. Agricultural waste products such as Sugarcane Bagasse Ash (SBA) and Banana Peel Ash (BPA), along with industrial byproducts such as Fly Ash Type C polymer, have demonstrated strong potential for improving concrete sustainability while maintaining desirable mechanical and durability properties [13], [16], [17], [30]. Previous studies have shown that geopolymer systems can significantly reduce greenhouse gas emissions while improving resistance to chemical degradation and environmental exposure [15], [19], [20], [31].

Experimental evaluation of geopolymer concrete compositions is highly time-consuming and resource-intensive because researchers must conduct extensive curing, testing, and validation procedures for every concrete formulation [3], [15]. A single experimental cycle may require several weeks of curing and considerable laboratory resources before meaningful performance metrics can be obtained [15], [18]. In addition, the growing complexity of geopolymer compositions makes it increasingly difficult to manually evaluate nonlinear interactions between different agricultural waste materials and resulting concrete properties [25], [30]. Consequently, there is an increasing demand for intelligent computational systems capable of predicting concrete performance characteristics prior to physical experimentation [24], [27].

Artificial Intelligence (AI) and Machine Learning (ML) techniques provide effective solutions for modeling complex relationships between geopolymer compositions and concrete properties

[11], [24], [32]. By learning from experimental datasets, machine learning algorithms can rapidly predict mechanical and chemical characteristics of sustainable concrete mixtures while significantly reducing experimental cost, labor, and testing duration [21], [22], [23]. Previous studies have demonstrated that machine learning algorithms such as Artificial Neural Networks, Random Forests, Support Vector Machines, and ensemble learning approaches can successfully predict compressive strength, durability, and curing behavior of concrete systems [2], [21], [22], [23], [24], [28], [29]. Among these methods, Support Vector Regression (SVR) has shown particularly strong performance in nonlinear concrete datasets because of its ability to effectively capture complex interactions among material compositions and output variables [24], [28].

This research proposes an Artificial Intelligence-based predictive modeling framework for sustainable geopolymer concrete utilizing agricultural waste materials including Sugarcane Bagasse Ash, Banana Peel Ash, and Fly Ash Type C polymer. The proposed framework aims to predict key concrete performance characteristics such as compressive strength, flexural strength, initial setting time, and final setting time using multiple machine learning regression algorithms. The study evaluates the predictive capabilities of Ridge Regression, Elastic Net Regression, Partial Least Squares Regression, and Support Vector Regression in modeling geopolymer concrete behavior. The primary objective of this work is to develop an accurate and scalable predictive analytics framework capable of accelerating sustainable material discovery while minimizing the need for extensive laboratory experimentation [11], [24], [32].

The proposed framework demonstrates how Artificial Intelligence can contribute to sustainable infrastructure research by enabling rapid evaluation of geopolymer compositions and improving the efficiency of material optimization processes [11], [24], [32]. The integration of agricultural waste materials with predictive machine learning approaches has the potential to reduce environmental impact, lower experimental costs, and support the development of environmentally responsible construction materials for future infrastructure systems [15], [16], [30], [31].

2. Literature Review

Recent advancements in sustainable construction materials have encouraged researchers to investigate the use of agricultural and industrial waste products in geopolymer concrete production as alternatives to conventional Portland cement systems [3], [12], [15]. The growing environmental concerns associated with cement manufacturing, including excessive carbon dioxide emissions and depletion of natural resources, have accelerated the development of sustainable binder systems capable of reducing the environmental footprint of infrastructure projects [1], [15], [31]. Geopolymer concrete has emerged as a promising sustainable material because it utilizes aluminosilicate-rich industrial and agricultural waste products to partially or completely replace traditional cementitious materials [12], [14], [33].

Several studies have demonstrated that agricultural waste materials such as Sugarcane Bagasse Ash, rice husk ash, and Banana Peel Ash possess strong pozzolanic properties that can improve the mechanical and durability characteristics of concrete systems [13], [16], [17], [30]. Sugarcane Bagasse Ash has been shown to enhance compressive strength, flexural strength, and long-term durability due to its silica-rich composition and reactivity within geopolymer systems [16], [17]. Similarly, Banana Peel Ash has demonstrated beneficial effects on curing behavior and setting time reduction, making it suitable for applications requiring rapid stabilization and early strength development [17], [30]. Previous studies have also investigated fly ash-based geopolymer systems and reported improvements in chemical resistance, sulfate resistance, and durability under aggressive environmental conditions [14], [19], [20], [34], [35].

Traditional approaches for evaluating geopolymer concrete properties primarily rely on laboratory experimentation and destructive testing procedures [3], [15]. Although these methods provide accurate measurements, they are expensive, labor-intensive, and time-consuming because each concrete composition requires extensive curing and validation before meaningful performance metrics can be obtained [15], [18]. Furthermore, the increasing complexity of geopolymer formulations makes it difficult to manually analyze the nonlinear interactions between multiple agricultural waste components and resulting concrete properties [25], [30]. Consequently, researchers have increasingly explored Artificial Intelligence and Machine Learning approaches for predictive modeling and optimization of sustainable concrete systems [24], [27], [32].

Machine learning algorithms such as Artificial Neural Networks (ANNs), Random Forests, Support Vector Machines (SVMs), and ensemble learning techniques have demonstrated strong predictive performance in modeling compressive strength and durability behavior of concrete mixtures [4], [21], [22], [23], [24]. Yeh [23] demonstrated the effectiveness of Artificial Neural Networks in predicting the compressive strength of high-performance concrete. Chou and Bui [22] further demonstrated the effectiveness of machine learning approaches for recycled aggregate concrete analysis, highlighting the growing role of data-driven techniques in sustainable infrastructure research.

Support Vector Regression (SVR) has received particular attention because of its ability to model nonlinear relationships between input variables and concrete performance outputs [24], [28], [29]. Nikoo et al. [28] demonstrated that Support Vector Machines achieved strong predictive accuracy inestimatingconcreteproperties, particularly on nonlinear datasets involving complex material interactions. Similarly, Golafshani et al. [24] reported that machine learning techniques significantly improved predictive performance for sustainable concrete systems compared to traditional empirical approaches. These findings suggest that SVR may be highly suitable for geopolymer concrete datasets involving multiple agricultural waste materials and nonlinear curing behaviors [24], [28].

In addition to predictive performance, recent studies have emphasized the growing importance of Artificial Intelligence in the development of sustainable construction materials and smart infrastructure systems [11], [24], [32]. AI-driven predictive analytics frameworks have the potential to reduce experimental costs, accelerate sustainable material discovery, and improve decision-making processes for infrastructure engineers and material scientists [24], [27], [32]. However, many existing studies primarily focus on conventional concrete systems and do not extensively investigate agricultural-waste-based geopolymer materials [15], [30]. Furthermore, relatively few studies integrate multiple agricultural waste materials with advanced machine learning regression techniques for predictive analysis of compressive strength, flexural strength, and setting times simultaneously [24], [30].

Therefore, this research addresses an important gap in the literature by developing an Artificial Intelligence-based predictive modeling framework specifically designed for sustainable geopolymer concrete systems utilizing Sugarcane Bagasse Ash, Banana Peel Ash, and Fly Ash Type C polymer. The proposed framework integrates multiple machine learning regression models to predict key concrete performance characteristics while supporting rapid and cost-effective evaluation of sustainable geopolymer formulations [11], [24], [32].

3. Research Methodology

3.1 Dataset Description

The dataset used in this research consisted of experimentally generated geopolymer concrete compositions involving three primary sustainable geopolymer materials: Fly Ash Type C polymer, Sugarcane Bagasse Ash (SBA), and Banana Peel Ash (BPA). These materials were selected due to their availability as agricultural and industrial waste products and their potential environmental benefits when used as partial replacements for conventional cement. The dataset contained multiple input-output relationships designed to capture the effects of varying geopolymer ratios on concrete performance characteristics. Input variables included the percentages of Fly Ash Type C polymer, Sugarcane Bagasse Ash, and Banana Peel Ash used within each concrete mixture. Output variables included Initial Setting Time (IST), Final Setting Time (FST), Compressive Strength after 3 Days (CS-3d), Compressive Strength after 7 Days (CS-7d), Compressive Strength after 28 Days (CS-28d), Compressive Strength after 24 Hours at 170°F, and Flexural Strength (FS). These outputs were selected because they represent critical indicators of concrete quality, curing behavior, and structural integrity. The dataset served as the foundation for training and evaluating multiple machine learning regression models capable of learning complex relationships between geopolymer compositions and resulting concrete performance.

3.2 System Architecture

The proposed framework was designed as an integrated predictive analytics system capable of processing geopolymer composition data and generating performance predictions for sustainable concrete mixtures. The workflow begins with preprocessing the experimental geopolymer data, followed by training and evaluation of multiple machine learning regression models. The trained models then generate predictions for compressive strength, flexural strength, and concrete setting times based on varying geopolymer ratios. The architecture was intentionally designed as a lightweight predictive framework capable of rapid deployment and experimental evaluation. Proposed framework in shown in Figure 1.

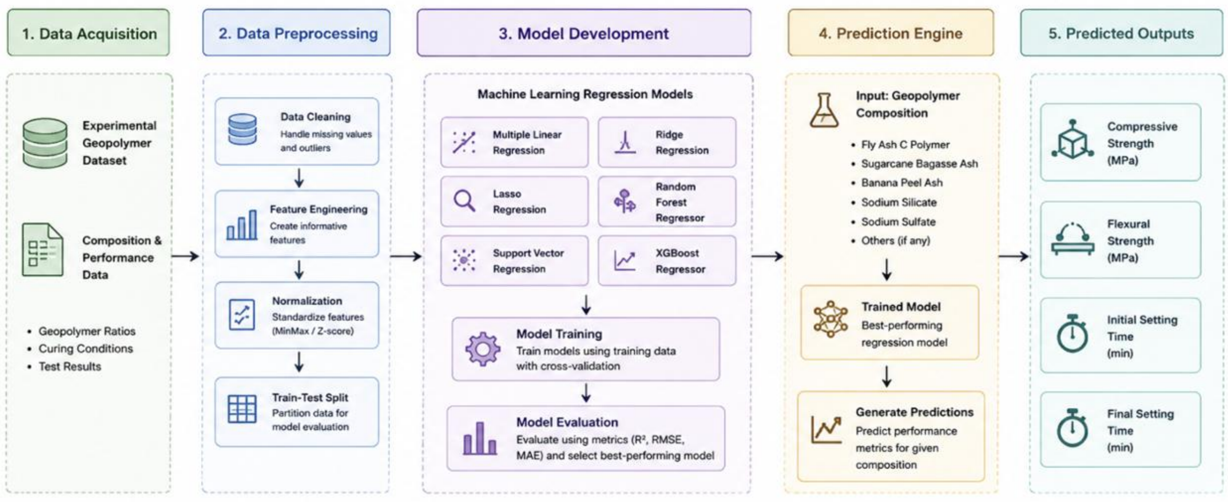

Figure 1: Proposed Framework

3.3 Machine Learning Models

This research evaluated four machine learning regression algorithms to determine the most effective predictive model for geopolymer concrete analysis. The first model implemented was Ridge Regression, a linear regression algorithm that incorporates L2 regularization to reduce overfitting and improve model stability when working with smaller datasets. Ridge Regression is particularly useful when predictor variables exhibit multicollinearity, which was present within the geopolymer composition dataset.

The second model utilized was Elastic Net Regression, which combines both L1 and L2 regularization penalties. Elastic Net is advantageous when datasets contain highly correlated variables because it balances feature selection and coefficient shrinkage simultaneously. The model was evaluated to determine whether its hybrid regularization capabilities could improve predictive performance compared to standard Ridge Regression.

The third model implemented was Partial Least Squares Regression (PLS), which transforms the original predictor variables into latent variables before regression analysis. PLS is commonly used for datasets with limited observations and highly correlated inputs because it can effectively reduce dimensionality while preserving important predictive information.

The final model evaluated was Support Vector Regression (SVR), which utilizes kernel-based learning techniques to model nonlinear relationships between inputs and outputs. Unlike the linear regression models, SVR can capture complex nonlinear interactions among geopolymer compositions and concrete properties. A Radial Basis Function (RBF) kernel was implemented because it provided superior flexibility and adaptability for nonlinear prediction tasks. Each machine learning model was trained and tested using standardized datasets, and performance was evaluated using multiple statistical metrics including R2 score, Mean Absolute Error (MAE), and Root Mean Squared Error (RMSE).

3.4 Software Environment

The computational environment for this research was implemented using Python along with several supporting scientific computing and machine learning libraries. Pandas was utilized for data preprocessing and manipulation, NumPy was used for numerical computations, matplotlib supported statistical visualization and graph generation, and scikit-learn was employed for machine learning model development and evaluation. Additional libraries, such as joblib, were used for model serialization and deployment. The computational framework was intentionally designed to remain lightweight and reproducible while supporting rapid experimentation and predictive analysis.

3.5 Evaluation Metrics

Model performance was evaluated using:

Coefficient of Determination (R2)
Mean Absolute Error (MAE)
Root Mean Squared Error (RMSE)

These metrics were used to compare predictive accuracy across all machine learning models.

4. Feature Analysis of Geopolymers

4.1 Fly Ash Type C Polymer

Feature analysis revealed that Fly Ash Type C polymer had predominantly negative effects on the mechanical and curing properties of the resulting geopolymer concrete mixtures. Increasing the concentration of Fly Ash Type C significantly reduced compressive strength across multiple curing durations, including 3-day, 7-day, and 28-day measurements. In addition, the polymer negatively impacted flexural strength, thereby reducing the overall structural performance of the concrete. The analysis also demonstrated that Fly Ash Type C increased both the initial and final setting times, resulting in slower curing behavior. Pearson correlation analysis further confirmed strong negative relationships between Fly Ash Type C and most strength-related output variables. These findings suggest that excessive incorporation of Fly Ash Type C may weaken geopolymer concrete performance and should therefore be minimized in sustainable concrete formulations[13,17, 30].

4.2 Sugarcane Bagasse Ash (SBA)

Sugarcane Bagasse Ash demonstrated the most positive influence on the strength-related properties of geopolymer concrete. The experimental analysis showed that increasing SBA concentration improved compressive strength after 7 days, 28 days, and after 24 hours of heating at 170°F. In addition, SBA significantly enhanced flexural strength, indicating improved structural durability and resistance to deformation. Unlike Fly Ash Type C, Sugarcane Bagasse Ash exhibited only minimal influence on initial setting time, although it slightly increased the final setting time of the concrete mixtures. Correlation and regression analyses consistently identified SBA as the most beneficial agricultural waste additive among the evaluated geopolymer materials. These results indicate that increasing SBA concentration can substantially improve the overall structural integrity and long-term performance of sustainable geopolymer concrete systems.

4.3 Banana Peel Ash (BPA)

Banana Peel Ash demonstrated unique and highly beneficial effects on the curing behavior of geopolymer concrete. The feature analysis showed that increasing BPA concentration significantly reduced both the initial and final setting times, allowing the concrete to cure more rapidly. This characteristic makes BPA particularly useful for construction applications requiring faster setting and early structural stabilization. In addition to improving curing speed, BPA also contributed moderate improvements in flexural strength and early compressive strength. However, its influence on long-term compressive strength was less significant compared to Sugarcane Bagasse Ash. The experimental findings suggest that BPA can serve as an effective sustainable additive when rapid curing behavior is desired while still maintaining acceptable mechanical properties.

5. Experimental Results

5.1 Correlation Analysis

Pearson correlation analysis was conducted to evaluate the relationships between geopolymer input variables and concrete performance outputs. The analysis revealed that Sugarcane Bagasse Ash exhibited strong positive correlations with compressive strength and flexural strength, indicating that increasing SBA concentration generally improved the mechanical performance of the geopolymer concrete. In contrast, Banana Peel Ash demonstrated strong negative correlations with initial and final setting times, confirming its effectiveness in accelerating the curing process. Fly Ash Type C exhibited negative correlations across most output variables, particularly strength-related metrics, indicating that higher concentrations negatively impacted the structural properties of the concrete. These findings were highly consistent with the regression-based feature analysis and provided additional statistical validation for the observed material behaviors.

5.2 Machine Learning Model Performance

5.2.1 R^2 Performance

The performance evaluation of the machine learning models demonstrated that Support Vector Regression consistently outperformed all other regression models across nearly every output variable. The nonlinear learning capability of SVR enabled the model to capture complex relationships between geopolymer compositions and concrete properties more effectively than the linear regression-based approaches. Representative R^2 scores obtained using SVR included 0.855 for Initial Setting Time (IST), 0.860 for Final Setting Time (FST), 0.915 for Compressive Strength after 28 days (CS-28d), 0.942 for Flexural Strength (FS), and 0.979 for Compressive Strength after 24 hours at 170°F. In comparison, Ridge Regression, Elastic Net Regression, and Partial Least Squares Regression produced significantly lower predictive performance due to their inability to fully capture nonlinear material interactions within the dataset. Table 1 shows the results of R^2 performance.

Table 1: R^2 Performance.

Variable	Ridge	Elastic Net	PLS	SVR
IST	0.047	0.047	0.064	0.855
FST	0.539	0.539	0.546	0.860
CS-3d	0.662	0.662	0.662	0.731
CS-7d	0.196	0.196	0.200	0.505
CS-28d	0.769	0.770	0.769	0.915
FS	0.902	0.899	0.896	0.942
170F/24h	0.900	0.902	0.901	0.979

5.2.2 Mean Absolute Error (MAE)

The Mean Absolute Error analysis further confirmed the superior predictive performance of Support Vector Regression. SVR produced the lowest MAE values across nearly all concrete performance metrics, indicating higher predictive accuracy and stronger model generalization capability. The highest prediction errors were observed for compressive strength after 7 days, likely due to nonlinear scaling effects between Sugarcane Bagasse Ash and Banana Peel Ash during intermediate curing periods. Nevertheless, SVR maintained considerably lower error rates compared to the linear regression-based models.Table 2 shows the results of the Mean Absolute Error.

Table 2: Mean Absolute Error results.

Variable	Ridge	Elastic Net	PLS	SVR
IST	60.30	60.30	60.23	14.60
FST	38.93	38.92	38.10	17.87
CS-3d	179.90	179.90	179.90	130.91
CS-7d	502.00	502.01	501.91	207.03
CS-28d	184.47	184.47	184.47	77.41
FS	0.119	0.119	0.119	0.086
170F/24h	119.52	119.17	120.17	52.90

5.2.3 Root Mean Squared Error (RMSE)

Root Mean Squared Error analysis demonstrated that Support Vector Regression also achieved the lowest RMSE values across most output variables. Lower RMSE values indicate reduced large-scale prediction errors and improved prediction stability. The reduced error magnitude observed in SVR confirms its ability to model complex nonlinear relationships within geopolymer concrete datasets more effectively than traditional regression techniques.Table 3 shows the results of the Root Mean Squared Error (RMSE)

Table 3: Root Mean Squared Error (RMSE)results.

Variable	Ridge	Elastic Net	PLS	SVR
IST	65.95	65.95	65.51	24.17

FST	44.45	44.44	43.70	23.95
CS-3d	243.60	243.60	243.60	188.02
CS-7d	580.07	580.07	581.96	311.70
CS-28d	221.47	221.47	221.47	101.03
FS	0.144	0.145	0.145	0.110
170F/24h	152.38	152.07	152.11	76.59

5.2.4 Best Performing Model

Among all evaluated machine learning algorithms, Support Vector Regression demonstrated the best overall predictive performance. The superior accuracy of SVR can primarily be attributed to its ability to effectively model nonlinear relationships between geopolymer compositions and concrete performance characteristics. Unlike the linear regression-based approaches, SVR predicts each output individually while adapting efficiently to smaller datasets with complex feature interactions. The nonlinear behavior of geopolymer materials, particularly the interactions between Sugarcane Bagasse Ash and Banana Peel Ash, likely contributed to the significantly improved predictive capability of SVR compared to the other evaluated models.

6. Discussion

The experimental findings demonstrate the effectiveness of Artificial Intelligence techniques for sustainable geopolymer concrete prediction and analysis. The ability of machine learning models to accurately predict compressive strength, flexural strength, and setting times highlights the growing importance of data-driven methodologies in modern construction material research. The proposed system successfully reduced the need for repetitive physical experimentation by allowing material scientists to virtually evaluate concrete compositions before laboratory implementation.

The feature analysis results revealed meaningful insights regarding the impact of agricultural waste materials on concrete behavior. Sugarcane Bagasse Ash consistently showed positive effects on compressive and flexural strength, indicating that it may serve as an effective sustainable reinforcement material for geopolymer concrete systems. Conversely, Banana Peel Ash demonstrated substantial reductions in initial and final setting times, making it valuable for applications requiring faster curing processes. Fly Ash Type C exhibited negative correlations with several strength-related outputs, suggesting that excessive concentrations may weaken the overall concrete structure.

Among the evaluated machine learning algorithms, Support Vector Regression achieved the highest predictive accuracy across nearly all output variables. The superior performance of SVR can largely be attributed to its nonlinear learning capabilities and the use of the Radial Basis Function kernel, which enabled the model to better capture the complex relationships between geopolymer compositions and concrete properties. In contrast, the linear regression-based models,including Ridge Regression, Elastic Net Regression, and Partial Least Squares Regression,showed similar but comparatively weaker performance due to the nonlinear nature of the dataset.

Although the proposed framework achieved promising results, several limitations remain. The dataset utilized in this study was relatively small, limiting the generalizability of the machine learning models. Furthermore, environmental variables such as humidity, curing conditions, and long-term weather exposure were not incorporated into the predictive framework. Additional experimental samples and environmental factors would likely improve predictive performance and real-world applicability.

Despite these limitations, the proposed system demonstrates the potential of AI-driven predictive modeling as a practical decision-support tool for sustainable construction research. The integration of machine learning with an intuitive software platform provides a foundation for future smart-material engineering systems thatcan accelerate sustainable infrastructure development.

The results indicate that AI-based predictive modeling can significantly accelerate research on sustainable concrete. The proposed framework allows researchers to evaluate geopolymer combinations before conducting costly laboratory experiments.Sugarcane Bagasse Ash emerged as the most beneficial additive for strength enhancement, while Banana Peel Ash improved curing speed by reducing setting time. Fly Ash Type C negatively affected most performance variables and should likely be minimized in future formulations.The success of SVR suggests that nonlinear relationships exist between geopolymer compositions and concrete performance characteristics. Traditional linear models struggled to capture these complex interactions.Despite strong predictive performance, several limitations remain. The dataset size was relatively small.Environmental conditions were not extensively modeled.Real-world large-scale testing was limited.Additional geopolymer combinations were not evaluated.Future research should incorporate larger datasets, additional environmental variables, and advanced deep learning architectures.

7. Conclusion and Future Work

This research presented an AI-based predictive modeling framework for sustainable geopolymer concrete using agricultural waste materials. The proposed system integrated machine learning algorithms with a user-friendly web interface to predict compressive strength, flexural strength, and setting times of geopolymer concrete mixtures.Among the evaluated machine learning algorithms, Support Vector Regression achieved the best predictive performance across nearly all output variables. Feature analysis revealed that:Sugarcane Bagasse Ash positively influenced compressive and flexural strength.Banana Peel Ash reduced concrete setting times.Fly Ash Type C negatively impacted most strength properties.The developed framework provides a practical decision-support system for material scientists and demonstrates the growing importance of AI in sustainable infrastructure research.The proposed approach has the potential to reduce experimental costs, minimize environmental impact, and accelerate sustainable material innovation.

Future work for this research will focus on expanding the dataset with additional experimental samples to improve model generalization and predictive accuracy. Additional environmental and climatic variables may also be incorporated to better simulate real-world conditions affecting geopolymer concrete performance. The system can further be enhanced through deployment on scalable cloud-based infrastructure and integration of advanced deep learning architectures capable of modeling more complex nonlinear relationships. Future studies may also explore optimization algorithms that automatically recommend ideal geopolymer compositions based on desired mechanical properties. Furthermore, large-scale industrial validation studies and the incorporation of explainable AI techniques can improve system reliability, transparency, and adoption within the construction and material science industries.

Conflict of Interest

The authors declare no conflict of interest related to this research.

Funding Statement

This research did not receive external funding and was conducted as part of a collaborative academic and research initiative.

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