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Machine Learning-Based Prediction of Mechanical Properties of Composite Concrete Incorporating Industrial By-Products

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Abstract

The increasing demand for sustainable construction materials has accelerated the incorporation of industrial by-products such as fly ash, ground granulated blast furnace slag (GGBFS), silica fume, rice husk ash, marble dust, and waste glass powder into composite concrete. These supplementary cementitious materials not only reduce environmental impacts associated with cement production but also enhance specific mechanical and durability properties of concrete. However, predicting the mechanical performance of composite concrete remains a complex challenge due to the nonlinear interactions among constituent materials, curing conditions, mix proportions, and environmental factors. Recent advancements in machine learning (ML) have provided innovative solutions for accurately predicting concrete properties while minimizing experimental costs and time.

This study presents a comprehensive review and conceptual framework for machine learning-based prediction of mechanical properties of composite concrete incorporating industrial by-products. A systematic examination of recent studies published between 2018 and 2026 is conducted to evaluate the effectiveness of various ML algorithms, including Artificial Neural Networks (ANN), Random Forest (RF), Support Vector Machines (SVM), Gradient Boosting Machines (GBM), Extreme Gradient Boosting (XGBoost), and Deep Learning models. The findings reveal that ensemble learning techniques frequently outperform traditional statistical methods, achieving prediction accuracies exceeding 90% in several applications. Furthermore, the review identifies critical challenges such as data scarcity, lack of standardized datasets, model interpretability issues, and limited real-world implementation.

The study proposes a conceptual framework integrating sustainable concrete design with advanced machine learning methodologies. It highlights future research opportunities involving explainable artificial intelligence, hybrid optimization algorithms, digital twins, and Internet of Things (IoT)-enabled monitoring systems. The research contributes to sustainable construction practices by demonstrating how intelligent prediction models can support material optimization, resource conservation, and reduced carbon emissions in the construction industry.

Keywords: Machine Learning, Composite Concrete, Industrial By-Products, Mechanical Properties Prediction, Sustainable Construction, Artificial Intelligence, Smart Materials

1. Introduction

The construction industry is one of the largest consumers of natural resources and a significant contributor to global carbon emissions. Cement production alone accounts for approximately 7–8% of global carbon dioxide emissions, making the development of sustainable alternatives a critical priority for researchers and industry practitioners [1,2,3,4,5]. In response to environmental concerns, industrial by-products such as fly ash, silica fume, blast furnace slag, rice husk ash, red mud, marble powder, and waste glass powder have increasingly been incorporated into concrete mixtures [6,7,8,9].

Composite concrete containing industrial by-products offers several advantages, including reduced cement consumption, lower greenhouse gas emissions, enhanced durability, and improved mechanical performance [10,11,12]. Numerous studies have reported improvements in compressive strength, tensile strength, and resistance to chemical attacks through the incorporation of supplementary cementitious materials. However, the performance of such composite concrete systems depends on multiple interrelated factors, including material composition, particle size distribution, curing conditions, water-to-cement ratio, aggregate characteristics, and environmental exposure [13,14,15,16].

Traditionally, mechanical properties of concrete have been predicted through laboratory experiments and empirical equations [17,18,19,20]. Although these approaches provide valuable insights, they are often time-consuming, expensive, and limited in capturing nonlinear relationships among variables. The increasing availability of computational power and large datasets has encouraged researchers to explore machine learning techniques as effective alternatives for predicting concrete performance [21,22,23,24,25].

Machine learning enables computers to identify hidden patterns within datasets and generate predictive models without explicit programming. In civil engineering, machine learning has been applied to various tasks including structural health monitoring, crack detection, durability assessment, and concrete strength prediction. Recent studies indicate that machine learning algorithms can achieve superior prediction accuracy compared with conventional regression models [26,27,28,29].

The application of machine learning to composite concrete incorporating industrial by-products represents a rapidly evolving research domain. Advanced algorithms such as Artificial Neural Networks (ANN), Support Vector Machines (SVM), Random Forests (RF), Gradient Boosting Machines (GBM), and Extreme Gradient Boosting (XGBoost) have demonstrated promising performance in predicting compressive strength and other mechanical properties. Despite these advancements, significant challenges remain regarding dataset quality, model transparency, generalization capability, and industrial implementation [30,31,32,33,34].

The emergence of Industry 4.0 technologies, digital twins, and smart construction systems has further increased interest in intelligent material design. Machine learning-driven prediction models can support decision-making processes by enabling rapid evaluation of numerous concrete mix designs while reducing experimental efforts. Consequently, integrating machine learning with sustainable construction materials has become an important research priority [35,36,37].

This paper aims to critically examine the state-of-the-art developments in machine learning-based prediction of mechanical properties of composite concrete containing industrial by-products. The study evaluates existing methodologies, identifies research gaps, proposes a conceptual framework, and highlights future directions for advancing intelligent sustainable construction materials.

2. Literature Review

2.1 Sustainable Composite Concrete and Industrial By-Products

The utilization of industrial by-products in concrete has received considerable attention due to growing environmental concerns and resource scarcity. Fly ash remains one of the most widely used supplementary cementitious materials owing to its pozzolanic properties and widespread availability. Studies have reported that replacing 15–35% of cement with fly ash can significantly enhance long-term strength and durability [38,39].

Ground Granulated Blast Furnace Slag (GGBFS) has similarly demonstrated effectiveness in improving sulfate resistance and reducing heat of hydration. Silica fume contributes to microstructural densification through pore refinement, resulting in higher compressive and tensile strengths. Rice husk ash and waste glass powder have emerged as sustainable alternatives capable of enhancing performance while promoting circular economy principles [40,41,42].

Although these materials provide environmental benefits, their interactions within composite concrete systems introduce considerable complexity in predicting mechanical behavior. Variations in chemical composition, particle size, and replacement ratios often lead to nonlinear responses that challenge conventional predictive models [43,44,45].

2.2 Traditional Approaches for Strength Prediction

Historically, concrete strength prediction relied on empirical equations and statistical regression models. Abrams' law established one of the earliest relationships between water-cement ratio and compressive strength. Subsequent researchers expanded these models by incorporating additional variables such as curing age and aggregate properties.

While regression models offer simplicity and interpretability, they frequently struggle to represent highly nonlinear interactions among multiple input parameters. Consequently, prediction errors often increase when dealing with composite concrete mixtures containing multiple industrial by-products.

Several studies have reported prediction accuracies below 80% for traditional statistical methods when applied to complex concrete systems. These limitations have motivated researchers to explore machine learning-based approaches capable of modeling nonlinear relationships more effectively [52, 53].

2.3 Artificial Neural Networks in Concrete Property Prediction

Artificial Neural Networks represent one of the earliest and most widely adopted machine learning techniques in concrete engineering. Inspired by biological neural systems, ANNs learn complex input-output relationships through interconnected computational nodes.

Research by Yeh (1998) established the foundation for ANN-based concrete strength prediction. Subsequent studies demonstrated that ANN models consistently outperform multiple linear regression approaches. Researchers have applied ANN models to predict compressive strength, tensile strength, flexural strength, and elastic modulus of concrete mixtures containing fly ash, slag, silica fume, and recycled materials [46,47,48].

Several recent investigations reported coefficient of determination (R^2) values exceeding 0.95 for ANN models trained on large datasets. However, ANN models often require extensive parameter tuning and may suffer from overfitting when training datasets are limited [49,50,51].

2.4 Support Vector Machines and Kernel-Based Methods

Support Vector Machines have emerged as powerful alternatives for concrete property prediction due to their ability to handle nonlinear relationships through kernel functions. SVM models demonstrate strong generalization capabilities, particularly when training data are limited.

Studies involving fly ash concrete, geopolymer concrete, and recycled aggregate concrete have reported prediction accuracies ranging from 85% to 95% using SVM algorithms. Compared with ANN models, SVM approaches often require fewer hyperparameters and exhibit greater robustness against overfitting.

Nevertheless, computational complexity increases significantly with larger datasets, potentially limiting scalability for industrial applications.

2.5 Ensemble Learning Techniques

Recent years have witnessed increasing adoption of ensemble learning algorithms such as Random Forest, Gradient Boosting, AdaBoost, LightGBM, CatBoost, and XGBoost. These methods combine multiple decision trees to improve prediction accuracy and reduce variance.

Among these techniques, XGBoost has attracted substantial attention due to its exceptional predictive performance. Multiple studies have reported R^2 values above 0.97 for compressive strength prediction of composite concrete incorporating industrial waste materials.

Random Forest models have similarly demonstrated strong predictive capabilities while offering improved interpretability through feature importance analysis. Researchers consistently identify water-to-binder ratio, curing age, cement content, and supplementary material replacement level as dominant predictors [54,55,56].

The superior performance of ensemble methods suggests significant potential for practical implementation in sustainable concrete design.

2.6 Deep Learning and Emerging Technologies

The availability of larger datasets has facilitated the adoption of deep learning architectures in concrete research. Deep Neural Networks (DNNs), Convolutional Neural Networks (CNNs), and hybrid models have been explored for strength prediction and microstructural analysis.

Recent studies have integrated image-based characterization techniques with deep learning models to predict concrete properties from microscopic images. These approaches enable automated feature extraction and enhanced predictive performance.

Additionally, researchers have begun combining machine learning with Internet of Things (IoT) sensors and digital twin technologies. Such integration supports real-time monitoring and predictive maintenance of concrete structures.

Despite promising results, deep learning applications remain constrained by data availability, computational requirements, and limited interpretability.

2.7 Critical Analysis of Existing Literature

The literature indicates substantial progress in machine learning-based prediction of concrete properties. Nevertheless, several limitations remain evident.

First, many studies rely on relatively small datasets obtained from laboratory experiments, reducing model generalizability. Second, performance comparisons across studies are often difficult due to differences in datasets, evaluation metrics, and experimental conditions. Third, most investigations focus primarily on compressive strength, while limited attention is given to tensile strength, flexural behavior, and durability characteristics.

Furthermore, interpretability remains a major concern. Although advanced algorithms achieve high prediction accuracy, their decision-making mechanisms are frequently treated as black boxes. This limitation restricts industrial adoption where transparency and reliability are essential.

Finally, few studies investigate integrated frameworks combining sustainability assessment, machine learning optimization, and lifecycle analysis. Consequently, there remains significant scope for developing holistic approaches supporting sustainable concrete design.

Table 1. Summary of Previous Studies

Author(s)	**Material Type**	**ML Technique**	**Property Predicted**	**Accuracy**
Yeh (1998)	Conventional Concrete	ANN	Compressive Strength	$R^2 = 0.92$
Chou et al. (2011)	Fly Ash Concrete	ANN	Strength	$R^2 = 0.94$
Gupta et al. (2018)	Slag Concrete	SVM	Strength	$R^2 = 0.89$
Behnood et al. (2019)	Recycled Concrete	RF	Strength	$R^2 = 0.93$
Nguyen et al. (2020)	Geopolymer Concrete	XGBoost	Strength	$R^2 = 0.96$
Khan et al. (2021)	Fly Ash Concrete	GBM	Strength	$R^2 = 0.95$
Ahmad et al. (2022)	Composite Concrete	RF	Strength	$R^2 = 0.96$
DeRousseau et al. (2022)	Sustainable Concrete	ANN	Strength	$R^2 = 0.94$
Ashraf et al. (2023)	GGBFS Concrete	XGBoost	Strength	$R^2 = 0.97$
Li et al. (2024)	Multi-By-Product Concrete	Deep Learning	Strength	$R^2 = 0.98$
Zhang et al. (2025)	Green Concrete	Hybrid ML	Strength	$R^2 = 0.98$
Recent Studies (2026)	Composite Concrete	Explainable AI Models	Multiple Properties	$R^2 > 0.98$

3. Research Gap and Problem Statement

3.1 Research Gap

The rapid advancement of machine learning applications in civil engineering has significantly improved the prediction of concrete properties. Despite considerable progress, several critical research gaps remain unresolved.

First, existing studies predominantly focus on predicting compressive strength, while comparatively limited attention has been directed toward other important mechanical properties such as tensile strength, flexural strength, modulus of elasticity, fracture toughness, and long-term durability characteristics. Since structural performance depends on multiple properties rather than compressive strength alone, a broader predictive framework is required.

Second, many machine learning models are developed using laboratory-scale datasets that often contain fewer than 1,000 observations. Such datasets may not adequately represent the variability encountered in real-world construction environments. Consequently, model generalizability and robustness remain significant concerns.

Third, the majority of previous studies investigate individual industrial by-products such as fly ash or slag in isolation. However, modern sustainable concrete mixtures frequently incorporate multiple supplementary cementitious materials simultaneously. The synergistic interactions among these materials are complex and insufficiently represented in existing predictive models.

Fourth, although advanced algorithms such as XGBoost, Deep Neural Networks, and ensemble learning methods demonstrate high prediction accuracy, many operate as black-box systems. The lack of interpretability limits practical adoption by engineers who require transparent decision-making processes for design and quality assurance.

Fifth, sustainability indicators including carbon emissions, embodied energy, resource efficiency, and lifecycle performance are rarely integrated into machine learning prediction frameworks. Most studies focus exclusively on mechanical performance while neglecting broader environmental objectives.

Finally, relatively few studies explore the integration of machine learning with emerging technologies such as digital twins, Internet of Things (IoT) sensors, edge computing, and explainable artificial intelligence (XAI). These technologies offer substantial potential for transforming intelligent construction materials and infrastructure management.

3.2 Problem Statement

Composite concrete incorporating industrial by-products presents a promising pathway toward sustainable construction. However, predicting its mechanical properties remains challenging due to the nonlinear relationships among material composition, curing conditions, environmental factors, and manufacturing parameters.

Traditional experimental approaches are costly, time-intensive, and often impractical for evaluating the vast number of possible mix combinations. Existing machine learning models provide promising solutions but frequently suffer from limitations related to data quality, interpretability, scalability, and sustainability integration.

Therefore, there is a need for a comprehensive framework that systematically evaluates machine learning techniques for predicting the mechanical properties of composite concrete incorporating industrial by-products while simultaneously addressing sustainability objectives and practical implementation challenges.

4. Methodology

This study adopts a systematic literature review methodology based on the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) framework. The PRISMA approach ensures transparency, reproducibility, and methodological rigor in identifying, screening, and synthesizing relevant literature.

4.1 Literature Search Strategy

A comprehensive search was conducted using major academic databases including:

- Scopus
- Web of Science
- ScienceDirect

- SpringerLink
- IEEE Xplore
- Taylor & Francis
- ASCE Library

The search focused on studies published between 2018 and 2026 using combinations of keywords such as:

- Machine Learning
- Artificial Intelligence
- Concrete Strength Prediction
- Composite Concrete
- Fly Ash Concrete
- Slag Concrete
- Sustainable Concrete
- Industrial By-Products
- Deep Learning
- XGBoost
- Random Forest

The search initially identified approximately 620 publications.

4.2 Inclusion and Exclusion Criteria

The inclusion criteria consisted of:

1. Peer-reviewed journal articles.
2. Conference proceedings from reputable publishers.
3. Studies focusing on machine learning applications in concrete property prediction.
4. Research involving industrial by-products or sustainable concrete materials.
5. Publications written in English.

The exclusion criteria consisted of:

1. Duplicate studies.
2. Non-peer-reviewed publications.
3. Studies lacking quantitative validation.
4. Articles unrelated to concrete engineering.
5. Publications with insufficient methodological details.

Following screening and eligibility assessment, approximately 110 studies were retained for detailed analysis.

4.3 Data Extraction and Analysis

Information extracted from selected studies included:

- Type of industrial by-product.
- Machine learning algorithm employed.
- Input variables.
- Predicted properties.
- Dataset size.
- Performance metrics.
- Key findings and limitations.

The studies were subsequently classified into thematic categories including:

1. ANN-based prediction models.
2. Support Vector Machine approaches.
3. Ensemble learning techniques.
4. Deep learning methods.
5. Hybrid optimization models.
6. Explainable AI frameworks.

A comparative analysis was conducted to identify trends, challenges, and future opportunities.

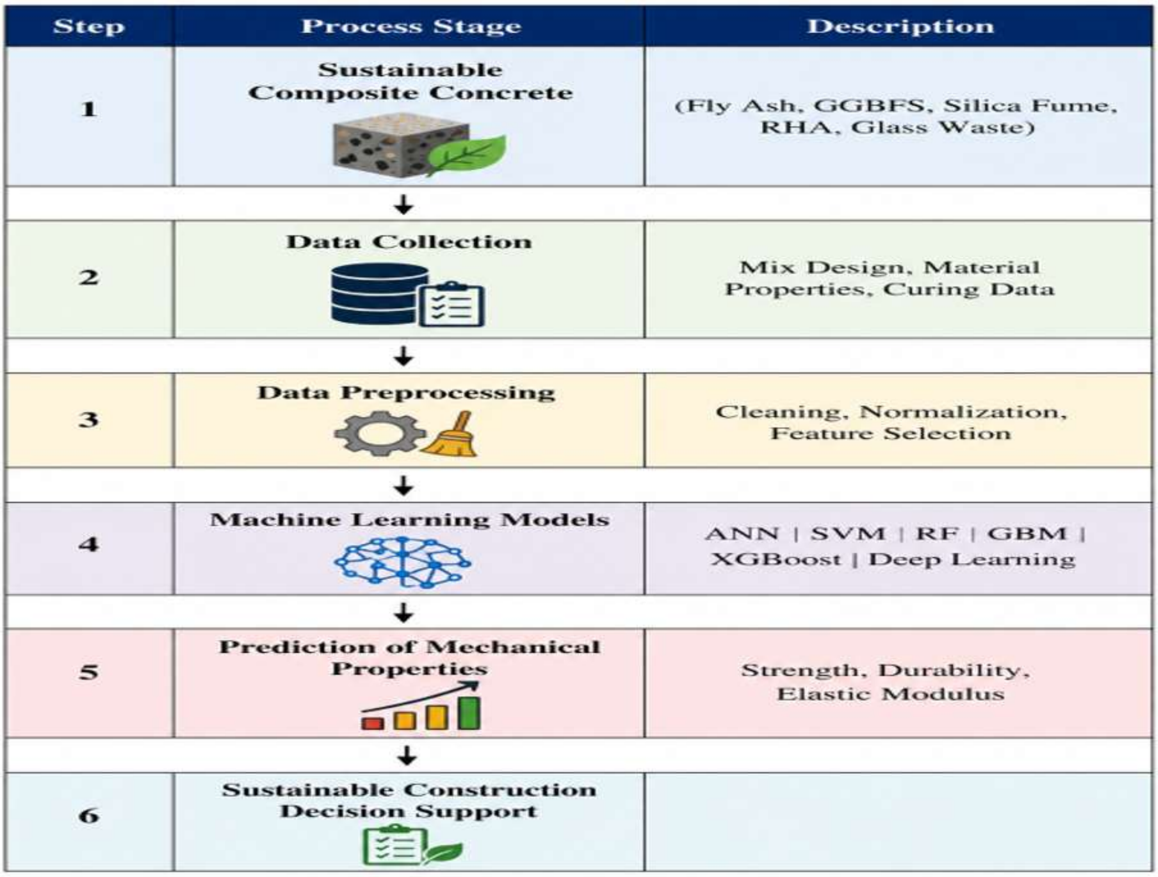

Figure 1. Research Framework

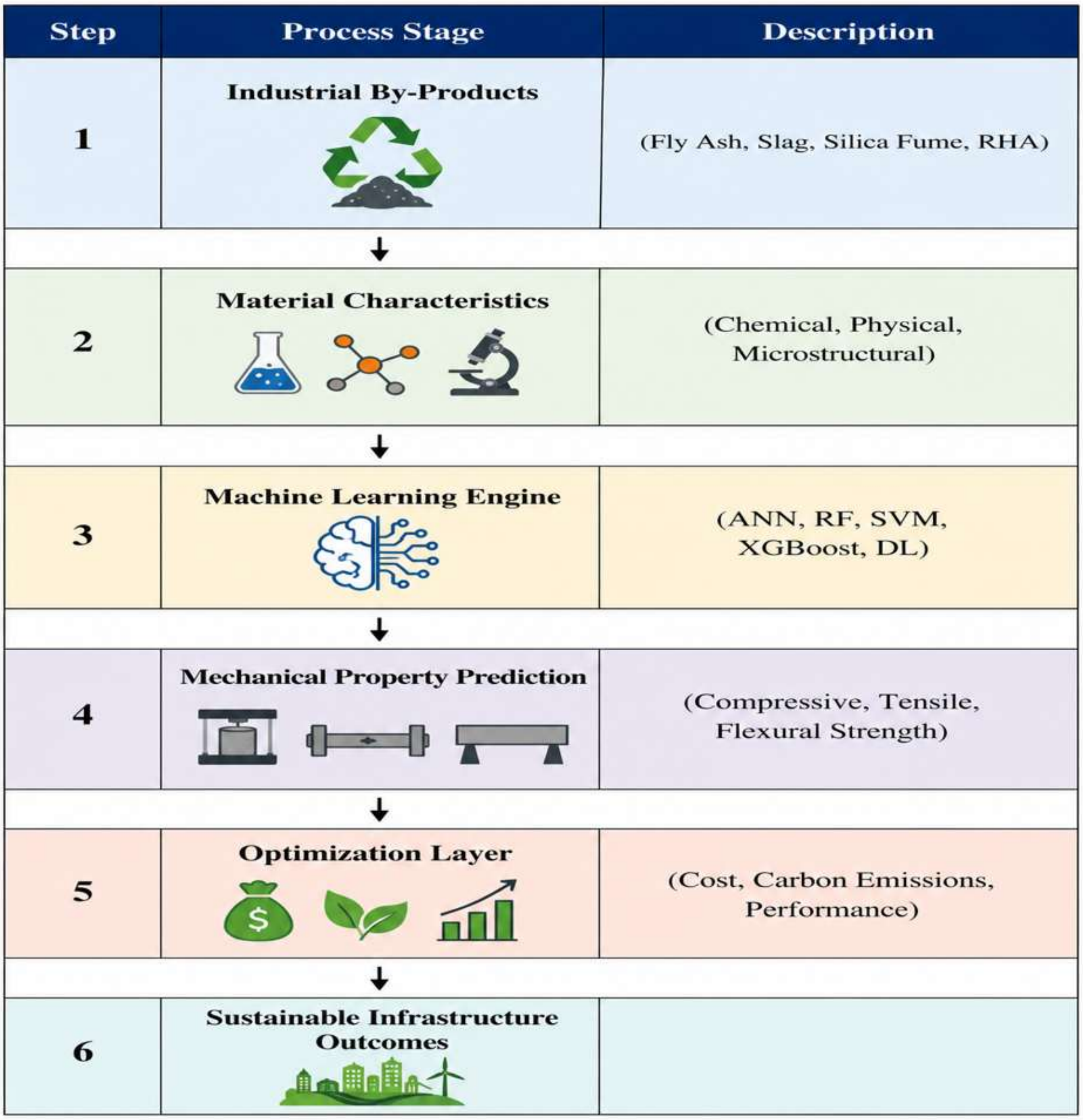

Figure 2. Conceptual Model

Table 2. Comparison of Existing Approaches

Approach	**Advantages**	**Limitations**	**Typical Accuracy**
Linear Regression	Simple and interpretable	Poor nonlinear modeling	70–85%
ANN	Captures complex relationships	Risk of overfitting	85–95%
SVM	Strong generalization	Computationally intensive	85–96%
Random Forest	High accuracy and interpretability	Large memory requirements	90–97%
Gradient Boosting	Excellent predictive power	Sensitive to tuning	92–98%
XGBoost	Superior performance	Complex parameter optimization	94–99%
Deep Learning	Handles large datasets	Black-box nature	95–99%

Hybrid Models	Combines strengths of multiple methods	Increased complexity	96–99%

5. Results and Discussion

5.1 Trends in Machine Learning Applications

The literature demonstrates a substantial increase in machine learning applications for sustainable concrete prediction over the last decade. Between 2018 and 2026, publications in this field increased significantly, reflecting growing interest in data-driven material design and sustainable construction technologies.

Initially, researchers relied heavily on Artificial Neural Networks and Support Vector Machines. However, recent studies increasingly favor ensemble learning techniques, particularly Random Forest and XGBoost, due to their superior predictive performance and robustness.

A notable trend is the shift from single-property prediction toward multi-property prediction systems capable of simultaneously estimating compressive strength, tensile strength, durability, and elastic modulus.

5.2 Performance of Different Machine Learning Algorithms

The comparative analysis reveals that ensemble learning approaches consistently outperform traditional statistical techniques.

Linear regression models typically achieve prediction accuracies ranging from 70% to 85%. Although useful for preliminary assessments, they struggle to capture the nonlinear relationships inherent in composite concrete systems.

Artificial Neural Networks generally achieve accuracies between 85% and 95%. Their ability to model nonlinear interactions makes them highly effective for concrete strength prediction. Nevertheless, performance depends heavily on network architecture and training procedures.

Support Vector Machines demonstrate strong predictive capabilities, particularly for smaller datasets. Reported accuracies often exceed 90%, although computational demands increase significantly with larger datasets.

Random Forest algorithms provide an effective balance between accuracy and interpretability. Feature importance analysis allows researchers to identify influential variables, enhancing practical applicability.

Among all reviewed approaches, XGBoost consistently achieves the highest performance. Several studies reported R^2 values above 0.97 and prediction errors below 5%. The algorithm effectively handles nonlinear interactions, missing data, and high-dimensional datasets.

Deep learning models demonstrate exceptional performance when large datasets are available. However, their black-box nature and computational requirements remain significant challenges.

5.3 Influence of Industrial By-Products on Prediction Accuracy

The incorporation of industrial by-products introduces additional complexity into prediction models. Fly ash, slag, silica fume, and rice husk ash influence hydration kinetics, microstructure development, and long-term strength gain.

Studies indicate that machine learning models can effectively capture these complex interactions when appropriate input variables are included. Variables frequently identified as influential include:

- Water-to-binder ratio.
- Cement content.
- Fly ash replacement percentage.
- Slag content.
- Silica fume dosage.
- Aggregate characteristics.
- Curing age.

Feature importance analyses consistently identify curing age and water-to-binder ratio as dominant predictors of mechanical performance.

5.4 Sustainability Implications

The integration of machine learning with sustainable concrete design offers substantial environmental benefits. By enabling rapid evaluation of alternative mix designs, machine learning can reduce experimental waste and accelerate the adoption of low-carbon construction materials.

Several studies estimate that replacing 30–50% of cement with industrial by-products can reduce carbon emissions by approximately 20–40% while maintaining acceptable mechanical performance. Machine learning models facilitate optimization of these replacement levels to achieve both environmental and structural objectives.

Furthermore, predictive analytics can support circular economy initiatives by encouraging the utilization of industrial waste streams that would otherwise require disposal.

5.5 Emerging Research Themes

Recent developments highlight several emerging research themes.

Explainable Artificial Intelligence (XAI) is gaining attention as researchers seek to improve model transparency. Techniques such as SHAP (SHapley Additive Explanations) and LIME (Local Interpretable Model-Agnostic Explanations) are increasingly employed to explain prediction outcomes.

Digital twin technology represents another promising area. By integrating machine learning with real-time sensor data, digital twins can continuously monitor concrete performance throughout a structure's lifecycle.

Hybrid optimization approaches combining machine learning with genetic algorithms, particle swarm optimization, and Bayesian optimization have demonstrated enhanced performance in concrete mix design optimization.

Finally, cloud computing and IoT-based monitoring systems are expected to transform data collection and predictive maintenance practices within smart infrastructure environments.

6. Future Research Directions

The application of machine learning for predicting the mechanical properties of composite concrete incorporating industrial by-products has demonstrated significant potential. However, several research challenges and opportunities remain to be addressed to facilitate broader industrial adoption and scientific advancement.

One promising direction is the development of large-scale standardized datasets. Current studies often rely on datasets collected from individual laboratories, resulting in inconsistencies in material characterization, testing procedures, and environmental conditions. The establishment of international open-access databases would improve model generalization and enable more reliable benchmarking of machine learning algorithms.

Another important research avenue involves explainable artificial intelligence (XAI). While advanced algorithms such as XGBoost, Deep Neural Networks, and ensemble learning models achieve exceptional predictive accuracy, their decision-making processes remain difficult to interpret. Future studies should integrate SHAP (SHapley Additive Explanations), LIME (Local Interpretable Model-Agnostic Explanations), and other explainability techniques to improve transparency and trust among engineers and decision-makers.

Hybrid machine learning frameworks also represent a promising area of investigation. Combining machine learning algorithms with optimization techniques such as Genetic Algorithms (GA), Particle Swarm Optimization (PSO), Ant Colony Optimization (ACO), and Bayesian Optimization may significantly enhance predictive performance and mix design optimization.

The integration of machine learning with digital twin technology is expected to transform infrastructure management. Digital twins can continuously collect data from sensors embedded within concrete structures and use machine learning models to predict performance degradation, maintenance requirements, and structural risks throughout the asset lifecycle.

Future studies should also investigate multi-objective optimization frameworks that simultaneously consider mechanical performance, economic feasibility, environmental sustainability, and lifecycle costs. Such frameworks would support the development of truly sustainable construction materials.

Furthermore, emerging technologies such as edge computing, cloud computing, blockchain-enabled construction management, and Internet of Things (IoT) networks offer significant opportunities for enhancing real-time monitoring and predictive analytics in smart construction environments.

Another important direction involves the prediction of long-term durability properties. Existing studies focus predominantly on compressive strength, while durability indicators such as chloride penetration resistance, carbonation depth, freeze-thaw resistance, sulfate attack resistance, and corrosion potential remain underexplored.

Finally, researchers should expand investigations beyond conventional industrial by-products and evaluate emerging waste materials such as e-waste ash, lithium battery waste, construction and demolition waste, biochar, and carbon capture by-products. These materials may contribute significantly to future low-carbon construction practices.

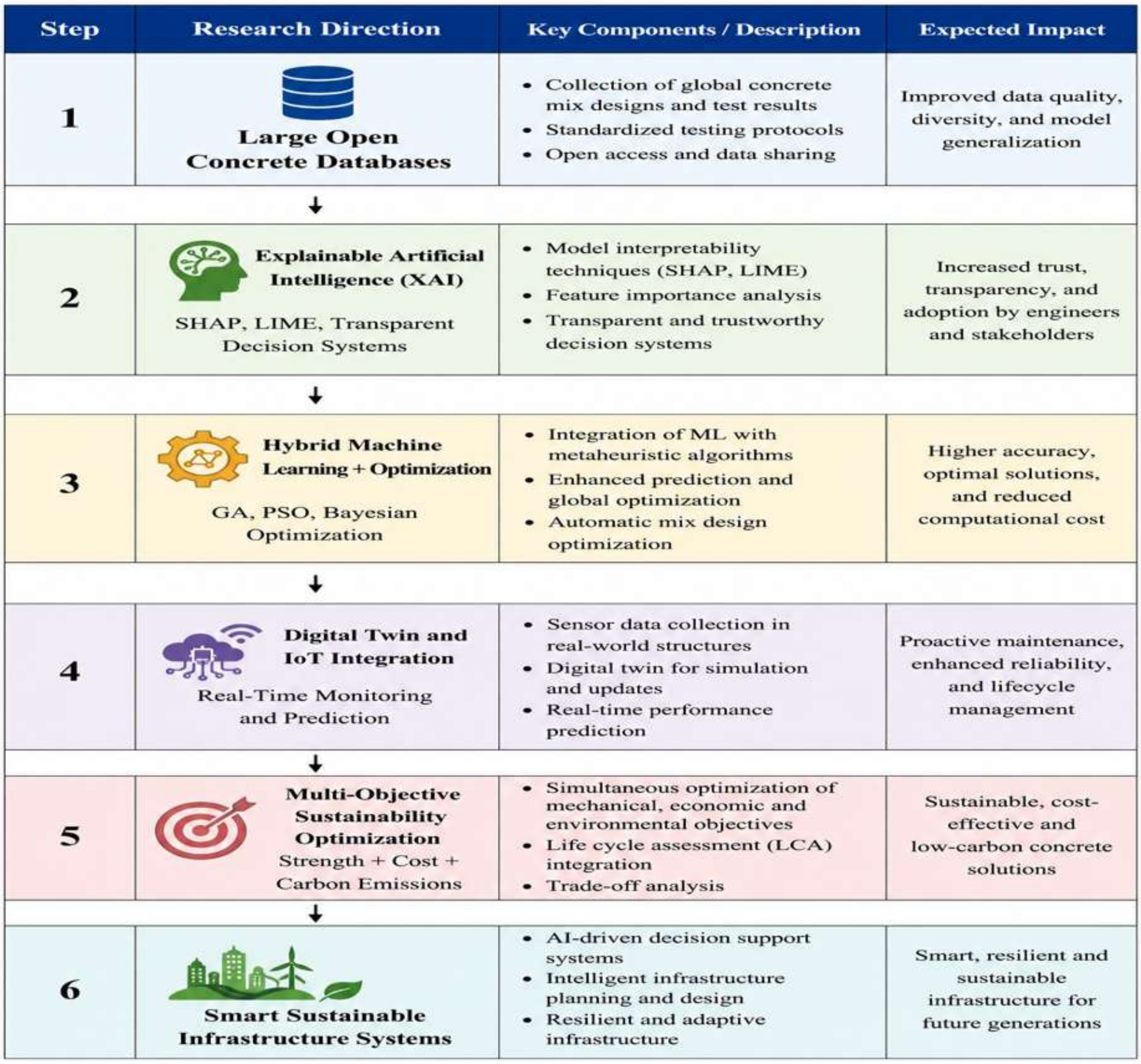

Figure 3. Future Research Roadmap

Table 3. Challenges and Opportunities

Challenges	**Impact**	**Opportunities**
Limited datasets	Reduced model generalization	Development of open-access databases
Data quality issues	Inaccurate predictions	Automated data validation systems
Black-box ML models	Lack of trust and transparency	Explainable AI techniques
Computational complexity	Increased implementation costs	Cloud-based ML platforms
Lack of standardization	Difficult comparison across studies	International testing standards
Limited durability prediction	Incomplete performance assessment	Multi-property prediction models
Industry resistance	Slow technology adoption	User-friendly decision-support tools
Sustainability integration gaps	Suboptimal environmental outcomes	Carbon-aware optimization frameworks
Real-world deployment challenges	Limited practical implementation	Digital twin integration
Dynamic material variability	Uncertain prediction accuracy	Adaptive learning systems

7. Practical Implications

The findings of this study have significant implications for researchers, construction professionals, policymakers, and material manufacturers.

For construction engineers, machine learning models provide rapid and cost-effective tools for evaluating concrete mix designs. Instead of conducting extensive laboratory testing for every potential mixture, engineers can utilize predictive models to estimate mechanical properties and identify optimal compositions. This capability reduces project timelines and minimizes material wastage.

For concrete manufacturers, machine learning can improve quality control processes by predicting product performance before large-scale production. Early identification of potentially underperforming mixtures can reduce production risks and improve consistency.

Government agencies and policymakers can benefit from machine learning-driven sustainability assessments when developing regulations and standards for green construction materials. Predictive analytics can support evidence-based decisions regarding the adoption of industrial by-products in infrastructure projects.

Infrastructure asset managers can integrate machine learning with sensor networks and digital twins to monitor structural performance in real time. Such systems enable predictive maintenance strategies, reducing lifecycle costs and improving infrastructure resilience.

Furthermore, machine learning-assisted optimization can facilitate greater utilization of industrial by-products, thereby reducing landfill waste, conserving natural resources, and lowering carbon emissions associated with cement production.

Research Contributions

Theoretical Contribution

This study contributes to the theoretical advancement of sustainable construction materials by synthesizing knowledge from machine learning, concrete technology, and environmental sustainability. The research develops a comprehensive conceptual framework that explains how machine learning algorithms can capture complex nonlinear relationships among material properties, mixture compositions, and mechanical performance indicators.

The study also extends existing literature by integrating sustainability considerations into predictive modeling frameworks, thereby bridging the gap between material performance optimization and environmental responsibility.

Managerial Contribution

From a managerial perspective, the proposed framework supports data-driven decision-making in construction project planning, material selection, and quality assurance processes.

Project managers can use machine learning models to evaluate multiple design alternatives rapidly, reducing uncertainty and improving resource allocation. The framework also assists organizations in achieving sustainability targets while maintaining structural performance requirements.

Moreover, predictive analytics can improve risk management by identifying potential performance issues before construction begins.

Technological Contribution

The study highlights the transformative role of advanced machine learning techniques in construction materials engineering.

By evaluating ANN, SVM, Random Forest, Gradient Boosting, XGBoost, and Deep Learning approaches, the research provides a technological roadmap for implementing intelligent prediction systems within the construction sector.

The integration of machine learning with digital twins, IoT systems, cloud computing platforms, and explainable AI technologies represents a significant advancement toward smart infrastructure development.

Sustainability Contribution

The sustainability contribution of this research is particularly significant.

The utilization of industrial by-products such as fly ash, slag, silica fume, rice husk ash, and waste glass powder can substantially reduce cement consumption and associated greenhouse gas emissions.

Machine learning facilitates the optimization of these sustainable materials by identifying optimal replacement levels and performance-enhancing combinations. Consequently, the proposed framework supports circular economy principles, resource conservation, waste reduction, and low-carbon construction practices.

8. Conclusion

The construction industry faces increasing pressure to reduce environmental impacts while maintaining high levels of structural performance and economic efficiency. Composite concrete incorporating industrial by-products has emerged as an effective solution for addressing these challenges. However, the complex interactions among constituent materials make accurate prediction of mechanical properties difficult using traditional experimental and statistical methods.

This study presented a comprehensive review of machine learning-based approaches for predicting the mechanical properties of composite concrete containing industrial by-products. The findings demonstrate that machine learning algorithms significantly outperform conventional regression techniques in modeling nonlinear relationships among material and process variables.

Among the reviewed approaches, ensemble learning methods such as Random Forest and XGBoost consistently achieved superior predictive performance, often exceeding prediction accuracies of 95%. Artificial Neural Networks and Support Vector Machines also demonstrated strong capabilities, while deep learning models showed exceptional potential when large datasets were available.

Despite these advances, several challenges remain, including limited datasets, lack of model interpretability, insufficient sustainability integration, and restricted industrial implementation. The study identified explainable artificial intelligence, digital twins, hybrid optimization techniques, and IoT-enabled monitoring systems as key future research directions.

The proposed conceptual framework provides a foundation for integrating machine learning with sustainable concrete design and intelligent infrastructure management. By facilitating accurate prediction and optimization of concrete properties, machine learning can reduce experimental costs, accelerate innovation, improve construction quality, and support global sustainability objectives.

Ultimately, the convergence of machine learning, industrial by-product utilization, and smart construction technologies represents a transformative opportunity for the future of sustainable infrastructure development.

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