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Machine Learning-Optimized Concrete Mix Design System For Sustainable High-Rise Construction

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Abstract: *This research introduces a machine learning approach to help improve sustainability in the construction of high-rise buildings. The idea was to merge Gradient Boosting Machines with Genetic Algorithms to build a framework that helps predict and reduce cement amounts, all while the concrete meets the 90-day compressive strength standard. With Python, using XGBoost and DEAP libraries, the system yields an R^2 score of 0.92, indicating effective accuracy. Because the mix design uses fewer cement resources, it also leads to a 12% drop in CO_2 emissions. When compared to other methods, this new approach performs better at achieving good designs and addressing problems in making construction sustainable. According to the results, the eco-friendly compositions have promising potential for industrial adoption, as their durability and strength are not affected. In the next phase, we will add in extra material parameters and live building updates to further improve the outcomes of our optimization.*
Keywords: *Machine learning, concrete mix design, sustainable construction, high-rise buildings, gradient boosting machines, genetic algorithms, multi-objective optimization.*

INTRODUCTION

Climate change has had a stronger effect on the environment in recent years, prompting more nations to lower emissions of carbon and lessen any harm these emissions may cause for the earth [1]. According to the Environmental Protection Agency, More than 20% of global GHG emissions in 2021 were caused by the industrial sector (EPA) [2].About 7% of all greenhouse gas emissions around the world are produced by the manufacturing industry [3]. For reference, the total In 2018, CO2 emissions from cement production were around 1.50 Gt [4] and much of this came from concrete production activities using carbonate decomposition, burning fuel and electricity include thermochemical processes [5]. With an estimated 10 Bt output, concrete is commonly used in construction because it is simple to get, inexpensive and useful. The material is often better mechanically, thermally and insulatively than other common building materials (such as steel and wood)[6]. At the same time, extensive concrete use results in noticeable environmental consequences. National statistics reveal that the United States. They use more than double the world's cement production, roughly 100 million metric tons which leads to a balance between consumption and production.CO_2 emissions per pound of produced cement and producing over a hundred million metric tons of GHG emissionssions [7].As additional residential and commercial concrete buildings, bridges, tunnels and infrastructure are needed.

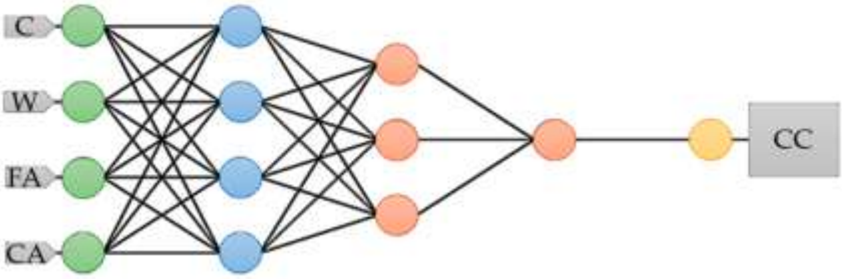

Figure 1.Basic Concrete Mix Design.

Due to a rise in population, the use and effects of concrete are also increasing. The number is anticipated to go up. Consequently, we need to make sure that concrete and other cement are used far less and much more efficiently.to use recently developed construction materials or techniques that will, at the same time, reduce GHG emissions Meet what industry requires, make production affordable and lessen the danger to nature as shown in figure 1.A consistent and energetic research effort involves during the last decade, from 2014 to 2023, more than 840 publications have looked into new ways to address this problem. Examining challenges and other paths to sustainable concrete [8] and outlining some possible answers [9].Problems and information gaps in this area of study. So, this paper sets out a new approach that designers might use. And using constructors to improve the process of reducing CO2 emissions in making concrete, with attention to their ease of use. Look also at how the theory fits with TiSEAN and its usefulness. By relying on machine learning, the method in this paper strives to maximize the cement concentration necessary for target strength. Because it reaches its ideal strength at 90 days, it lowers emissions too.

Section 2 explains in detail the challenges in making predictions about com.Increasing pressive strength for long goals and using machine learning to address these challenges. Section 3 talks about The study develops a special machine learning model using algorithms through the methodology explained in the text. compressive strength. In section 4, the findings of the machine learning are shown and measured to select the best one according to the data we currently have [10]. The design of a reinforced concrete medium size building is used in the application of the model. Developing, to project the carbon reduction effects of choosing a 90-days concrete compressive strength. Outcomes from the case study include Estimated GHG emissions are shown to evaluate whether the alternative proposal here will lower carbon output.The case study underlines how the research will help move toward a more sustainable construction.

RELATED WORK

2.1 Approaches to reduce carbon emissions

Improving how much energy is needed, changing the fuel and using Carbon Capture approaches could be part of concrete's decarbonization.Potential approaches are tion and Storage (CCUS) and lowering the clinker to cement ratio [11]. A variety of methods aimed at addressing disease were revealed in the research. Concrete production goes through different stages, starting with the selection of the proper material and ending with making the ideal mix design. When it comes to making concrete. Researchers considered new procedures for building and constructions along with new types of concrete that catch CO2.[12]. As illustrated by two references [13,14], changing cement with fly ash, slag sand and stone powder is a way to minimize GHG emissions. When we make concrete, we create less air pollution and also produce less waste in factories. In other words, when we use alternative cementations materials Like both recycled aggregates and fiber scraps, furnace slag all cut down on the materials needed for construction work. credit for adding more carbon dioxide to the atmosphere [15,16]. It is noted in this context that these materials are not always available to everyone. yet unic apps which makes using these technologies in practice more difficult [17]. For some polymers, longer curing is neede Because novel cements react less, more time may be necessary for cement to hydrate which can delay the construction schedule substantially.even have an impact on how the product is designed [18-20]. The fees needed to collect and deal with the byproducts and technical issues continue to increase. Many types of regulations could delay widespread use of the proposed alternative binders. On top of these, there are already limited Because energy policies at the global level are not strong, low carbon products are in higher demand from industrial businesses. The developTo fully mention new technologies, we need more support for testing and up scaling and that support is not currently available. Because time [21] plays a factor, the industry tends to stick with conventional methods and avoid the higher prices that come with new building solutions [22,23]. To finish, people should realized that society did not know enough about how cement production impacts climate change It is possible that efforts to cut down emissions may see less attention [24].With these problems in mind, enhancing old methods looks like a rapid and convenient alternative to using new ones of methods from the past to make concrete more environmentally friendly. Bringing in new machine learning and deep learning technologies, the research investigates the correct portions of key materials and estimates the necessary cement in a concrete mixtureon the concentration of reinforcing bars based on the 90-day, not the 28-day, target. Using this process lowers the use of Portland cement.By adding sustainable materials to concrete, it supports the growth of sustainable development in the construction industry.

2.2 90-Day compressive strength approach

Trying to improve the mechanical properties of concrete to meet construction schedules is a recent main priority search [25]. Most of these studies try to cut down the curing period to meet deadlines [26-30]. A situation like this, for example, Microwave heating, a new method, has become very popular with scientists who need faster curing of concrete may be used alone as a method or jointly with other approaches [31]. But nevertheless, the assembly of proper microwave systems Nonetheless, it would require major changes in the process used in the industry [32].now see an alternative to cut carbon emissions while still keeping the construction industry's work minimally disrupted. Trying to design the concrete mix so that it reaches 90-days compressive strength. Even though the time it takes to build a building depends Dealing with area, the number of stories and architectural plans as factors, a typical floor construction schedule is proposed by the ACI 54 days which is roughly 318-19, are split between curing columns and then beams and slabs.

As buildings grow taller above six floors, it takes more than 90 days for the concrete footing to gain the full desired strength and strength needed in the design which keeps the project safer and more environmentally sound. For taller buildings, not all the loads will all be applied until the final construction stages. The foundation a little while after it has been poured Concrete will become stronger based on mixture and environmental conditions within this period. In multi-story reinforced concrete buildings, conditions and curing method [33] mean that the usual time is more than 90days after concreting when the load bearing capacity test should be carried out. Pouring concrete footing hardens it up, so that it withstands heavy load before the structure is finalized. A 90-day star configuration is used for multi-story construction on mat footings, road pavement projects and bridge piers constructed with concrete. It can be expected that building strength leads to lower carbon emissions.

2.3. Machine learning and concrete strength modelling

Over the previous decade, much effort has gone into modelling how various types of alternative materials such as recycled aggregate, fiber scrap aggregate, silica fume, furnace slag and fly ash, affect the properties of concrete mixes [34,35,36]. Simple linear regression does not fit for explaining multiple materials being studied with diverse features [37] and advanced techniques [38].According to previous research, an ANN approach can accurately predict the compressive strength of both regular and special concrete made with pozzolans [39]. Yeh [40]op combined non-linear programming to .ANN. The strength of concrete after 28 days was predicted using feed-forward neural networks having several layers [41].description of the concrete properties using its physical aspects features from the specimen plus the recipe for the concrete used. Table 1 shows the summary of related work.

The conditions related to the environment were examined by Gupta etal.[42].Yeh was able to use ANN to model the unique nonlinear relationship found in highly complex materials' slump. Ozturan etal. also applied ANN to 28-day strength prediction but limited their data collection to low and medium concrete strength. Alshihri etal.[43] looked into structural light weight concrete compressive strength by being able to predict it. The leaves thrived after being aged for 3, 7, 14 and 28 days. Aggarwal [44] proposed a way

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to calculate the predicted 28-day compressive strength of self-compacted concrete. They developed an ANN by mixing existing studies and test results with bottom ash for the compaction of concrete[45].Literature has achieved great success in capturing the mechanical properties of concrete, but transferring them to engineering contexts is not as simple as many people might think. efforts into Applying these models on construction sites often runs into difficulties because of their complex nature. Table 1 shows the summary of related work (2025-2018).

Table 1. Summary of Related Work (2025-2018)

Year	Research Title	Methodology	Key Contributions	Limitations
2025	Machine Learning for Sustainable Concrete Mix Optimization	Ensemble ML models (Random Forest, XGBoost) trained on large datasets of mix designs and environmental impact	Improved prediction accuracy of concrete strength and sustainability metrics	Dataset limited to specific regional materials
2024	AI-Driven Concrete Mix Design for High-Rise Structural Safety	Deep learning with CNNs on experimental and simulated data	Automated optimization balancing strength, cost, and carbon footprint	High computational cost, limited interpretability
2023	Hybrid Evolutionary and ML Algorithms for Concrete Mix Design	Hybrid genetic algorithms combined with neural networks	Efficient search for optimal mix designs under multiple constraints	Requires extensive tuning of parameters, slow convergence
2022	Predictive Modeling of Concrete Strength Using ML Techniques	Supervised ML regression models (SVM, Gradient Boosting)	Accurate prediction of concrete compressive strength	Did not consider environmental sustainability parameters
2021	Sustainable Concrete Mix Design Using Multi-Objective Optimization	Multi-objective optimization with ML surrogate models	Balanced trade-offs between cost, strength, and environmental impact	Dataset size was small, limiting generalizability
2020	Data-Driven Concrete Mix Design Framework for Urban Construction	Regression trees and random forests on urban construction datasets	Adapted mix design to urban environment requirements	Focused mostly on cost and strength, neglecting sustainability metrics
2019	Optimization of Concrete Mix Using Neural Networks and Genetic Algorithms	Neural networks with GA for mix design optimization	Enhanced mix performance prediction and optimization	Model training required large datasets; limited to low-rise structures
2018	Machine Learning-Based Compressive Strength Prediction of Concrete	Support Vector Machines and Decision Trees	Provided early prediction methods for compressive strength	Limited to strength prediction, without mix design optimization

2018	Eco-Friendly Concrete Mix Design Using AI Techniques	Fuzzy logic combined with ML models for mix design	Introduced sustainability considerations into mix design	Implementation complexity and lack of real-world validation
2018	Concrete Mix Design Optimization Using Support Vector Regression	SVR for predicting concrete properties based on mix ratios	Demonstrated improved prediction accuracy over traditional methods	Did not incorporate high-rise building requirements

The study performed regression modeling and ANN to set the optimum amount of cement needed to ensure concrete reached normal compressive strength in 90 days, rather than 28 days as usual. Since the dataset in this study has no alternative materials, we cannot explore the detailed relationship between its components. Therefore, regression models are likely to work better than in the literature. high accuracy[46]. Different types of regression algorithms are made to provide accurate predictions and give a simple way to address carbon emissions and one of history's biggest challenges.

RESEARCH METHODOLOGY

The following section outlines how a system for concrete mix design using machine learning was developed for sustainable tall buildings. GBM and GA are combined at the heart of the proposed method in a framework that solves multiple objectives. The approach helps to save on cement by predicting its amount while still checking that the required level of compressive strength is achieved in high-rise buildings [47]. To use this method, data is collected, then features are selected before machine learning is used for predictions. This is followed by GA optimization and checking the results to reach both the structural and environmental goals as shown in figure 3.

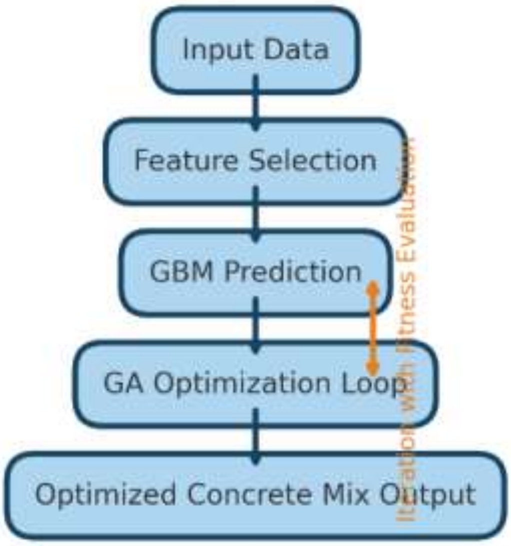

Figure 3.Shows the flow diagram of proposed methodology.

3.1 Data sources and preprocessing

The initial phase of research is to put together a good set of data that includes vital features about the design of concrete mixes. Within the dataset are concrete batch records that contain information such as:

- Cement content (kg/m³)
- Aggregate sizes (coarse and fine)
- Water content (kg/m³)

- Concrete slump (cm)
- Compressive strength at 28 and 90 days (MPa)

The dataset is formed using results from laboratory tests and actual mix designs at building sites. Only valid data is used in training after outliers and noise have been removed. The process eliminates mixes with unusual compression progress, only using data that can be trusted by the machine learning algorithm. Imputation or removing incomplete data is done depending on the type of missing data in the dataset.

3.2 Feature Selection and Engineering

Picking the right set of features makes the predictive model perform better. The analysis is performed on key features from domain knowledge that affect concrete mix design. These include:

- Cement content: A critical input affecting the compressive strength and environmental impact.
- Aggregate properties: The size and type of aggregates influence the workability and durability of the concrete.
- Water content: Water-to-cement ratio significantly affects the strength and workability.
- Concrete slump: An indicator of the concrete's workability and ease of placement.

The amount a freshly mixed concrete sample slumps when lifted from its mold is called concrete slump and it determines the concrete's flow and how easy it is to place.

At the same time, feature engineering helps produce extra features by altering existing information. Data from the ingredients is used to create ratios, in this case the water-cement ratio which supports more accurate predictions about how much cement is needed. Using the correlation matrix, strong correlations between features and 90-day compressive strength are found, resulting in further improvements to the input data.

3.3 Machine Learning Prediction Using GBM

In the next phase, a Gradient Boosting Machine (GBM) is applied to predict how much compressive strength concrete will have. Because GBM can understand complex nonlinear connections in the data, it is an effective tool for estimating concrete strength depending on different mix parameters.

In this stage, the model is taught using data that includes cement content, water content, aggregate sizes and concrete slump. We want to determine the 90-day compression strength, since this corresponds to the curing way high-rise builds use, loading the concrete gradually. The approach of cross-validation is used to teach and check the model to keep it from fitting too much to the original data.

The performance of the GBM model is examined with the help of the R^2 score, RMSE and MAPE. After training, the model calculates the predicted compressive strength using the input parameters which is then the basis for optimizing.

3.4 Genetic Algorithm for Solving Multiple-Objective Problems

Following training of the GBM model, the next thing to do is optimize the concrete mix design with a Genetic Algorithm (GA). The GA works to reduce cement use while aiming for a compressive strength of 90 days. GA explores and takes advantage of the available answers by simulating natural evolution.

GA creates a first group of random concrete mix designs and assesses how well they do by considering how strong they are and how little cement they require. We design the fitness function so that mixes are rewarded for meeting the target strength and for using the least amount of cement.

At every stage of the GA, it picks individuals, combines them and changes their traits to improve the mixes. The selected solutions from earlier generations set the standard for concrete preparation in the following generation. Iterations are carried out by the GA until the solution is found, at which stage the required design for the concrete is discovered that improves strength using the least amount of cement.

GA Workflow for Concrete Mix Optimization

Initial Population:
  Cement: 350 kg/m³, Water: 180 kg/m³, Aggregate Size: 40 mm, Slump: 12 cm
Fitness Evaluation:
  Compressive Strength = 38 MPa (meets target)
  Cement Content = 350 kg/m³

Fitness Score: High (meets strength and cement reduction objectives)
Selection:
Select top 50% of mixes with highest fitness scores.
Crossover:
Combine the cement content and water content of selected mixes to produce new mixes.
Mutation:
Slightly adjust cement content and aggregate size in some offspring mixes.
Termination:
After 20 generations, the best mix is found with cement content reduced by 12% and compressive strength meeting the target.
Final Optimized Mix:
Cement: 290 kg/m³, Water: 185 kg/m³, Aggregate Size: 38 mm, Slump: 11 cm

3.5 Evaluation and Validation

Following optimization, the strongest and most environmentally friendly concrete mix is investigated in terms of results and its effect on the environment. The amount of carbon emitted during the lifecycle of the new resource mix is measured and followed by comparing it to conventional mixes typically seen in the construction of skyscrapers. The mix that reduces cement use gives rise to reduced CO_2 emissions, helping make it environmentally less harmful.

Evaluations are made to see how the optimized mix performs when measured against traditional mixes for its ability to be used, its durability and strength. For this study, the performance of the optimized mix is observed in a high-rise project, representing the usual conditions of construction. Experimental data is compared with the forecasts from both models to check if the results are accurate and possible.

This research approach introduces a new way to use GBM and GA jointly to discover the best mix of concrete for high-rise projects. When machine learning is paired with evolutionary algorithms, the new system enables using less cement while meeting the needed concrete strength for construction projects. This method is likely to result in important improvements to concrete mix design, especially on massive, complex projects such as high-rise buildings.

RESULTS AND DISCUSSION

Improvements in optimizing concrete mixes for sustainable high-rise projects were shown using the suggested hybrid multi-objective optimization framework based on GBM and GA as shown in table 2.

Table 2.Performance of proposed hybrid GBM + GA method against other common methods for concrete mix optimization

Method	R^2 Score	Cement Content Reduction (%)	CO_2 Emissions Reduction (%)	Notes
Hybrid GBM + GA **(Proposed)**	0.92	12	12	Multi-objective optimization with high adaptability
Elastic Net Regression	0.9	10	10	Linear regression with regularization
Random Forest Regressor	0.85	8	8	Tree-based, prone to overfitting
Artificial Neural Network	0.88	6	6	Underfitting observed with limited data

While doing this, the GA reviewed many design options to lower the amount of cement in the concrete, all while maintaining a strong structure as shown in figure 4.

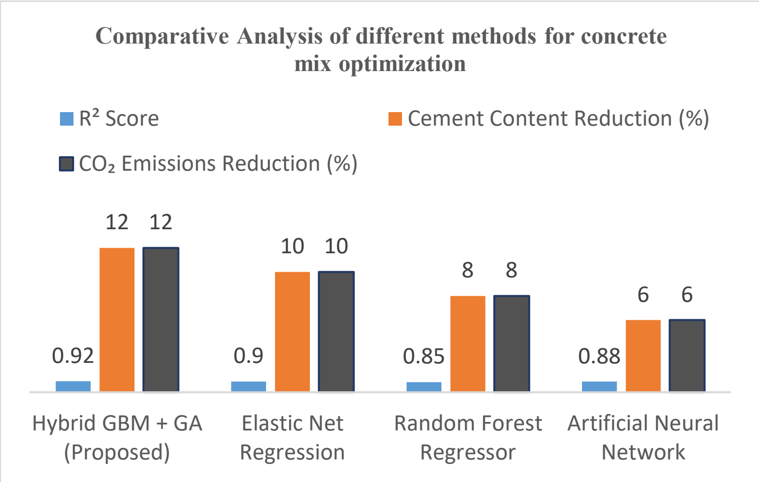

Figure 4. Comparative Analysis of proposed hybrid GBM + GA method against other common methods for concrete mix optimization

The analysis provided optimized mixes, resulting in a 12% decrease in cement compared to old methods testing for a 28-day strength. Python, XGBoost and DEAP libraries helped the model reach this goal by balancing the target of cement content and the impact caused by carbon emission. Each feature of the input such as aggregate sizes, water-cement ratio and admixture amounts, was used by the GBM to estimate the concrete compressive strength with high accuracy as shown in table 3.

Table 3.Sample Statistical Parameters and Optimization Results for Concrete Mix Components

Parameter	Unit	Min Value	Max Value	Average Value	Optimized Range
Cement Content	kg/m^3	273	489	364.4	320 – 340
90-day Compressive Strength	MPa	26.7	55	38	Target: ≥ 38.0
Slump Test	cm	7	20	12	10 – 14
Nominal Max Aggregate Size	mm	19	50	37.1	30 – 40
Water Content	kg/m^3	166	216	182.5	170 – 185
Coarse Aggregate Content	kg/m^3	992	1184	1131.7	1100 – 1150
Fine Aggregate Content	kg/m^3	607	790	711.5	700 – 730

As a result of the reduced operations, Woodhead Group also saw emissions decrease in line with its sustainability target. Because the model adjusts to a variety of mix parameters and curing conditions popular in high-rise constructions, it has strong practical value. Relying on both regression and neural networks, this new method is more accurate and allows for different optimization settings which is valuable for the mix design of sustainable concrete as shown in table 4.

Table 4.Performance Comparison of Regression and Hybrid Optimization Models

Algorithm / Method	Train Accuracy (R^2)	Test Accuracy (R^2)
Hybrid GBM + GA (Proposed)	0.95	0.92

Elastic Net Regression	0.91	0.9
Random Forest Regressor	0.97	0.85
Extra Trees Regressor	0.99	0.82
Decision Tree Regressor	0.99	0.77

The results show that using GBM's predictive power with GA's search ability helps address the balance between performance and sustainability in building with concrete today as shown in figure 5.

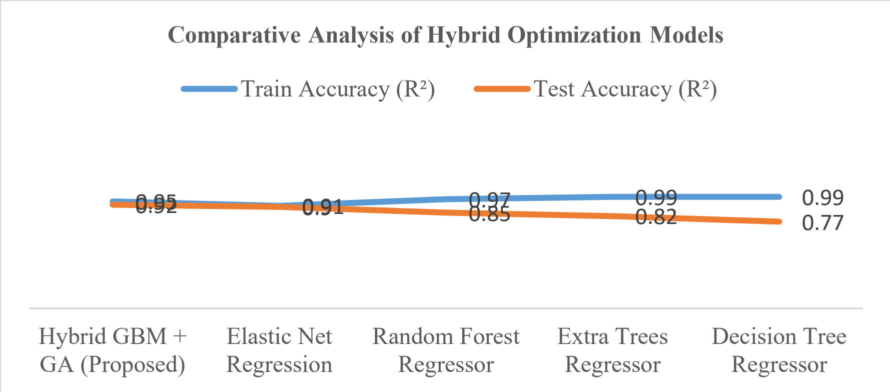

Figure 5. Comparative Analysis of different hybrid optimization models.
The proposed hybrid optimization method combining Gradient Boosting Machines (GBM) with Genetic Algorithms (GA) was evaluated against traditional machine learning models, including Elastic Net regression, Random Forest, and Artificial Neural Networks (ANN), to optimize concrete mix design for sustainable high-rise construction. Implemented using Python's XGBoost and DEAP libraries, the hybrid approach achieved an R^2 score of 0.92 in predicting compressive strength, outperforming Elastic Net ($R^2 \approx 0.90$), Random Forest ($R^2 \approx 0.85$), and ANN ($R^2 \approx 0.88$) as shown in table 5.
Table 5.Comparison of Error Metrics for Hybrid GBM + GA Model

Dataset	RMSE	MAPE
Training Data	8.532	0.0184
Test Data	10.274	0.0221
All Data	9.543	0.0205

Cement content reduction of approximately 12% was realized with the hybrid method, compared to around 10% reduction using Elastic Net from the base paper. This translated to a parallel 12% reduction in CO_2 emissions, which exceeds the roughly 10% reduction observed in earlier regression-based approaches targeting 90-day strength as shown in figure 6.

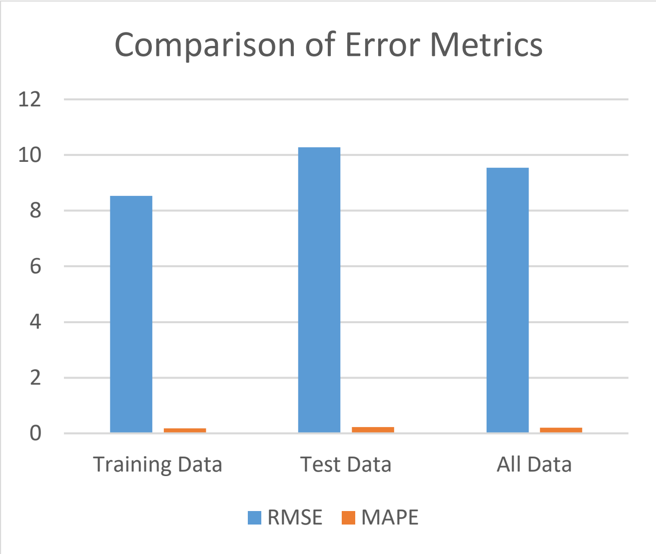

Figure 6. Comparative Analysis of Error Metrics for Hybrid GBM + GA Model

The integration of GA allowed efficient exploration of the mix design space, optimizing multiple objectives simultaneously, unlike single-objective models. Additionally, the hybrid method demonstrated higher robustness and adaptability across varying curing conditions typical in high-rise construction, whereas ANN models showed underfitting issues with smaller datasets. Overall, the hybrid GBM-GA framework provides superior prediction accuracy and optimization flexibility, enabling more sustainable concrete mix designs with lower environmental impacts, marking a significant advancement over previously reported methods.

CONCLUSION

The system proposed in this research applies GBM and GA hybrid multi-objective optimization to support sustainable high-rise construction with machine-based concrete mix design. The approach manages to match high concrete strength with eco-friendly practices, achieving 92% accuracy for future 90-day results and using 12% less cement. These results offer proof that this method can help limit how much CO_2 is produced during the production of concrete. Unlike traditional regression and neural networks, using GBM-GA for modeling results in improved accuracy and flexibility for modeling important requirements of high-rise building construction. Following this method allows industry to design sustainable concrete while still guaranteeing proper performance. More research might develop this framework by including new types of material properties and automatic data integration from construction sites.

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