ISSN (O): 2320-5407
ISSN (P): 3107-4928
Journal Homepage: - www.journalijar.com
INTERNATIONAL JOURNAL OF ADVANCED RESEARCH (IJAR)
Article DOI: 10.21474/IJAR01/23299
DOI URL: http://dx.doi.org/10.21474/IJAR01/23299

***RESEARCH ARTICLE***

# ARTIFICIAL INTELLIGENCE-DRIVEN PREDICTIVE ANALYTICS FRAMEWORK FOR SUSTAINABLE GEOPOLYMER CONCRETE USING AGRICULTURAL WASTE MATERIALS

**Justin Adams, Sydney Babb, Landon Blair, Duncan Howard, Sai Nethra Betgeri, Sudhir S. Amritphalem and Naga Parameshwari Betgeri**

## *Manuscript Info*

***Manuscript History***
Received: 15 February 2026
Final Accepted: 18 March 2026
Published: April 2026

***Key words:-***
Artificial Intelligence, Machine Learning, Geopolymer Concrete, Sustainable Construction Materials, Random Forest Regression, Agricultural Waste Materials, Sugarcane Bagasse Ash, Banana Peel Ash, Fly Ash Type C, Predictive Analytics, Sustainable Infrastructure, Compressive Strength Prediction, Green Construction, Environmental Sustainability, Smart Material Engineering

## *Abstract*

The rapid growth of the construction industry has significantly increase d the global demand for conventional concrete materials, resulting in substantial environmental concerns due to excessive cement production and industrial carbon emissions. Traditional Portland cement manufact uring contributes heavily to greenhouse gas emissions and environment al degradation, motivating researchers to investigate sustainable alterna tives capable of reducing the environmental impact of infrastructure development. Geopolymer concrete has emerged as a promising sustainable construction material because it allows the incorporation of agricultural and industrial waste materials while maintaining desirable structural and durability characteristics. This research presents an Artificial Intelligence driven predictive analytics framework for sustain able geopolymer concrete utilizing agricultural waste materials includin g Sugarcane Bagasse Ash (SBA), Banana Peel Ash (BPA), and Fly Ash Type C polymer. The developed system integrates Random Forest Regression models with predictive analytics pipelines that estimate initial setting time,final setting time, compressive strength, and flexural strength across multiple geopolymer compositions. The framework was implemented using Python, Scikit-learn, FastAPI, SQLite databases, and locally hosted predictive services. Experimental evaluation demons trated approximately 75% predictive accuracy despite limited dataset availability. The proposed framework significantly reduces the time and cost associated with traditional laboratory experimentation while supporting sustainable material optimization and environmentally responsible infrastructure research.



## Introduction:-

Concrete remains one of the most essential construction materials utilized worldwide because of its durability, strength, and versatility in infrastructure development [1], [2]. Modern transportation systems, commercial buildings, industrial facilities, and residential structures heavily depend on concrete as a foundational construction material. Despite its widespread application, conventional Portland cement production contributes significantly to global environmental pollution due to its carbon-intensive manufacturing process [1], [5]. Cement manufacturing

**Corresponding Author:-** Justin Adams

alone accounts for a substantial percentage of global carbon dioxide emissions, making sustainable alternatives increasingly important for reducing the environmental footprint of the construction industry [2], [5].Recent advancements in sustainable material science have encouraged researchers to explore geopolymer concrete systems capable of partially or completely replacing traditional cementitious materials [3], [4], [5]. Geopolymer concrete utilizes industrial and agricultural waste products such as Fly Ash, Sugarcane Bagasse Ash, and Banana Peel Ash to develop environmentally sustainable construction materials with acceptable mechanical and durability characteristics [6], [7], [8]. These agricultural waste products not only reduce dependence on conventional cement but also provide productive applications for waste materials that would otherwise contribute to environmental disposal problems [6], [7].

Traditional geopolymer concrete experimentation is highly time-consuming, labor-intensive, and resource-demanding because researchers must conduct multiple curing procedures, destructive testing operations, and validation experiments before obtaining meaningful performance metrics [5], [10]. A single geopolymer concrete experiment may require several days or weeks of curing before compressive strength and setting-time characteristics can be evaluated [4], [10]. Additionally, the increasing complexity of geopolymer mixtures makes it difficult to manually evaluate nonlinear interactions between multiple composition variables and resulting concrete properties [8], [9]. Artificial Intelligence and Machine Learning techniques provide effective solutions for modeling complex relationships between geopolymer compositions and concrete performance characteristics [15], [18], [19], [20]. Machine Learning algorithms can learn from experimental datasets and rapidly generate predictive outputs without requiring prolonged laboratory experimentation [16], [17], [18]. This research proposes an Artificial Intelligence-driven predictive analytics framework capable of estimating concrete setting times, compressive strength, and flexural strength using Random Forest Regression models trained on geopolymer concrete datasets [11], [16]. The developed framework aims to reduce experimental cost, accelerate material discovery, and support sustainable infrastructure research through predictive automation and intelligent material evaluation [19], [20], [21].

**System Architecture:-**

The proposed predictive analytics framework was designed as a locally hosted Artificial Intelligence system integrating Machine Learning pipelines, database services, predictive evaluation modules, and REST API communication mechanisms [11], [12]. The architecture was intentionally designed to support lightweight deployment while maintaining scalability for future Machine Learning expansion and larger experimental datasets [20]. At the highest architectural level, the framework consists of predictive analytics services, structured data processing modules, database management systems, and local analytical deployment services. The back-end architecture was implemented using Python 3.12 and FastAPI services running through a Uvicorn server environment. FastAPI routers were utilized to process prediction requests, manage geopolymer datasets, validate incoming data, and execute Machine Learning prediction pipelines. SQLite databases were integrated into the framework to efficiently store geopolymer sample records, prediction outputs, and user-generated experimental data. The predictive analytics engine was developed using Scikit-learn Machine Learning libraries along with NumPy and Pandas preprocessing modules [12], [13]. Experimental geopolymer datasets containing multiple agricultural waste composition variables were normalized and structured before model training and evaluation. Matplotlib visualization libraries were incorporated to support statistical trend analysis and graphical evaluation of prediction outputs [14]. The overall architecture was designed to provide rapid local deployment while minimizing computational overhead and supporting future scalability for larger predictive infrastructure applications [20].

**Machine Learning Methodology:-**

The Machine Learning component of the proposed framework utilized Random Forest Regression because of its strong predictive performance on relatively small experimental datasets and its ability to model nonlinear relationships between geopolymer composition variables and concrete performance outputs [11], [16]. Random Forest Regression was selected after evaluating the nature of the experimental dataset, which contained multiple interacting agricultural waste variables and nonlinear material behavior patterns. The algorithm provided strong stability, reduced overfitting risk, and improved generalization performance for sustainable geopolymer concrete prediction tasks [11]. The training dataset consisted of approximately thirty experimental geopolymer concrete samples containing varying concentrations of granulated blast-furnace slag, Sugarcane Bagasse Ash, Banana Peel Ash, sodium silicate, and sodium sulphate [6], [7], [8]. These composition variables served as input features for the Machine Learning model. Multiple output variables including Initial Setting Time (IST), Final Setting Time (FST), Compressive Strength after 3 days, Compressive Strength after 7 days, Compressive Strength after 28 days, Compressive Strength after 24 hours at 170°F, and Flexural Strength were simultaneously predicted using multioutput regression techniques [16], [18]. Prior to model training, the dataset underwent preprocessing and normalization using StandardScaler techniques to reduce feature variability and improve predictive consistency [12], [13]. The Random Forest Regression model utilized 200 decision trees with controlled maximum depth settings to minimize overfitting while maintaining prediction accuracy [11]. During model execution, incomplete or inconsistent dataset entries were filtered to preserve prediction reliability and reduce training instability. Runtime validation mechanisms were also implemented to prevent prediction execution prior to successful model initialization and training completion.

**Experimental Results and Analysis:-**

Experimental evaluation demonstrated that the developed Artificial Intelligence framework successfully generated predictive outputs for multiple geopolymer concrete performance characteristics despite the relatively small experimental dataset size [18], [19], [20]. The Random Forest Regression model achieved approximately 75% predictive accuracy across the evaluated output variables, demonstrating the effectiveness of Machine Learning techniques for sustainable concrete analysis and predictive infrastructure research [11], [16]. The developed framework significantly reduced the amount of time required for geopolymer concrete evaluation compared to traditional laboratory testing procedures [4], [5]. Conventional geopolymer experimentation often requires several days or weeks of curing before compressive strength and setting-time measurements can be obtained [4], [10]. In contrast, the developed Machine Learning framework generated predictive outputs within seconds, enabling researchers to rapidly evaluate multiple geopolymer compositions without requiring prolonged laboratory experimentation [19], [20].

Feature analysis revealed that Sugarcane Bagasse Ash positively influenced compressive strength and flexural strength characteristics of geopolymer concrete systems [6], [7]. Banana Peel Ash demonstrated significant reductions in both initial and final setting times, making it highly beneficial for applications requiring rapid curing behavior and early structural stabilization [6], [7]. Conversely, Fly Ash Type C demonstrated mixed performance characteristics and negatively affected several strength-related outputs at higher concentrations [8], [9], [10]. These findings further validated the effectiveness of Machine Learning techniques for analyzing nonlinear geopolymer interactions and predicting sustainable concrete behavior [18], [19].

**Table 1. Prediction Variables**

| Output Variable | Description |
|---|---|
| IST | Initial Setting Time |
| FST | Final Setting Time |
| CS-3d | Compressive Strength after 3 Days |
| CS-7d | Compressive Strength after 7 Days |
| CS-28d | Compressive Strength after 28 Days |
| 170F/24h | Compressive Strength after 24 Hours at 170°F |
| FS | Flexural Strength |

Table 1 presents the primary output variables predicted by the Artificial Intelligence-based geopolymer concrete framework. These variables represent the key mechanical and curing properties used to evaluate the performance and structural behavior of geopolymer concrete mixtures. Initial Setting Time (IST) and Final Setting Time (FST) measure the amount of time required for the concrete mixture to begin and complete the curing process, respectively. These parameters are important because they determine workability, construction scheduling, and curing efficiency.The compressive strength variablesincluding CS-3d, CS-7d, and CS-28d—represent the compressive strength of the concrete after 3 days, 7 days, and 28 days of curing. These measurements are critical indicators of concrete durability and structural reliability over time. The 170F/24h variable represents the compressive strength of the geopolymer concrete after curing for 24 hours at 170°F, which evaluates high-temperature curing performance and accelerated strength development. Flexural Strength (FS) measures the ability of the concrete to resist bending and cracking under applied loads, making it an important parameter for structural applications such as pavements, beams, and slabs. Together, these variables provide a comprehensive assessment of geopolymer concrete behavior and long-term structural performance.

**Table 2. Model Configuration**

| Parameter | Value |
|---|---|
| Machine Learning Algorithm | Random Forest Regression |
| Number of Trees | 200 |
| Maximum Tree Depth | 5 |
| Dataset Size | ~30 Experimental Samples |
| Programming Language | Python 3.12 |
| ML Framework | Scikit-learn |
| Database System | SQLite |
| API Framework | FastAPI |

Table 2 summarizes the configuration settings and technologies used for the Machine Learning framework and predictive analytics system. The predictive model utilized Random Forest Regression as the primary Machine Learning algorithm because of its strong ability to handle nonlinear relationships and provide stable predictions on relatively small datasets. The model was configured using 200 decision trees, allowing the system to improve prediction stability and reduce variance by averaging multiple decision-tree outputs.

The maximum tree depth was limited to five levels in order to reduce overfitting while maintaining strong generalization capability across unseen geopolymer compositions. The dataset consisted of approximately thirty experimental geopolymer samples containing varying agricultural and industrial waste material compositions. Python 3.12 was selected as the primary programming language because of its extensive support for scientific computing and Machine Learning libraries. Scikit-learn was used as the Machine Learning framework for model development and evaluation, while SQLite served as the database system for storing geopolymer composition data and prediction records. FastAPI was utilized as the API framework to support efficient communication between predictive services and analytical modules. Overall, the configuration was intentionally designed to provide lightweight deployment, efficient computation, and scalable predictive analytics functionality.

**Table 3. System Performance Results**

| Performance Metric | Observation |
|---|---|
| Prediction Accuracy | ~75% |
| Prediction Time | Less than 5 Seconds |
| Database Stability | Stable under stress testing |
| Authentication Validation | Successfully implemented |
| Spreadsheet Import/Export | Successfully implemented |
| System Responsiveness | Stable across multiple resolutions |

Table 3 presents the overall performance evaluation results of the developed predictive analytics framework. The Random Forest Regression model achieved approximately 75% prediction accuracy across the evaluated geopolymer concrete output variables. Although the experimental dataset size was relatively small, the model successfully generated stable and reliable predictions for concrete setting times and strength characteristics. One of the most significant advantages of the proposed framework was its ability to generate predictions in less than five seconds. Traditional geopolymer concrete testing procedures often require several days or weeks of curing and destructive testing before obtaining meaningful results. The predictive framework dramatically reduced this evaluation time by enabling rapid computational analysis of geopolymer compositions.

The database stability results demonstrated that the SQLite database system maintained reliable operation even during stress-testing scenarios involving multiple requests and data-processing operations. Authentication validation was also successfully implemented to support secure user access and controlled dataset management. Spreadsheet import/export functionality enabled researchers to efficiently upload and analyze experimental datasets while exporting prediction results for additional analysis. The system responsiveness results confirmed that the application maintained stable operation across multiple screen resolutions and operating environments, demonstrating strong usability and deployment flexibility.

**Table 4. Material Impact Analysis**

| Material | Observed Impact |
|---|---|
| Sugarcane Bagasse Ash (SBA) | Improved compressive and flexural strength |
| Banana Peel Ash (BPA) | Reduced initial and final setting times |
| Fly Ash Type C | Negative effect on strength at higher concentrations |
| Sodium Silicate | Assisted geopolymer activation |
| Sodium Sulphate | Improved curing stability |

Table 4 summarizes the observed effects of each major geopolymer material on the resulting concrete performance characteristics. Sugarcane Bagasse Ash (SBA) demonstrated the most beneficial influence on concrete strength properties. Increasing SBA concentration improved compressive strength and flexural strength, indicating enhanced structural integrity and durability of the geopolymer concrete mixtures. These results suggest that SBA can serve as an effective sustainable reinforcement material for environmentally friendly construction applications. Banana Peel Ash (BPA) primarily influenced the curing behavior of the geopolymer concrete. The experimental analysis showed that BPA significantly reduced both initial and final setting times, allowing the concrete to cure more rapidly. This characteristic makes BPA particularly useful for applications requiring faster setting behavior and early structural stabilization.

Fly Ash Type C demonstrated mixed performance characteristics within the geopolymer system. At higher concentrations, the material negatively affected compressive strength and other strength-related properties, indicating that excessive incorporation may weaken overall structural performance. However, the material still contributed to geopolymer activation and chemical binding processes when used in controlled quantities. Sodium Silicate played a critical role in assisting geopolymer activation by promoting the chemical reactions necessary for binder formation and concrete stabilization. Sodium Sulphate contributed to curing stability and improved consistency during the geopolymerization process. Together, these materials formed the foundation of the geopolymer concrete system and influenced the final mechanical and curing behavior of the resulting mixtures.

**Social and Environmental Impact:-**

The proposed Artificial Intelligence-driven predictive analytics framework provides significant benefits for sustainable infrastructure development and environmentally responsible construction research [20], [21]. By enabling rapid prediction of geopolymer concrete performance characteristics, the system substantially reduces the need for excessive laboratory experimentation, destructive testing, and material waste generation [19], [20]. The framework allows researchers to evaluate multiple geopolymer compositions within seconds rather than waiting several weeks for physical curing and validation procedures [4], [10]. The utilization of agricultural waste products such as Sugarcane Bagasse Ash and Banana Peel Ash further contributes to environmental sustainability by redirecting waste materials toward productive infrastructure applications [6], [7]. These agricultural byproducts are often discarded or burned, contributing to environmental pollution and waste management challenges. Incorporating such materials into geopolymer concrete systems supports waste reutilization while simultaneously reducing dependence on conventional cement-based materials [5], [6]. The developed framework also benefits researchers and infrastructure engineers by accelerating sustainable material discovery and reducing experimental costs associated with repetitive concrete testing procedures [19], [20]. The successful integration of Artificial Intelligence within geopolymer concrete research demonstrates the growing importance of predictive analytics and Machine Learning techniques in future sustainable infrastructure applications [20], [21].

## Conclusion:-

This research successfully demonstrated the development of an Artificial Intelligence-driven predictive analytics framework for sustainable geopolymer concrete systems utilizing agricultural and industrial waste materials [20], [21]. The integration of Random Forest Regression models, FastAPI services, SQLite databases, and predictive Machine Learning pipelines enabled rapid estimation of concrete performance characteristics while minimizing dependence on prolonged laboratory experimentation procedures [11], [12]. Experimental evaluation demonstrated stable predictive performance with approximately 75% accuracy despite the relatively limited experimental dataset size [16], [19]. The developed framework significantly reduced material evaluation time while supporting sustainable infrastructure research and predictive material optimization [20]. Feature analysis further demonstrated the positive effects of Sugarcane Bagasse Ash and Banana Peel Ash on geopolymer concrete behavior while highlighting the nonlinear interactions among multiple geopolymer composition variables [6], [7], [8]. The developed framework establishes a strong foundation for future Artificial Intelligence applications within sustainable infrastructure and smart material engineering research [20], [21]. Future work may include expanding the experimental dataset, integrating advanced ensemble learning algorithms, incorporating cloud-based deployment infrastructure, and improving predictive visualization analytics to further enhance system scalability and prediction accuracy [15], [20].

## References:-


[1] Davidovits, J. Geopolymer Chemistry and Applications. Institute Geopolymere, France, 2008.
[2] Mehta, P. K., and Monteiro, P. J. M. Concrete: Microstructure, Properties, and Materials. McGraw-Hill Education, 2014.
[3] Provis, J. L., and Van Deventer, J. S. J. Geopolymers: Structures, Processing, Properties and Industrial Applications. Woodhead Publishing, 2009.
[4] Hardjito, D., and Rangan, B. V. "Development and Properties of Low-Calcium Fly Ash-Based Geopolymer Concrete." Curtin University Research Report, 2005.
[5] Singh, B., et al. "Geopolymer Concrete: A Review of Some Recent Developments." Construction and Building Materials, vol. 85, pp. 78–90, 2015.
[6] Abdel-Gawwad, H. A., and Abo-El-Enein, S. A. "Sustainable Utilization of Agricultural Waste Ashes in Geopolymer Systems." Journal of Cleaner Production, vol. 176, pp. 108–118, 2018.
[7] Sata, V., et al. "Pozzolanic Activity of Agricultural Waste Ashes." Cement and Concrete Composites, vol. 34, no. 1, pp. 94–100, 2012.
[8] Bernal, S. A., et al. "Performance of Alkali-Activated Slag Materials." Cement and Concrete Research, vol. 41, no. 1, pp. 1–8, 2011.
[9] Fernández-Jiménez, A., and Palomo, A. "Composition and Microstructure of Alkali Activated Fly Ash Binder." Cement and Concrete Research, vol. 35, no. 10, pp. 1984–1992, 2005.
[10] Lloyd, N., and Rangan, B. "Geopolymer Concrete with Fly Ash." Proceedings of the Second International Conference on Sustainable Construction Materials and Technologies, 2010.
[11] Breiman, L. "Random Forests." Machine Learning, vol. 45, no. 1, pp. 5–32, 2001.
[12] Pedregosa, F., et al. "Scikit-Learn: Machine Learning in Python." Journal of Machine Learning Research, vol. 12, pp. 2825–2830, 2011.
[13] McKinney, W. "Data Structures for Statistical Computing in Python." Proceedings of the Python in Science Conference, pp. 56–61, 2010.
[14] Hunter, J. D. "Matplotlib: A 2D Graphics Environment." Computing in Science & Engineering, vol. 9, no. 3, pp. 90–95, 2007.
[15] Goodfellow, I., Bengio, Y., and Courville, A. Deep Learning. MIT Press, 2016.
[16] Chou, J. S., and Bui, D. K. "Modeling Compressive Strength of Recycled Aggregate Concrete by Machine Learning." Construction and Building Materials, vol. 115, pp. 20–27, 2016.
[17] Yeh, I. C. "Modeling of Strength of High-Performance Concrete Using Artificial Neural Networks." Cement and Concrete Research, vol. 28, no. 12, pp. 1797–1808, 1998.
[18] Nikoo, M., et al. "Application of Support Vector Machine for Predicting Concrete Properties." Engineering Applications of Artificial Intelligence, vol. 24, no. 2, pp. 361–369, 2011.
[19] Golafshani, E. M., et al. "Predicting the Compressive Strength of Sustainable Concrete Using Machine Learning Techniques." Journal of Building Engineering, vol. 33, 2021.
[20] Kumar, R., et al. "Artificial Intelligence Applications in Sustainable Construction Materials." Journal of Materials Research and Technology, vol. 15, pp. 3400–3415, 2021.
[21] Betgeri, S. N., et al. "Artificial Intelligence and Machine Learning Approaches for Sustainable Infrastructure and Material Optimization." Proceedings of IATM Spring 2026 Conference, 2026.