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ENHANCING MANUFACTURING STRENGTH THROUGH FLY ASH-BASED PROCESSES USING GENETIC-CHIMP OPTIMIZED ADAPTABLE GRADIENT BOOSTING

Ashuvendra Singh[1]
Sunit Kumar
Avinash Ranger

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ABSTRACT

In the construction industry, acquiring the ideal concrete production strength is crucial for maintaining the durability and structural integrity of buildings and other public infrastructure. Concrete's compressive strength, a crucial mechanical characteristic must adhere to strict criteria for quality and sustainability. This research proposes a Genetic-Chimp Optimized Adaptable Gradient Boosting (GCO-AGB) refers to a revolutionary strategy developed by researchers in this field to improve the manufacturing strength of concrete through the use of fly ash-based procedures. This procedure is started by preprocessing gathered data on concrete manufacture using Z-score normalization to ensure the accuracy and consistency of the data. The effectiveness of the suggested strategy is examined by comparing the study findings to performance measures like Root Mean Square Error (RMSE), Coefficient of Determination (R^2), Mean Absolute Error (MAE), and Duration (S). The study's findings show that it is possible and efficient to use machine learning techniques, in particular GCO-AGB, to detect and classify concrete production strength in the context of fly ash-based procedures. The construction industry's search for improved structural performance and sustainability has bright prospects because to this new approach's better efficiency in assessing and improving concrete manufacturing processes when compared to standard manufacturing techniques.

1. INTRODUCTION

The production of concrete is one of the most used building techniques worldwide. Making concrete and the materials that go into it uses a lot of energy. In addition to using natural resources, it generates carbon dioxide, an enormously detrimental environmental effect. To lower CO_2 emissions, supplementary cementitious materials (SCMs) were utilized in concrete. Consequently, using SCMs in concrete that is useful and sustainable strategy (Patel et al., 2019). Sand, water and cement are combined to

[1] Corresponding author: Ashuvendra Singh
Email: ce.ayadav@gmail.com

form the composite material known as concrete, which goes through the bonding and hardening of the individual sand grains. It comprises silica (Si_2O), calcium oxide (CaO), and other binders. Kilns are used in this procedure to heat a combination of clay and limestone to a temperature around 1450 °C. About 50% of the carbon dioxide emissions linked to cement manufacture are caused by heat, which changes limestone chemically into calcium oxide.

The principal source of emission in the heating process, responsible for remaining fifty percent of emissions from cement manufacturing is the burning of coal and gas (Gopalakrishna and Dinakar (2023)). India generated about fifteen billion tonnes of Construction and Demolition waste (C and D) garbage, and less than ten percent of the trash was used. The improper or frequent disposal of these solid wastes in landfills would necessitate additional storage space and increase carbon emissions, posing environmental issues. Most C&D wastes comprise renewable materials like natural stone, leftover concrete and brick, among many others. Therefore, incorporating C&D wastes as Recycled aggregates (RA) in concrete composites is a long-term engineering breakthrough (Yalcinkaya et al., 2019). One of the primary materials used in constructions as concrete. Environmental issues caused by the concrete industry include global warming, the loss of natural resources, air pollution, and waste (Bakhoum et al., 2023). The thermal breakdown of calcium carbonate required to produce cement clinker and the combustion of fossil fuels used to heat the cement-making process, cement, an essential ingredient in concrete, is a substantial contributor to greenhouse gas emissions. Cement is responsible for around 88% of the emissions from concrete mix. As a result, the amount of cement used in concrete manufacturing directly affects how much CO_2 is released. In addition, the cement industry produces a significant quantity of dust, sulfur dioxide (SO_2), and nitrous oxide (NO_x) air pollutants (Jumaa et al., 2022). Concrete has a reputation for strong and long-lasting. It is excellent for various uses, including buildings, bridges and roads, as it handles huge weights and is weatherproof. Concrete is formed into different shapes and sizes, opening up various design options. It is used for anything, from straightforward architectural buildings to plain walkways. Concrete is less expensive than other building materials like steel or wood, especially when you consider its long lifespan and little maintenance needs. As a result of its large thermal mass, concrete stores and releases heat. This aids in managing indoor temperatures and when combined with insulation, can result in energy savings in buildings (Bheel et al., 2020). This study proposes an alternative machine learning technique called genetic-chimp-optimized adaptable gradient boosting (GCO-AGB) for constructing strong concrete utilizing fly ash-based techniques.

1.1 Contribution of the study

- The preprocessing method used to Z-score normalization and gather the concrete manufacturing dataset utilized.
- To create a Fly Ash-Based Process using genetic-chimp optimized adaptable gradient boosting
- The findings demonstrate that the proposed method is highly successful in analyzing concrete manufacture compared to standard methodologies.

The following parts of the article: An overview of related works is given in Section 2, a more thorough explanation of the methodology is provided in Section 3, and Section 4 presents and discusses experimental data sets, simulation findings, and discussion. The study is concluded in Section 5 and offers suggestions for more research.

2. RELATED WORKS

The paper (Althoey et al., 2023) determined the ideal proportion of waste glass by evaluating how waste glass (WG) behaves when it'sused in theplace of some sand in a concrete mixture. Since natural limestone supplies are quickly depleted of ordinary Portland cement (OPC) owing to production, it's imperative to employ industrial by products to substitute cement, use fly ash (FA), also produced a lot of carbon dioxide (CO_2). The paper (Singh et al., 2023) compared geopolymer concrete (GPC) to traditional OPC concrete to determine the best proportion of ground granulated blast furnace slag (GGBS), design mix should include FA and silica fume (SF) for greatest mechanical performance and environmental friendliness. Results showed that RA-based GPCs performed better mechanically and microstructurally due to the positive synergistic effects of FA, GGBS, and SF. The paper (Juang and Kuo 2023) investigated several superplasticizers (SPs) at high substitution quantities of long-term replacement cement employing FA and GGBFS, respectively, ground-granulated blast furnace slag. To lessen cement's negative environmental impact, supplemental cementitious materials (SCMs) are more popular as cement replacements. Artificial neural networks (ANN) and support vector machines (SVM) are examples of soft computing approaches that are used (Ramachandra and Mandal (2023)) to decide the FA concrete type among the chosen concrete types. Every result shows that ANN and SVM models predict the kind of FA concrete to be built more affordable, higher-grade and stronger concrete using local resources to meet particular structural and non-structural application needs. The paper (Yang et al., 2023) created an FA-based geopolymer concrete (FGPC), a feasible and long-lasting solution. But a quick fix is needed because FGPC is much more brittle than conventional concrete. This improves the FGPC's mechanical characteristics and fracture toughness. These findings are supported by SEM and FPT studies. The paper (Ahmad et al., (2022)) determined the compressive strength of fly ash-based geopolymer concrete employing supervised machine learning techniques, decision trees, bagging regressors, and AdaBoostregressors. A sensitivity analysis was also performed to determine that each parameter contributed to the results prediction. By saving time, effort, and money, using machine learning (ML) techniques to predict concrete's mechanical properties would be advantageous for civil engineering. The paper (Onyelowe et al., (2022)) desired to promote safer, more environmentally friendly concrete production and benefit the environment was concerned with suggesting intelligent mix models for FA-based concrete that include water, cement, fine and coarse aggregates (CAg) and FA. Utilizing closed-that model equations is the most effective technique to anticipate that FA and cement will be needed to produce the required strength levels while minimizing environmental impact. The paper (Abdalla and Salih (2022)) compared the impact of two key chemical components, cement mortar's long-term compressive strength is influenced by several elements, notably the concentrations of silicon dioxide (SiO_2) and calcium oxide (CaO) of substances found in cement kiln dust (CKD) and FA. According to the results of the sensitivity analysis, the most important factor in estimating for curing duration affects CKD and FA's ability to change a cement mortar's compressive strength. The paper (Ren et al., 2021) suggested using the ensemble classification and regression tree (En_CART) method to determine the breaking strength of concrete made using synthetic sand. Through increasing MS content, manufactured sand (MS)-concrete's compressive strength was observed to rise and decline. With an increase in MS-concrete's strength level, the ideal MS content marginally rises. The compressive strength of MS concrete has been discovered to enhance when stone powder has added at a specific MS content. For MS-concrete with lower strength and greater strength, the ideal stone powder content in MS is higher and lower, respectively. The paper (Sherwani et al., 2021) investigation, the dry density and void content were calculated. Additionally, tests were done on the created previous concrete's compressive strength, splitting tensile, permeability, and abrasion resistance. The findings indicated that by substituting 100% fly ash aggregate (AFA) for natural aggregate, the dry density of previous concretes could be reduced by up to 20.3%, the void content and abrasion value could be raised by up to 20.8%, and 153.8%, respectively. The paper (Roshani et al., 2021) presented a unique approach for predicting the mechanical properties of concrete by including FA using ANN. The outputs were specified as the modulus of elasticity, tensile and compressive strengths, and density of concrete samples. The expected predictions and experimental findings were found to be in good agreement. To determine, using FA affects the mechanical characteristics of concrete, straightforward yet useful equations are offered to advance the research's findings. The paper (Patil et al., 2021) assessed the pozzolanic of FA and BA in bagasse ash. Utilizing compression tests on mortar cube specimens created by replacing cement with bagasse ash and FA, the strength activity index (SAI) was computed by weight. The paper (Rutkowska et al., 2018) examined the effects of partial substitution of these ashes for Portland cement on the concrete's strength parameters as contrasted compared to a control concrete and concretes that had traditional admixtures such siliceous and calcareous FA. Through the assessment of heavy metals leachability, it was investigated if applying fly ashes to municipal sewage sludge (FAMSS) impacts the ecosystem.

2.1 Problem statement

The construction sector faces a substantial issues related to the strength and quality control of concrete manufacturing. Concrete strength changes jeopardize infrastructure and buildings' structural integrity and can raise maintenance costs and safety issues. Therefore, solving the issue of maintaining constant and dependable concrete stability throughout the production process is utmost significance. This issue statement underlines the need for a solution to guarantee concrete products' consistent and reliable strength and underscores fretting about changes in concrete strength throughout manufacture. Process improvement, quality assurance procedures, and material improvements address this issue to improve concrete's overall performance and stability.

3. MATERIALS AND METHODS

The steps in introducing metrics for genetic-chimp optimized adaptable gradient boosting (GCO-AGB). The method gathering for a dataset utilizes a preprocess of the z-score normalization method. They developed a GCO-AGB manufacturing method. The outcomes demonstrate a model's capacity to raise the resilience and the effectiveness of manufacture by considering both evaluations, demonstrating its potential value to upcoming manufacturing strength is shown (figure 1).

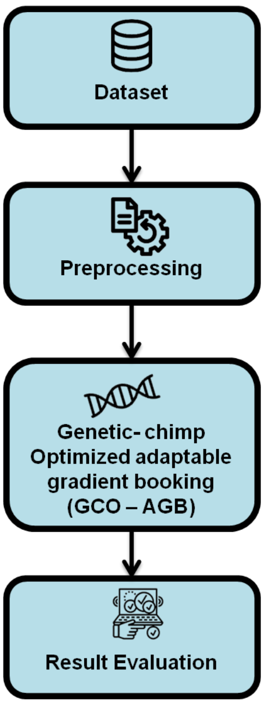

Figure 1. Flow of the proposed method

3.1 Dataset

Eight input factors in all were taken into account: “Ground granulated blast furnace slag (GGBS), cement (C), water (W), fly ash (F), superplasticizer (S), coarse aggregate (CA), fine aggregate (FA), and concrete age (T)”. As an output parameter for the targeted data sets, compressive strength was used. There have been utilized 1030 data in total. (Table 1) provides information on the parameters' range and abbreviations (Shubham et al., 2023).

Table 1. Dataset

Parameter	Notation	Minimum	Maximum
GGB	G	0	359.4
Cement	C	102	540
Water	W	0	247
Fly ash	F	121.8	200.1
Superplasticizer	S	0	32.2
The concrete's age	T	1	82.60
Fine aggregates	FA	594	992.4
Coarse aggregates	CA	801	1145
Compressive strength	CS	2.33	82.60

3.2 Pre-processing

Z-score Normalization is the name of the parameter. As a result, the unstructured data is normalized using the z-score parameter using the following formulas:

$$v_i{}' = \frac{v_i - E}{std\ (E)} \tag{1}$$

$v_i$is Z-score values normalized to one.$v_i$is the value of ith column's row E.

$$std\ (F) = \sqrt{\frac{1}{(m-1)}\sum_{j=1}^{m}(u_j - \bar{F})^2} \tag{2}$$

$$\bar{F} = \frac{1}{n}\sum_{j=1}^{m} u_j \tag{3}$$

Assume for this approach that we have five rows, $X, Y, Z, U, and\ V$, with various variables or columns that are 'n' in each row. Therefore, the normalized ones in each row above are calculated using the z-score method. All values for a row are set to zero for example a row's standard deviation equals zero and all values are similar.

3.3 Genetic-chimp optimized adaptable gradient boosting (GCO-AGB)

3.3.1 Genetic algorithm

A mathematical method called the GA replicates how biological organisms evolve. The most appropriate organism will live according to one straightforward principle. To employ this optimization concept, the problem must have a collection of solutions, suitable standards, and a technique for integrating existing responses to produce new ones. The GA shows the response as an ordered set of stages, much as how biological species pass on information to the following generation in a variant of a structured following of genes called chromosomes. This permits the solutions to be subjected to genetic operations by the GA. The crossover mixing method flips the heads and tails of both current approaches to produce new strategies based on existing ones. In altering one of the solution's steps, one is cause mutation, this is the random alteration of genetic material rays, chemicals, and copying errors. The cycle of the algorithm starts with creating a collection of chosen solutions for individuals under investigation, then involves selecting the best-fitting solutions and discarding the remainder after assessing each solution's fitness utilizing fitting criteria. Every remaining explanation is combined to create new ones, which restores the population size to its former state. Then the cycle continues. The solutions' fitting becomes each cycle until it reaches an acceptable level.

3.3.2 Chimp optimized algorithm

A population-based approach called Chimp optimization was motivated by the distinct sexual incentive of chimpanzees during collective hunting. Only two entire African species of gigantic gorillas, chimpanzees are renowned for their high level of intellect due to their enormous brain-to-body ratio compared to humans. Chimpanzees may form colonies, and as time goes on and the individuals migrate about the environment, the colony's size fluctuates. Because not all chimpanzees include the same intelligence and degree of ability, the colony is made up of different groups that function dynamically with various traits.

There are four different types of chimps that are permitted to hunt in the chimpanzee colony: the driver, the barrier, the chaser, and the attacker. To successfully hunt, this variety is crucial from every different perspective. Male chimpanzees hunt better than female chimps. If they managed to catch and kill something, food was given to every member of the hunting group and even bystanders. The attacker is expected to expend more mental effort in predicting the movement of the prey in the future and it is rewarded with a large piece of meat after a successful hunt.

The mechanism for place upgrading involves searching for a chimpanzee's location while considering the location of another chimpanzee's position.

The last position was placed arbitrarily in the circle established as the position of the attacker, barrier, chaser, and driving chimps. For instance, four optimal groups appraised the prey sites, while a third chimp upgraded its positions. Driving, blocking, pursuing, and attacking come about as a result of group mathematical processes.

The following mathematical formulae were used to represent the desire and pursuit of the prey:

$$C = \left|D.B_{prey}(n) - m.B_{chimp}(n)\right| \tag{4}$$

$$B_{chimp}(n+1) = B_{prey}(t) - x.C \tag{5}$$

When n is the number of iterations in the current cycle, d, m, and x are the coefficient vectors, the vector denoting where the chimpanzees are located and the vector denoting where the prey is located. The following computations are made for the vectors d, m,and x:

$$X = 2.L.rand_1 - L \tag{6}$$

$$D = 2.rand_2 \tag{7}$$

$$N = chaotic\_value \tag{8}$$

Where the random vectors from 0 to 1 are designated as $rand1$and $rand21$. Finally, m specifies the chaotic vector computed based on various chaotic maps and vectors shown as a result of the sexual stimulation of chimpanzees from the hunting process. The flowchart of COA is shown in (Figure 2).

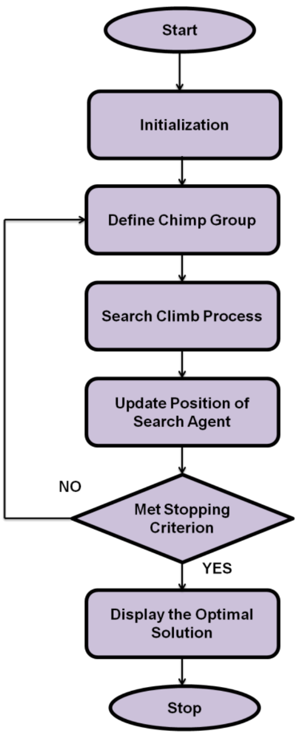

Figure 2. Flowchart of COA diagram

To apply chimpanzee behaviour statistically, it's seen as the best option available in attacker, driver, barrier, and chaser that is best informed about probable prey's location. As a result, 4 of the best solutions so far discovered were kept, and additional chimpanzees were needed to update their locations following the best chimpanzee locations. The formulae that followed this relationship were written,

$$C_{Attacker} = |\,D_1 B_{Attacker} - n_1 B| \tag{9}$$

$$C_{Barrier} = |\,D_2 C_{Barrier} - n_2 B| \tag{10}$$

$$C_{Chaser} = |\,D_3 C_{Chaser} - n_3 B| \tag{11}$$

$$C_{Driver} = |\,D_4 C_{Driver} - n_4 B| \tag{12}$$

If the arbitrary numbers between -1 and 1, the chimpanzee's future location between their current location and their location of prey.

$$B_1 = B_{\ Attacker} - w_1\,(C_{Attacker}) \tag{13}$$

$$B_2 = B_{\ Barrier} - w_2(\,C_{\ Barrier}) \tag{14}$$

$$B_3 = C_{Chaser} - w_3(C_{\ chaser}) \tag{15}$$

$$B_4 = B_{Driver} - W_4(C_{\ Driver}) \tag{16}$$

In each of the formulas:

$$W_{(m+1)} = \frac{W_1 + W_2 + W_3 + W_4}{4} \tag{17}$$

The typical method for changing a location or the chaotic process for changing a chimp location in optimization. The formula used in the math was expressed as follows:

$$B_{chimp}(m+1) = \begin{cases} B_{prey}(m) - w.C, & if\ \emptyset < 0.5 \\ \quad chaotic_{value,} if\ \emptyset > 0.5 \end{cases} \tag{18}$$

Where is a random integer between 0 and 1.

3.3.3 Adaptable gradient boosting (AGB)

A highly optimized approach is called adaptable Gradient Boosting (AGB) (XGBoost). To get the most significant outcomes in data mining and machine learning, particularly in Kaggle, data scientists have actively used XGBoost for regression and classification issues. With a minimal tweak to the regularized aim to improve the model's effectiveness, the same selection criteria used by the gradient tree-boosting technique are used in this scalable tree-boosting strategy. According to equation (19): A combination of the $l$tree predictions for a dataset serves as predicted results.

$$\hat{z} = \sum_{l=1}^{l} e_l(w_j), e_l \in E \tag{19}$$

Wherew_j is the i-th, a sampling of the training datasets' drug targets, $e_l(w_j)$ denotes the k-th tree's value, and function F represents all decision trees' values. This model minimizes regularized goals to teach functions.

$$q(\Theta) = \sum_j k(\hat{z}_j, z_j) + \Sigma_l \Gamma(e_l) \quad (20)$$

Where$\hat{z}_j$ stands for a prediction, z_j for target, and k is a loss function that assesses each training dataset's for a model. Complexity penalties for training tree functions are handled by item Γ's second item. The extra-regularized objective aids in managing a model's complexity and selection of prediction functions. More significantly, it addresses the problem of over fitting. Equation (20) shows their model's penalized complexity formula:

$$\Gamma(e) = \frac{1}{2}\lambda(\|w\|^2) + \gamma^S \quad (21)$$

When T is regression tree's total number of leaves, C denotes each leaf's value, and A and B are the constant coefficients. Since this model functions in an additive way, every time a predicted score equals a combination of scores for an old tree and a new tree, another tree is added to model. The gradient boosting procedure uses second-order Taylor expansion to eliminate enhanced loss function and constant item. Consider the set $I_j = i|q\ (x_i) = j$ as the leaf$j$. Equation (21) is added to enhance the model because it is insufficient to optimize it. Following the formulation of the final goal function using the t-th tree:

$$q^{(s)} = \sum_{j=1}^{m}\left[hjes(w_j) + \frac{1}{2}gje_s^2(w_j)\right] + \gamma^S + \frac{1}{2}\lambda\sum_{i=1}^{S}x_i^2$$

$$= \sum_{i=1}^{S}[(\sum_{j\in J_j}h_j)xi + \frac{1}{2}(\sum_{j\in J_j}g_j + \lambda)x_i^2] + \gamma^S \quad (22)$$

Where$g_i = \partial_{y^{\check{}}(t-1)} l(yi, y^{\check{}}{}_i{}^{(t-1)})$ provides the first order statistics for gradients $h_i = \partial^2{}_{y^{\check{}}(t-1)} l(yi, y^{\check{}}{}_i{}^{(t-1)})$reflects the loss function's second-order gradient statistics by defining, they may condense the mathematical expression $A_i = \sum_{j\in J_j} h_jandA_i = \sum_{j\in J_j} g_j$. The following formula is used to get the ideal weight j and the related ideal values from a tree structure q (x):

$$x_i^* = -\frac{B_i}{A_i+\lambda} \quad (23)$$

$$q^{(s)}(r) = -\frac{1}{2}\sum_{i=1}^{S}\frac{B_i}{A_i+\lambda} + \gamma^S \quad (24)$$

The following formula, when computed in its entirety, is used to determine the loss reduction from the leaf nodes following the tree's split:

$$q_s = \frac{1}{2}\left[\frac{(\sum_{j\in J_j}h_j)^2}{\sum_{j\epsilon J_K}g_j+\lambda} + \frac{(\sum_{j\in J_R}h_j)^2}{\sum_{j\epsilon J_Q}g_j+\lambda} - \frac{(\sum_{j\in J}h_j)^2}{\sum_{j\epsilon J}g_j+\lambda}\right] - \gamma \quad (24)$$

A *and* B are the instance sets' left and right nodes. Any node yields the optimal split and the outcomes rely on the loss function and regularization parameter$C$.

4. RESULT AND DISCUSSION

As a result of an ability to use a genetic-chimp optimized adaptable gradient boosting (GCO-AGB) alternative machine learning approach for generating concrete strength utilizing fly ash-based procedures, the results demonstrate that the proposed method is extremely efficient at assessing concrete manufacture compared with existing methodologies. By comparing the GCO-AGB result with those of existing methods, Random Forest (RF) (Almohammed, and Soni (2023)), Light Gradient Boosting Machine (LightGBM) (Alabdullah et al., 2022), and Categorical Boosting (CatBoost) (Beskopylny et al., 2022) the efficacy of the suggested methodology is shown. Root Mean Square Error (RMSE), Mean Absolute Error (MAE), coefficient of determination (R2), and Duration (s) are all demonstrated using the provided methodology.

The quality of the predictor is rated using RMSE. The square root of the MSE yields the RMSE that denotes the residuals' standard deviation. The difference between observed and expected outcomes is measured by RMSE that assesses the accuracy of predictive models.

$$RMSE = \sqrt{\frac{\sum_{i=1}^{N}(P_i - \hat{P}_i)^2}{N}} \quad (25)$$

Table 2. Numerical outcomes of RMSE

Method	RMSE (%)
Random Forest (RF) (Almohammed and Soni (2023))	0.1546
Light GBM Alabdullah et al., (2022))	0.0479
Cat Boost (Beskopylny et al., 2022)	0.0364
GCO-AGB [proposed]	0.0234

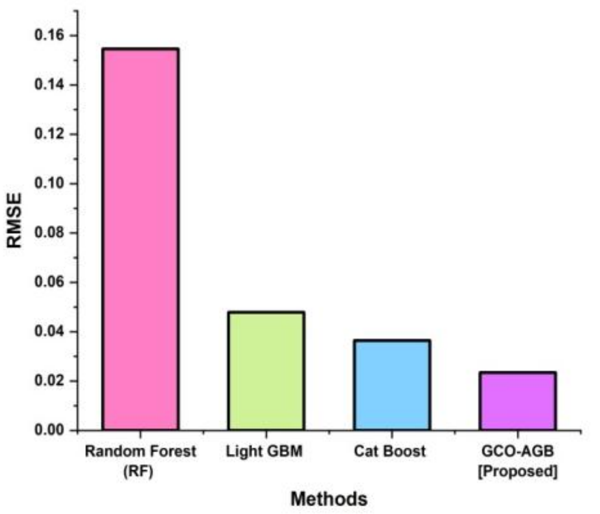

Figure 3. Graphical representation of RMSE

(Table 2) and (Figure 3) show the RMSE for the proposed system and the current system, respectively. The suggested method has an exceptionally low RMSE, demonstrating its excellent capability to analyze and forecast the data with limited residual errors effectively. Comparatively, the GCO-AGB achieved (0.0234), the RF achieved (0.1546), the LightGBM obtained (0.0479), and the CatBoost achieved (0.0364). It proves the proposed process approach has lower error rates than the existing one.

Each squared difference between an observed variable's value and its anticipated value, divided by the total number of values for the variable, is used to compute MSE. This MAE assessment is essential for measuring prediction accuracy and assessing the efficacy of various production processes.

$$MAE = \frac{\sum_{i=1}^{N} | P_i - \hat{P}_i |}{N} \quad (26)$$

Table 3. Quantitative results of MAE.

Method	MAE (%)
Random Forest (RF) (Almohammed and Soni (2023))	0.1069
Light GBM Alabdullah et al., (2022))	0.0211
Cat Boost (Beskopylny et al., (2022))	0.0281
GCO-AGB [proposed]	0.0123

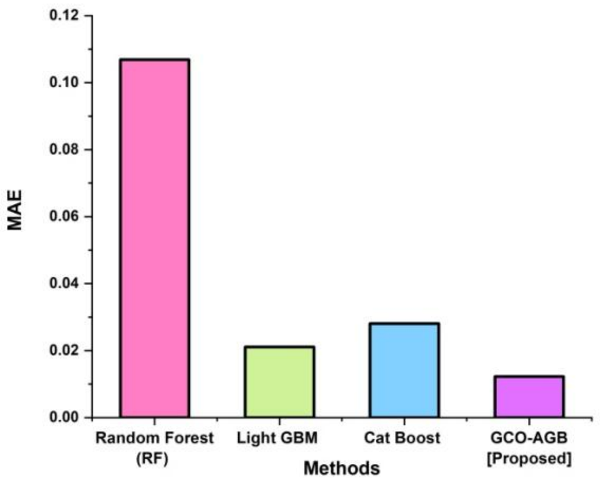

Figure 4. Visual depiction of MAE.

(Table 3) and (Figure 4) both show the MAE of the proposed system and the current system. The method recommended has a very low MAE that highlights its effectiveness in reducing prediction errors. Comparatively, the GCO-AGB achieved (0.0123), the RF achieved (0.1069), the LightGBM obtained b(0.0211), and the CatBoost achieved (0.0281). It proves the proposed process approach has lower error rates than the existing one.

The possibility for greater productivity, reduced expenses, and sustainability in manufacturing operations is demonstrated by a high R2 value that denotes a significant connection between applying fly ash-based methods and improved manufacturing results.

$$R^2 = \frac{\sum_{i=1}^{N} (P_i - \hat{P}_i)^2}{\sum_{i=1}^{N} (P_i - P_{maen})^2} \quad (27)$$

Table 4. Statistical data generated by R2.

Method	R^2
Random Forest (RF) (Almohammed and Soni (2023))	0.9670
Light GBM Alabdullah et al., (2022))	0.9968
Cat Boost (Beskopylny et al., (2022))	0.9981
GCO-AGB [proposed]	0.8925

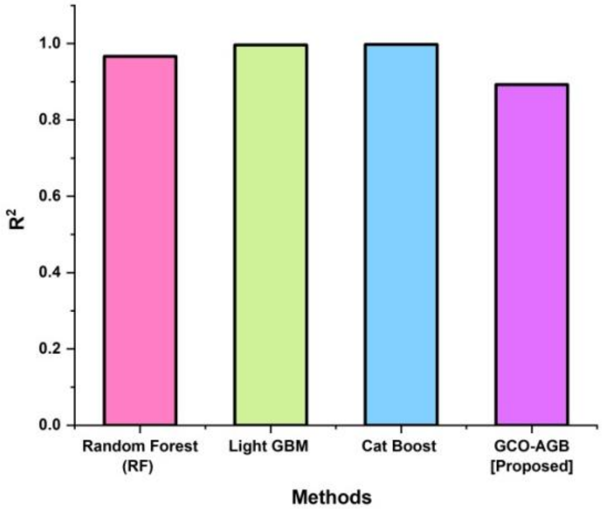

Figure 5. Graphical depiction of R2.

(Table 4) and (Figure 5) show the R^2 of the proposed and existing systems, respectively. The suggested method has a low R^2, indicating that its ability to forecast future events is limited in predicting the results' differences. Comparatively, the GCO-AGB achieved (0.8925), the RF achieved (0.9670), the LightGBM obtained (0.9968), and the CatBoost achieved (0.9981). It demonstrates a lower R^2 in the suggested process approach than in the existing one.

A crucial factor to consider in the context of sustainable industrial practices is the time duration (s) for boosting manufacturing strength using fly ash. The use of fly ash, coal combustion residue, as an additional cementitious ingredient in the industrial and building sectors has grown.

(Table 5) and (Figure 6) show the planned and current systems' durations (s). The proposed strategy is incredible short duration in seconds emphasizes its effectiveness. Comparatively, the GCO-AGB achieved (3.12), the RF achieved (4.07), the LightGBM obtained (5.19), and the CatBoost achieved (28.07). It demonstrates less duration in the suggested process approach than in the existing one.

Table 5. Numerical values derived from Duration (s).

Method	Duration (s)
Random Forest (RF) (Almohammed and Soni (2023))	4.07
Light GBM Alabdullah et al., (2022))	5.19
Cat Boost (Beskopylny et al., (2022))	28.07
GCO-AGB [proposed]	3.12

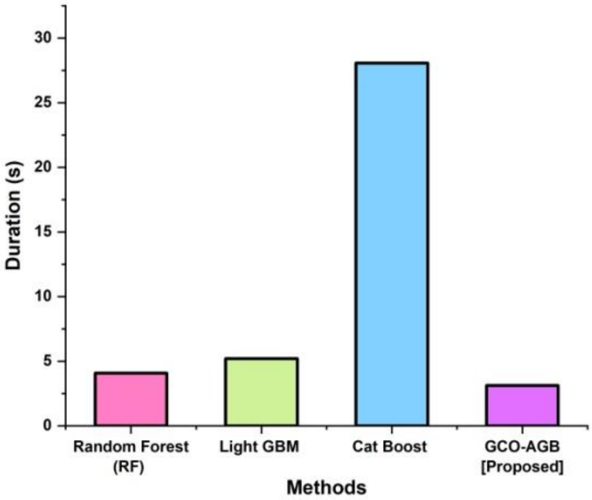

Figure 6. Visual representation of Duration (s).

5. DISCUSSION

One possible restriction is the requirement for considerable preparation of information and feature creation customized to the manufacturing sector. Utilizing fly ash in production entails intricate chemical and physical processes, making it challenging to modify LightGBM to capture these subtleties. Additionally, RF could have trouble detecting complex and non-linear connections in information, leading to the loss of crucial information that could improve fly ash consumption. Furthermore, RF models are difficult to read, making it challenging for manufacturers to comprehend the reasoning behind the model's suggestions completely. Essentially, CatBoost could have trouble coping with the fundamental complexities of manufacturing procedures and the variety of factors involved, especially working with high-dimensional data. In addition, CatBoost could not reflect the complex interconnections and linkages seen in industrial processes, which could result in less-than-ideal outcomes. The genetics GCO-AGB alternative machine learning approach could strengthen concrete using fly ash-based technology. The findings demonstrate the method's extraordinary efficacy in assessing concrete manufacture compared to other techniques.

6. CONCLUSION

The study proposed a manufacturing strength through fly ash-based processes using genetic-chimp-optimized adaptable gradient boosting. Concrete is an essential construction component and building longevity and structural integrity depend on its mechanical strength. Concrete manufacturing procedures, mixture design, material selection and quality control all play a role in achieving the appropriate compressive strength. The improved GCO-AGB model was evaluated with concrete manufacturing data and the (0.0234) for RMSE, (0.8925) coefficient of determination (R^2), (0.0123) gathering for MAE, and (3.12) Duration (S). As the construction industry strives to strike a balance between strength, sustainability and innovation, the manufacturing strength of concrete is positioned for significant breakthroughs in the future. We foresee the creation of eco-friendly concrete mixes using recycled resources and low-carbon cement substitutes since there is an increasing emphasis on environmental responsibility. Although it plays a vital role in building, concrete's manufacturing strength has limitations. It might be challenging to regulate quality when raw material variations cause strength variances.

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Ashuvendra Singh
Dev Bhoomi Uttarakhand University, Dehradun, India
ce.ayadav@gmail.com
ORCID 0009-0008-8333-225X

Sunit Kumar
Dev Bhoomi Uttarakhand University, Dehradun, India
mrsunit91@gmail.com
ORCID 0009-0001-6061-5408

Avinash Ranger
Dev Bhoomi Uttarakhand University, Dehradun, India
avinashrangar@gmail.com
ORCID 0009-0002-7588-1298

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