

Research Article

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Experimenting the compressive performance of low-carbon alkali-activated materials using advanced modeling techniques

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Abstract: Activated alkali materials (AAMs) are progressively utilized as an alternative to Portland cement concrete owing to their widespread application and reduced environmental impact. This research employed multi-expression programming (MEP) and gene expression programming (GEP) to create predictive models for the compressive strength (CS) of AAMs based on a dataset of 381 entries with eight distinct variables. To further assess the significance of the factors influencing the CS of AAMs, sensitivity analysis was employed. In comparison to GEP, MEP was better at predicting AAM's CS. The R^2 score of the GEP model was 0.953, which is lower than the MEP model's 0.970 level. This was further backed up by the results of the statistical study and Taylor's diagram. The results of the sensitivity analysis showed that specific surface area, aggregate volumetric ratio, and silicate modulus were the three most important parameters influencing the models' outcomes. In comparison to models built in Python, the produced

models yield novel empirical equations for AAM strength characteristic prediction. Researchers and professionals in the field could use these equations to find the best proportions for mix designs, cutting down on the need for repeated laboratory tests.

Keywords: alkali-activated materials, compressive strength, modeling

List of notations

AAMs	alkali-activated materials
Adm	admixture volumetric ratio
Ag	aggregate volumetric ratio
CS	compressive strength
ET	expression tree
GA	genetic algorithm
GPV	geopolymer paste volume to total concrete ratio
GGBFS	ground granulated blast furnace slag
GP	gene programming
GEP	gene expression programming
LBR	liquid-to-binder volumetric ratio
MEP	multi-expression programming
MAPE	mean absolute percentage error
MAE	mean absolute error
ML	machine learning
Ms	silicate modulus- $\text{SiO}_2/\text{Na}_2\text{O}$
NSE	nash-Sutcliffe efficiency
OPC	ordinary Portland cement
R	Pearson's correlation coefficient
R^2	coefficient of determination
RMSE	root mean square error
RRMSE	relative root mean square error
RSE	relative squared error
RT	reactivity
SHC	sodium hydroxide concentration
SSA	specific surface area
w/b	water/binder ratio

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1 Introduction

Currently, the percentage of CO₂ emissions caused by the manufacturing of ordinary Portland cement (OPC) is dropping, but current predictions indicate that it will account for an extra 8% of all emissions by 2050. The zero-emissions aim of the Paris Agreement is being called into question [1,2]. Discovering less detrimental substitutes for OPC is crucial in order to reduce the OPC business's carbon dioxide emissions [3]. The eco-friendliness and low-energy use of alkali-activated materials (AAMs) have made them a highly sought-after potential game-changing construction material in recent decades [4,5]. Industrial by-products, minerals, and mining waste are all examples of materials that include aluminosilicates. By reacting these materials with alkaline activators, they can be transformed into AAMs [6]. Among the several aluminosilicates that could be employed as AAMs building blocks are those that are discussed in detail, followed by red mud, fly ash, met kaolin, blast furnace slag, and ashes from rice husks [7–10]. A lot of people have used sodium activators to get the right technical attributes for a good price [11]. This includes sodium carbonate, water glass, and sodium hydroxide, to name a few. Utilization of AAMs has been widespread in the construction industry, with applications ranging from offshore structures to waterproof buildings, dwellings, and heavy metal immobilizations [12]. In chemical science, AAMs refer to a broad category that includes many different types of precursors that are activated by an alkaline solution. Geopolymers are AAMs made by polymerizing aluminosilicate minerals under alkaline conditions. Geopolymers, unlike AAMs, have a wide range of configurations and geometries. Their distinctive and easily controlled polymerization process makes them ideal for usage in high-performance concrete [6,13]. Despite some negatives, such as shrinkage cracking, AAMs are now more effective than OPC concrete [14]. The reason for the shrinkage cracking is due to rapid chemical reactions between the alkali activator and the precursor materials, leading to high internal stresses. These stresses result from the rapid formation of hydration products and the loss of moisture during the curing process, which contributes to volumetric changes and ultimately causes shrinkage. Besides shrinkage cracking, AAMs face disadvantages such as a high carbon footprint of activators, potential durability issues, limited standardization, workability challenges, and higher costs of raw materials [15–17]. Figure 1 shows the advantages of AAMs.

This machine learning (ML) research focuses on compressive strength (CS), a key structural material performance indicator. Numerous studies have explored the



Figure 1: Merits of AAMs [18].

influence of precursor type, curing conditions, water-to-binder ratio (w/b), and activator measure on CS to develop models and perform predictive assessments, with a particular emphasis on structural reliability. The purpose of the study by Yang *et al.* was to investigate how changing the water-to-binder ratio affected the mechanical characteristics of alkali-slag concrete that had been activated with chloroform [19]. The results indicated that the CS increased at a similar rate as OPC concrete when the w/b ratio was decreased. Alkali activation facilities commonly use both fly ash and ground granulated blast furnace slag (GGBFS) as precursors. According to Xie *et al.*, the mechanical strength of geo-polymer concrete stimulated by alkali and recycled aggregate was influenced by GGBFS and fly ash [20]. A higher ratio of GGBS to fly ash was shown to be correlated with an increased CS. The findings support previous research indicating that the use of NaOH to activate fly ash/slag blends leads to an enhanced CS, particularly when the proportion of slag is increased [21]. Table 1 provides a concise overview of the literature on ML, which shows that ML models are very accurate in predicting many concrete and mortar parameters. The number of building applications discovered by AAMs and utilization of ML is quite small. A big worry is that not enough is understood about how these various characteristics impact their CS performance.

In order to adjust the mechanical characteristics of AAMs, it is possible to modify the types and ratios of activators. In their pursuit of knowledge, Aydn and Baradan dug deeper into the topic of alkali activation by investigating the impacts of NaOH and Na₂SiO₃ to activate the

Table 1: Previous ML-based similar studies

Ref.	Materials investigated	Attributes projected	ML technique utilized	R^2 value (max)
[22]	GP-mortar	Flexural strength (FS)	Bagging regressor and support vector machine (SVM)	0.92
[23]	RHA-based concrete	CS	AdaBoost, extreme gradient boosting, and gradient boosting	0.89
[24]	Mining waste-based cements	CS	SVM, decision tree, and random forest	0.97
[25]	Geopolymer concrete	CS	MEP and GEP	0.97
[26]	Metakaolin-centered concrete	CS & FS	MEP and GEP	0.96

mechanical characteristics of slag from Turkey [27]. The specimens activated with NaOH had a lower CS than the slag mortars treated with Na_2SiO_3 , as shown in the results. The amount of Na_2O and the ratio of $\text{SiO}_2/\text{Na}_2\text{O}$ concentration were presented to exhibit a substantial impact on CS. For instance, after 28 days, mortars containing Na_2SiO_3 and NaOH, with a $\text{SiO}_2/\text{Na}_2\text{O}$ ratio of 1.2 and an 8% Na_2O slag component, attained the highest CS. Due to its sensitivity to temperature, curing is the first stage of geopolymerization. According to Rovnank, a geopolymer containing kaolin was tested using a range of curing temperatures (from 10 to 80°C) to regulate its impression on microstructural and mechanical attributes [28]. The CS of AAM designs should be determined by considering the aforementioned criteria. Uncovering the optimal computer science solution formerly required doing numerous experimental trials in the laboratory. Nevertheless, it is an expensive and time-consuming technique to prepare a big quantity of AAM specimens. Improved estimates of AAM CS can be obtained without squandering resources on ineffective batch experiments.

Soft computing has made it possible to more faithfully model the technical properties of a wide range of materials. Prediction accuracy relies heavily on data-fed ML models. Because of their complicated complexity and inherent unpredictability, construction materials are notoriously difficult to quantify accurately. A notable area of use for ML algorithms has been the estimation of engineering characteristics of construction materials. Different varieties of concrete, including both new and old, have had their characteristics studied using ML techniques. These types of concrete include fiber-reinforced concrete, lightweight concrete, self-compacting concrete, recycled aggregate concrete, and concrete integrated with phase change materials [29–33]. Several research have shown that powerful ML models are more effective than traditional physical and empirical methods in accurately assessing specific engineering attributes. To obtain accurate forecasts on the characteristics of concrete, it is important to address certain computational challenges. The intricate mechanisms of cement hydration and microstructure formation, along with the nonlinear relationship between time, temperature, and the activity of cement paste, present substantial challenges [34–36].

Training ML models with input data on combination proportions and curing circumstances allows for reliable prediction of desired attributes. The use of ML models has various benefits, such as generalizability, accuracy, and reproducibility in predictions, as well as minimal computing requirements and ease of use.

A reliable computational framework for CS prediction of AAM composites might be developed with the assistance of well-trained ML algorithms, according to the study. This study aims to analyze AAM's CS using strong ML models. We utilized publically available research material to create regression models that utilized gene expression programming (GEP) and multi-expression programming (MEP) to forecast the CS of AAMs. In all, there are 381 points in the dataset. All the models were double-checked using mathematical tests and Taylor's diagram. To find out how the variables affected the prediction, a sensitivity analysis was run. The invention of new techniques and instruments for conducting controlled assessments of material properties with minimal human involvement implies that the results may have extensive ramifications for the entire building industry.

2 Methods of research

2.1 Dataset selection and analysis

A dataset with 381 data points was analyzed using the MEP and GEP techniques in this study. The dataset was gathered from a laboratory experiment that attempted to estimate the CS of AAMs [37–60]. Eight parameters were used to predict the CS in this study: sodium hydroxide concentration (SHC), silicate modulus- $\text{SiO}_2/\text{Na}_2\text{O}$ (Ms), reactivity (RT), admixture volumetric ratio (Adm), geopolymer paste volume-to-total concrete ratio (GPV), aggregate volumetric ratio (Ag), liquid-to-binder volumetric ratio (LBR), and specific surface area (SSA). The data collection and consolidation processes relied heavily on thorough data pretreatment. Methods for

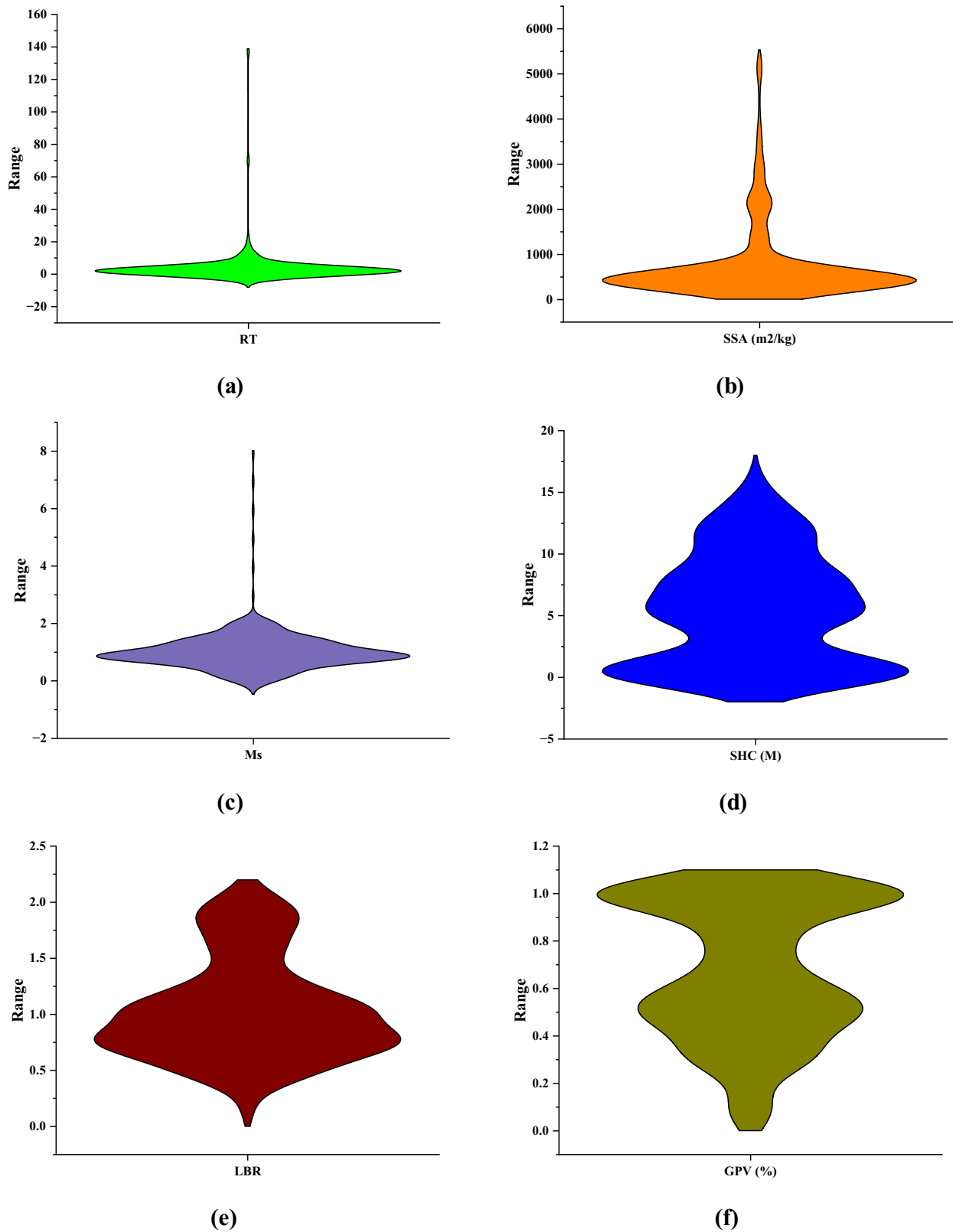


Figure 2: Database input/output violin plots: (a) RT; (b) SSA; (c) silicate modulus-SiO₂/Na₂O; (d) SHC; (e) liquid-to-binder ratio; (f) GPV; (g) aggregate volumetric ratio; (h) admixture; and (i) CS.

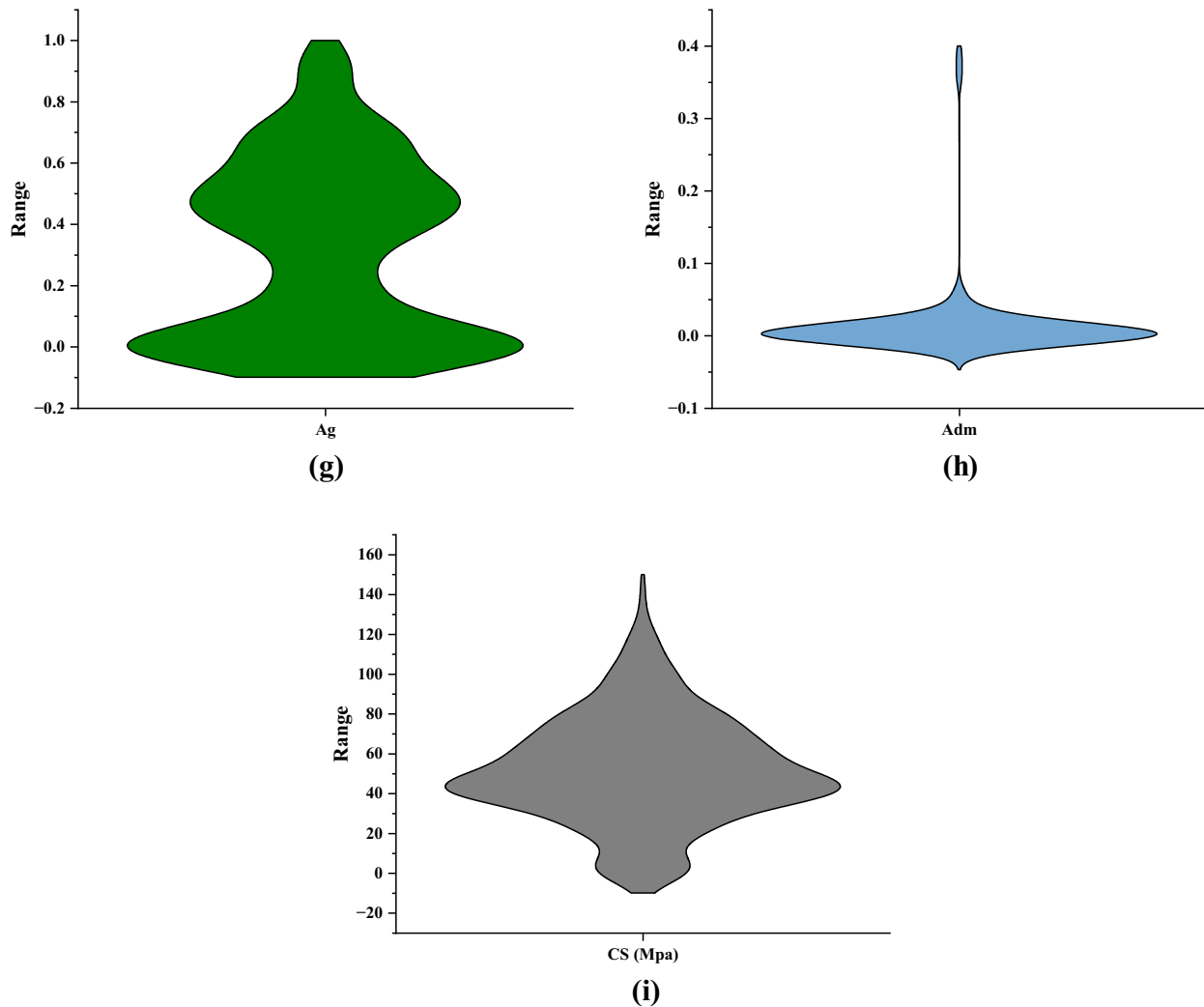


Figure 2: (Continued)

as in the previous case. Early convergence is protected by evolution, though [65,66]. Prior to implementing the GP methodology, it is essential to identify the following four factors: significant field activities, fitness evaluation, core purposeful operators (such as population extent and crossover), and results from method-specific endpoints [65]. Despite GP's recurring model construction, a crossover genetic processor handles most of the parse tree creation [48]. Nonlinear GP forms must fulfill the dual role of genotype and phenotype, resulting in increased complexity in the expressions for desired traits [66].

GP was initially proposed by Candida Ferreira, who also invented GEP. This method enhances traditional GP by encoding programs as linear chromosomes, which are then expressed as tree structures, improving the efficiency and capability of the evolutionary process [66]. GEP modeling employs parse trees and static-length lined chromosomes

based on population generation theory. By using basic, fixed-length chromosomes, the extended GP, also known as GEP, encrypts software of intermediate size. In order to forecast complex and nonlinear issues, one can use GEP to create equations [67,68]. Similar to GP, the circumstances for termination, the final set, and the fitness function are all supplied. The GEP method utilizes random numbers to generate chromosomes, which are then identified as such using the "Karva" dialectal before they are manufactured. The fundamental principle of GEP is a line that maintains a constant length. Conversely, the code dispensation of data that GP performs presents parse trees of variable lengths. Beginning with their definition as static-length genomes, these individual cords thereafter depict chromosomes through the use of nonlinear manifestation/parse trees characterized by pronged morphologies of varying sizes [65]. Different genetic codes are present in these genotypes and phenol strains [34].

GEP safeguards the genome across generations, thereby eradicating expensive structural transformations and replications. GEP chromosomes are uniquely structured with a “head” and a “tail,” allowing them to produce complex multi-gene expressions from a single chromosome. This efficient structure enhances the algorithm’s capability to evolve sophisticated solutions [65]. Mathematical, arithmetic, logical, and Boolean instructions are provided by these genes. Activators connect genetic instructions to their corresponding cell functions. Equations based on empirical data are now possible because of a new language called Karva, which can decipher these chromosomes. Following the expression tree (ET), a prominent revolutionary starts their journey at Karva. By using Eq. (1), ET assigns nodes to the underlying layer [67]. The extent and length of GEP gene K-expression can be influenced by the overall quantity of ETs

$$ET_{GEP} = \log \left(i - \frac{3}{j} \right), \quad (1)$$

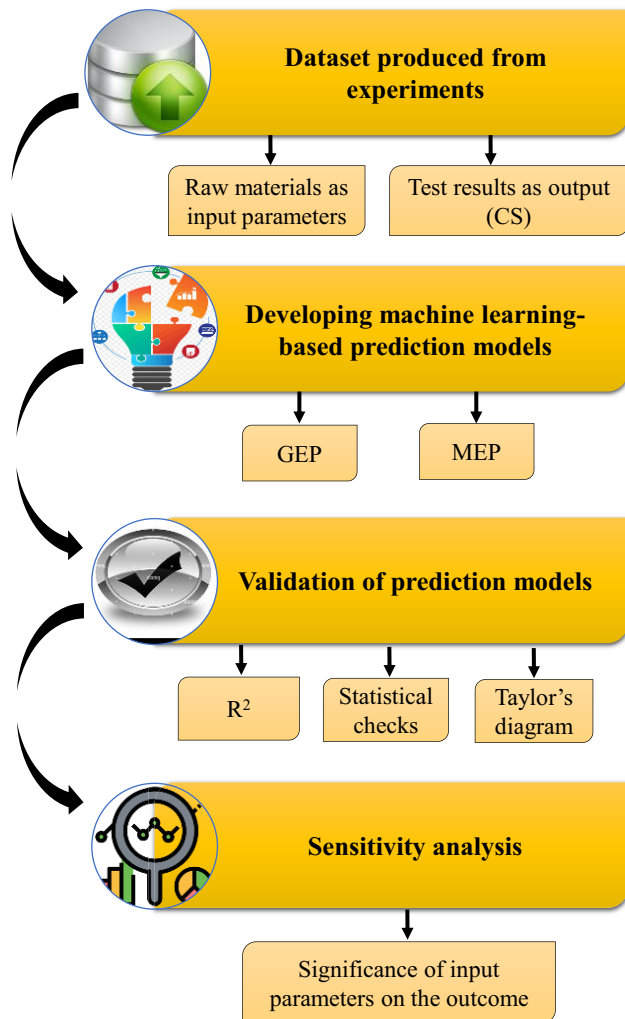


Figure 3: Comprehensive study approach overview.

where ET_{GEP} represents the output of the GEP model, where i and j are input variables.

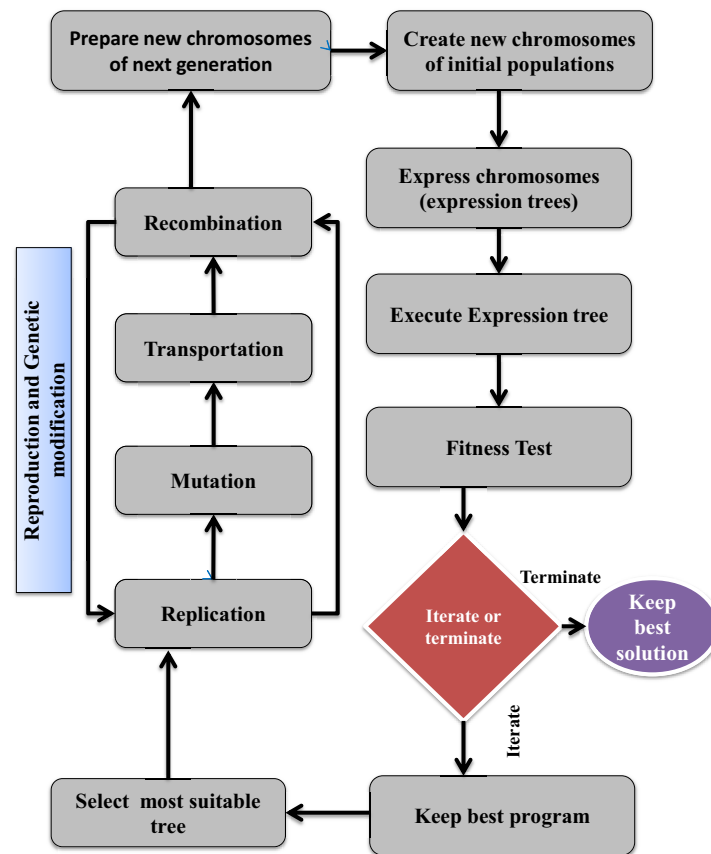
As an advanced ML method, GEP is able to function without prior associations. Figure 4 shows the many stages involved in creating GEP mathematical equations. Each cell possesses an equal amount of chromosomes from the moment of birth. In order to assess the health of individuals, it is necessary to verify the certification of these chromosomes as ETs. Only persons who possess the highest level of physical fitness and health are capable of reproducing. Optimal outcomes are achieved when highly accomplished individuals engage in an iterative process. The final result is the product of three generations of breeding, mutation, and crossover.

2.2.2 MEP model

Due to the fact that it makes use of linear chromosomes, the MEP is considered to be a demonstrative linear-based GP approach that is very advanced. The capability of MEP to encode several software options into a single chromosome is what differentiates it from other variants of the GP technique. With the help of fitness analysis, the result is achieved by selecting the chromosome that is most suitable [69,70]. This is what happens when a bipolar system couples twice, which results in the creation of two new generations, as Oltean and Grosan explain themselves. Each generation acquires a parent for themselves [71]. The process will continue to operate until the optimal software is identified, which occurs prior to the termination condition, as illustrated in Figure 5. When it comes to MEP, fitness analysis is vital for assessing the efficacy of evolving mathematical expressions used to fit datasets. By comparing the actual and desired results of a program, the fitness function finds the optimal set of chromosomes to reproduce. By utilizing selection, crossover, and mutation, MEP promotes fit programs. The algorithm can be trained to stay within predefined parameters by using iterative approaches to stop when the fitness level, number of generations, or improvement limit is reached. Evolution alters linear chromosomal elements through mutations in MEP. Variation in population genetics is enhanced by small chromosomal program mutations. Unique solutions are made possible by mutations that start early in the MEP optimization process and affect the genetic material of future generations. With mutations, the algorithm becomes better at adapting to fitness landscapes and searching solution spaces. Component merging is possible in the MEP model as it is in other ML paradigms. When engaging in MEP, it is crucial to take into account factors such as the algorithm or code

Table 3: Standardized MEP/GEP model factors

MEP		GEP	
Hyper-parameters	Settings	Hyper-parameters	Settings
Terminal set	Problem input	Data type	Floating number
Cross over probability	0.9	Constant per gene	10
Num. of generations	300	Two-point recombination rate	0.00277
Sub-population size	150	Head size	10
Mutation probability	0.01	Stumbling mutation	0.00141
Operators/variables	0.5	Inversion rate	0.00546
Number of generations	450	Mutation rate	0.00138
Number of threads	2	Linking function	Addition
Error	MSE, MAE	Genes	6
Problem type	Regression	General	CS
Code length	30	Chromosomes	250
Replication number	15	Lower bound	-10
Number of runs	15	Leaf mutation	0.00546
Number of sub-populations	60	Upper bound	10
Function set	+, −, ×, ÷, power, square root	One-point recombination rate	0.00277
		Gene recombination rate	0.00277
		One-point recombination rate	0.00277
		Function set	+, −, ×, ÷, power, square root
		RIS transposition rate	0.00546
		Random chromosomes	0.0026

**Figure 4:** Process flow diagram for the GEP method [23].

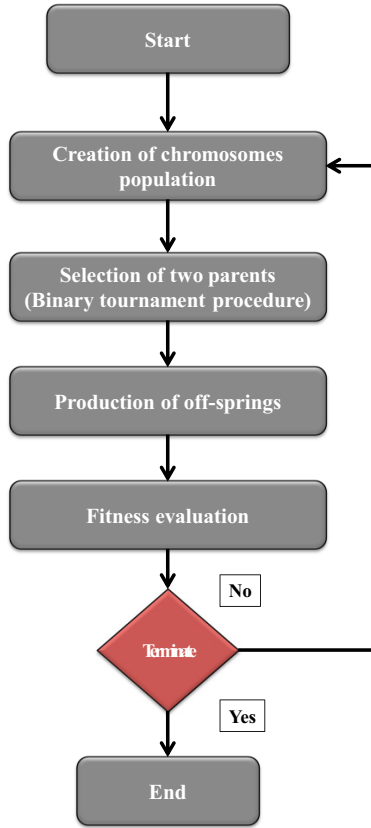


Figure 5: Methodology of the MEP flowchart [23].

length, the number of functions, the frequency of crossover, and the number of subpopulation [72]. When there are as many people as there are packages, it becomes more tedious and time-consuming to evaluate the population. As the code length grows, so does the size of the resulting mathematical expressions. Table 3 presents a comprehensive inventory of MEP characteristics that are necessary for constructing a reliable mechanical property model.

It is usual practice to use literature data sets during the evaluation and modeling stages of the MEP approach [73,74]. Several scholars have contended that widely used linear genetic programming techniques, such as the MEP, are more effective in predicting practical and tangible attributes. Grosan and Abraham came to the conclusion that the most successful technique based on neural networks was the combination of linear genomic programming and maximum likelihood estimation (MLP) [75]. The GEP's operational mode is marginally more advanced than the MEP's [72]. Although MEP has a lesser density than GEP, there are significant alterations between the two: (1) MEP allows for the processing of code again; (2) non-coding components, which are surrounded by chromosomes, do not need to be shown in a precise location; and (3) it

explicitly represents references to function parameters. [76]. Programs with precise syntax can be easily created because of the clear instructions found in the “tail” and “head” of a typical GEP gene. As a result, numerous individuals have the belief that the GEP possesses improved capabilities [71]. A more in-depth analysis of each of these genetic methods to engineering difficulties is required as a result of this finding.

2.3 Validation of models

In order to conduct statistical analysis on the models that were developed with the help of GEP and MEP, a test set was utilized. The calculated metrics for each model include the Pearson's correlation coefficient (R), mean absolute percentage error (MAPE), relative root mean square error (RRMSE), relative squared error (RSE), Nash–Sutcliffe efficiency (NSE), root mean square error (RMSE), and mean absolute error (MAE) [74,77–80]. MAE measures the average magnitude of errors in predictions. RRMSE is a normalized version of RMSE, making it unit-independent. MAPE expresses errors as a percentage, providing insight into relative accuracy. RMSE (root mean square error) emphasizes larger errors due to squaring. NSE compares model performance to the mean of observed data. R indicates the strength and direction of the linear relationship between observed and predicted values. RSE measures the proportion of variance unexplained by the model [81,82]. Using all these metrics provides a comprehensive evaluation of different aspects of model performance, helping to understand accuracy, bias, and error distribution. From Eqs. (2) to (8), the formulas for a variety of statistical indicators are provided.

$$R = \frac{\sum_{i=1}^n (a_i - \bar{a}_i)(p_i - \bar{p}_i)}{\sqrt{\sum_{i=1}^n (a_i - \bar{a}_i)^2 \sum_{i=1}^n (p_i - \bar{p}_i)^2}}, \quad (2)$$

$$\text{MAE} = \frac{1}{n} \sum_{i=1}^n |P_i - T_i|, \quad (3)$$

$$\text{RMSE} = \sqrt{\sum_{i=1}^n \frac{(P_i - T_i)^2}{n}}, \quad (4)$$

$$\text{MAPE} = \frac{100\%}{n} \sum_{i=1}^n \frac{|P_i - T_i|}{T_i}, \quad (5)$$

$$\text{RSE} = \frac{\sum_{i=1}^n (a_i - p_i)^2}{\sum_{i=1}^n (\bar{a} - a_i)^2}, \quad (6)$$

$$\text{NSE} = 1 - \frac{\sum_{i=1}^n (a_i - p_i)^2}{\sum_{i=1}^n (a_i - \bar{p}_i)^2}, \quad (7)$$

$$\text{RRMSE} = \frac{1}{|\bar{a}|} \sqrt{\frac{\sum_{i=1}^n (a_i - p_i)^2}{n}}. \quad (8)$$

The actual and predicted values for the i th data point are denoted by a_i and p_i , respectively, with n being the total number of data points. In addition, the mean of the test and forecasted values is denoted by $\bar{a}_i$ and $\bar{p}_i$, respectively. The correlation coefficient, commonly referred to as R , is an effective metric for assessing the extent to which a model can reliably forecast future results (a_i and p_i). It is indicated that there is a considerable correlation between the predicted and actual levels of output when the value of R is high [83]. Divisibility or reproduction does not alter the value of component R . Nevertheless, R^2 provides a more precise approximation of the genuine value, as it is calculated based on the

actual *versus* expected outcomes. Higher R^2 values, closer to 1, specify a more operative model-building method [84,85]. The suggested model has even better performance with fewer mistakes, much like MAE and RMSE, which exhibit substantial improvements as errors grow. Both methods, nevertheless, eventually approach zero as the number of mistakes increases [86,87]. Conversely, MAE really shines in continuous and smooth databases, as was revealed following a closer study [88]. The model often works better when the values of the errors that were calculated before are smaller.

Statistical validation is a powerful tool for assessing a model's ability to predict and another is to use a Taylor diagram. By comparing the models' deviations from the truth or the point of reference, this figure is helpful for analyzing the correctness and trustworthiness of the models based on the

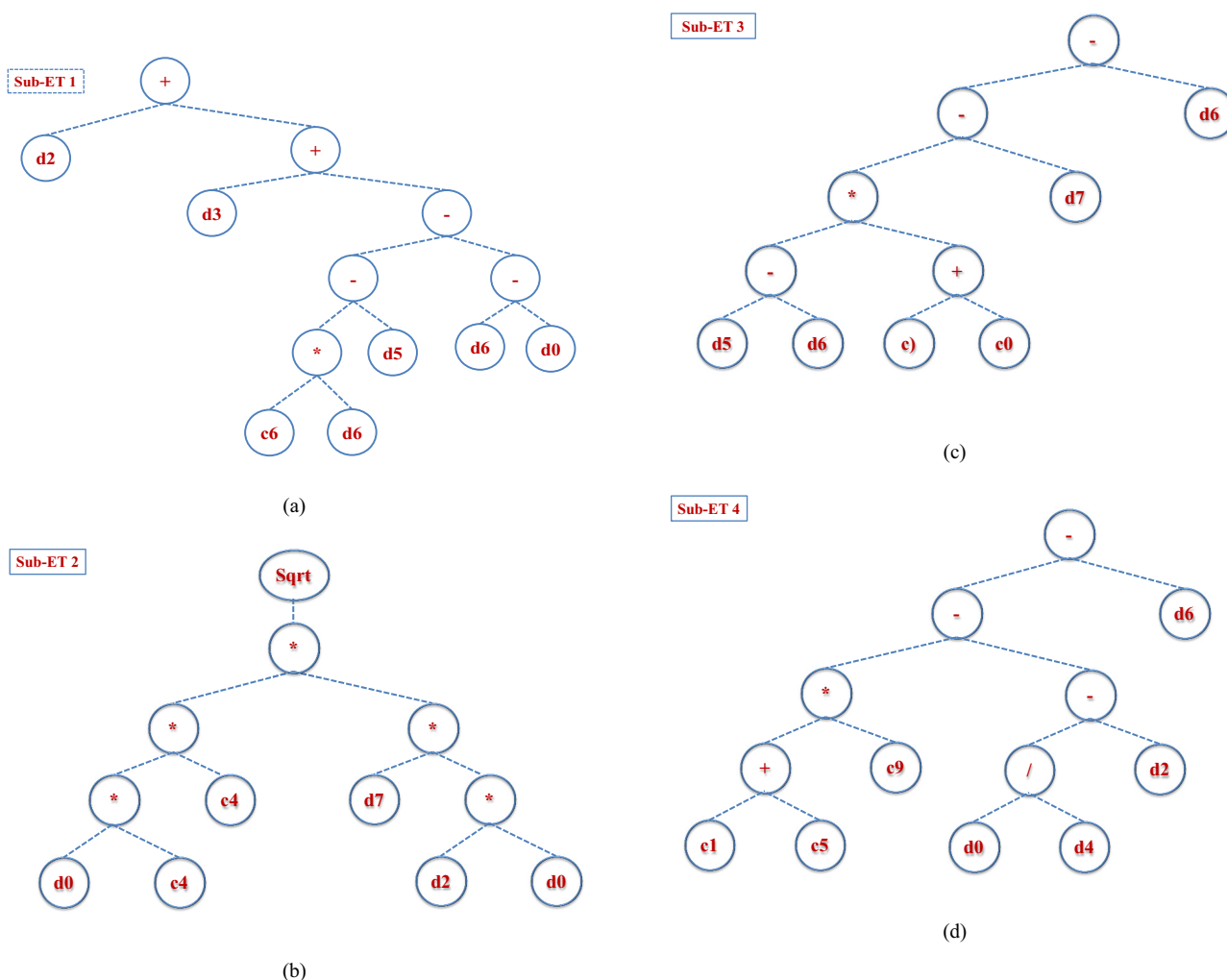


Figure 6: CS-GEP expression tree schematic, where d0: RT, d1: SSA, d2: Ms, d3: SHC, d4: LBR, d5: GPV, d6: Ag, d7: Adm. C0: 8.799, C1: -3.415, C4: 6.756, C5: -8.392, C6: -5.125, and C9: -3.436.

data [89,90]. The x - and y -axes indicate the standard deviation, the radial lines show the correlation coefficient, and the circular lines pinpointed at the real value point show the root-mean-squared error. These three metrics can be used to evaluate the ideal position of a model. The most trustworthy model is the one with the best forecast accuracy [89].

3 Research outcomes and scrutiny

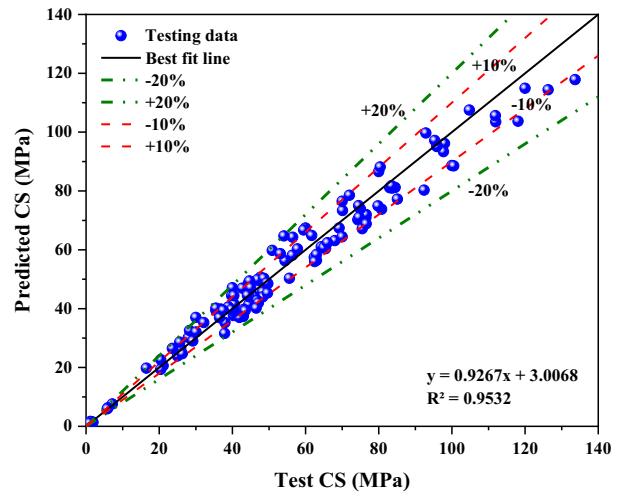
3.1 CS-GEP model

Figure 6(a)–(d) presents the results of models created utilizing the GEP method. These models utilize ETs to estimate CS based on mathematical relationships derived from genomic frequency and head size. An Expression Tree is a hierarchical structure representing mathematical expressions, where each node corresponds to a function or operation, allowing the GEP method to explore and optimize complex equations that best fit the data. Most of the sub-ETs in the AAM's CS models were built utilizing numerical operations such as division, multiplication, subtraction, addition, exponentiation, and square roots. The output of encoding these sub-ETs with the GEP method is an arithmetic formula. Using input data, these formulas can estimate the future CS of AAMs, as shown in Eq. (9). The resultant model can beat an ideal model in ideal circumstances given enough data. In Figure 7(a), a compact black line denotes an impeccable match to the data, whereas dotted red and green lines, respectively, reveal 10 and 20% deviations from the perfect match. The expected and experimental CS values are compared in this graphic to determine how well they line up. The values of CS that were predicted by the GEP model were very similar to the values that were measured. In the process of estimating the CS of AAMs, the GEP technique was shown to be highly effective. It achieved an R^2 value of 0.953 and predicted values within the 10 and 20% thresholds 72 and 97% of the time, respectively, suggesting a significant improvement in accuracy. The potential mismatch between the GEP model and the experimental results is illustrated in Figure 7(b), which is a graph that plots the experimental data against the absolute error. With an average absolute error of 3.95 MPa and a range that goes from 0.04 to 15.85 MPa, the results showed that the predictions made by the GEP equation are in good agreement with the facts that were obtained through experimentation. The distribution of the error values is bell-shaped, as seen in Figure 8. The strength measurements range from 22 values below 1.0 MPa to 37 values above

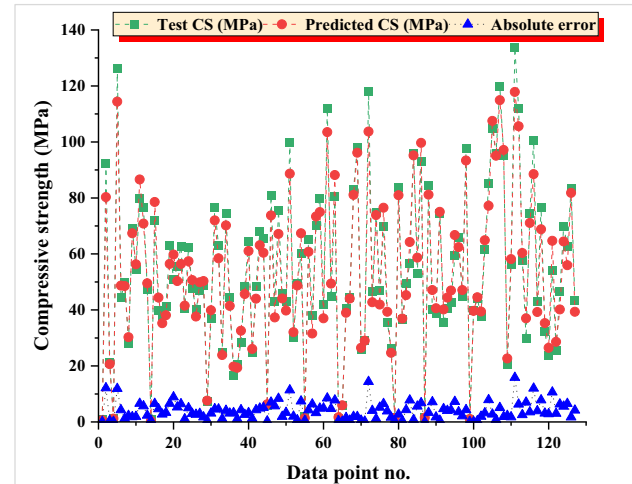
5.0 MPa, with 68 values between 1.0 and 5.0 MPa. It is important to note that maximal error frequencies are quite rare.

$$\begin{aligned} \text{CS(MPa)} = & \left(\text{Ms} + (\text{SHC} + (((-5.125 \times \text{Ag}) - \text{GPV}) - (\text{Ag} - \text{RT}))) \right. \\ & + (\sqrt{(6.756 \times (6.756 \times \text{RT})) \times (\text{Adm} \times (\text{Ms} \times \text{RT})))} \\ & + (((17.598 \times (\text{GPV} - \text{Ag})) - \text{Adm}) - \text{Ag}) \\ & \left. + \left[40.568 - \left(\frac{\text{RT}}{\text{LBR}} - \text{Ms} \right) \right] - \text{Ag} \right) \end{aligned} \quad (9)$$

where RT: reactivity, Ag: aggregate volumetric ratio, Ms: silicate modulus ($\text{SiO}_2/\text{Na}_2\text{O}$), GPV: geopolymers paste volume to total concrete ratio, LBR: liquid-to-binder volumetric



(a)



(b)

Figure 7: CS-AAM's GEP model: (a) predicted-test CS connection and (b) error distribution.

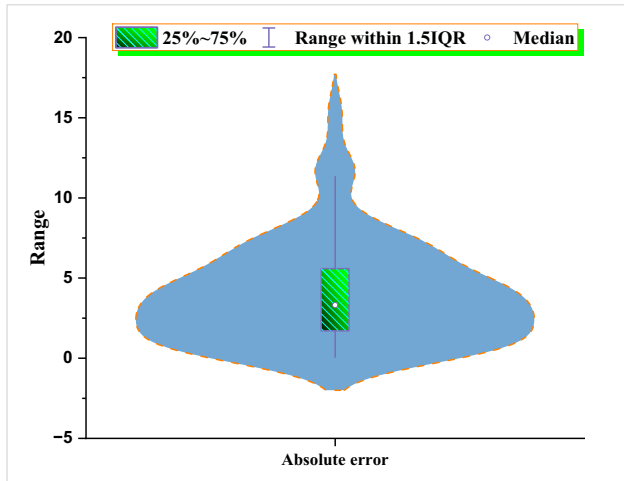


Figure 8: Error analysis with a violin plot.

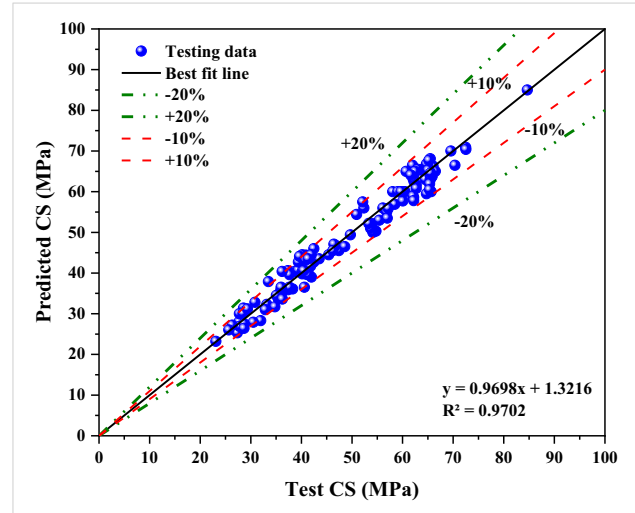
ratio, SHC: sodium hydroxide concentration, SSA: specific surface area, Adm: admixture volumetric ratio, and CS: compressive strength.

3.2 CS-MEP model

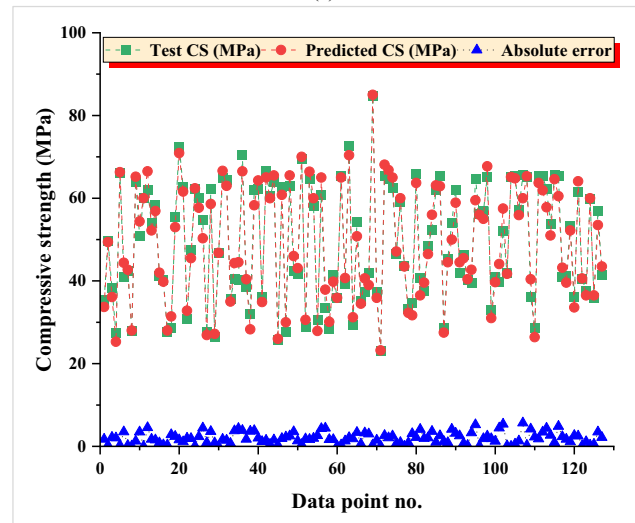
In order to determine the CS of AAMs, a mathematical formula was developed using empirical data from the MEP experiments. This model takes into account the effects of the eight independent factors. Eq. (10) presents the ultimate mathematical equation set that was developed through modeling

$$\begin{aligned}
 \text{CS (MPa)} = & \left(\frac{2\text{LBR}}{\sqrt{\text{SSA}}^{\text{GPV}}} + \sqrt{\sqrt{\text{SSA}}} \right) \\
 & + \left(\frac{6\text{LBR}}{\sqrt{\text{SSA}}^{\text{GPV}}} + 2\sqrt{\sqrt{\text{SSA}}} \right) \\
 & + \left(\frac{((2(\sqrt{\text{SSA}})^{\text{GPV}}))^{\text{Ms}} \cdot \text{Ag} + 2\sqrt{\text{SSA}}^{\text{GPV}}}{\text{RT}^{2(\text{GPV} \times \left(\text{GPV} - \frac{2\text{LBR}}{\sqrt{\text{SSA}}^{\text{GPV}}} \right))}} \right) \\
 & \times 2\text{Ms} \times \text{LBR}, \quad (10)
 \end{aligned}$$

where RT: reactivity, Ag: aggregate volumetric ratio, Ms: silicate modulus ($\text{SiO}_2/\text{Na}_2\text{O}$), GPV: geopolymer paste volume to total concrete ratio, LBR: liquid-to-binder volumetric ratio, SHC: sodium hydroxide concentration, SSA: specific surface area, Adm: admixture volumetric ratio, CS: compressive strength.



(a)



(b)

Figure 9: CS-AAM's MEP model: (a) predicted-test CS connection and (b) error distribution.

Figure 9(a) demonstrates the durability of the MEP model against oversimplification and its high level of training, as evidenced by an exceptional R^2 value of 0.970. Furthermore, it demonstrates a reasonable level of performance when applied to previously untested data. The CS-MEP model demonstrates higher accuracy compared to the CS-GEP model, as demonstrated by its improved R^2 value. The solid black line in Figure 9(a) represents a complete alignment with the data, whereas the dashed red and green lines indicate deviations of 10 and 20% from this line, respectively. The recorded CS values closely corresponded to the estimation of the MEP model. The MEP method effectively determined the CS (confidence score) of AAMs (advanced analytical models), with predictions falling under the 10%

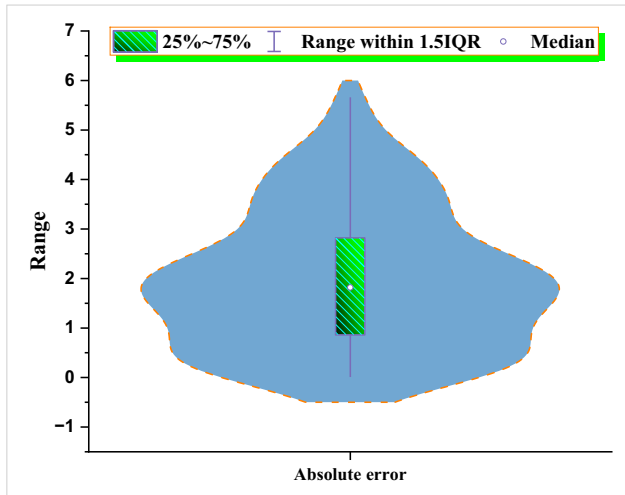


Figure 10: Error analysis with a violin plot.

criterion 94.4% of the time and within the 20% threshold 100% of the time, highlighting its outstanding accuracy.

Figure 9(b) displays the results of the study, carried out in MEP simulations, of the absolute disparities between the target and observed values. The data provided indicates that MEP forecasts exhibit an average error margin of 1.97 MPa, with errors ranging from 0.01 to 5.66 MPa. Additionally, the mean error values remain below 5.66 MPa, with 22 values falling below 1.0 MPa, 68 values ranging from 1.0 to 5.0 MPa, and 37 values exceeding 5.0 MPa. For instance, when looking at outlier values, the MEP model shows less fluctuation in outcomes than the GEP model. Models developed using MEP and GEP have the makings of excellent predictors. However, applying the MEP equation leads to smaller error standard deviations and correlation coefficients. The MEP equation's adaptability and brevity have made it quite popular. Figure 10 shows that the MEP model has a lower error level and a higher correlation coefficient than the GEP model, suggesting that it is the superior model.

Table 4: Statistical analysis results

Property	CS (MPa)	
	GEP	MEP
MAE	3.954	1.968
MAPE	8.400	4.200
RMSE	5.035	2.411
R	0.977	0.985
RSE	0.286	0.244
NSE	0.970	0.980
RRMSE	0.732	0.552

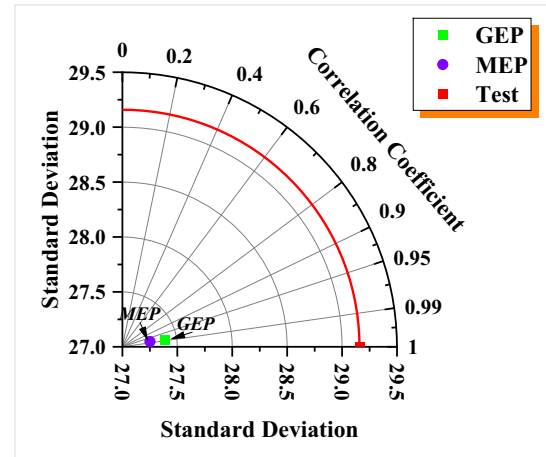


Figure 11: Models validating employing Taylor's diagram.

3.3 Model's validation

Calculations for efficacy and error, including R , RMSE, MAE, RRMSE, RSE, NSE, and those derived from Eqs. (2) to (8), are summarized in Table 4. Higher accuracy in model predictions is associated with smaller error values. Notably, the CS-MEP model surpasses its CS-GEP counterpart, with a substantial reduction in MAE from 3.954 to 1.968 MPa, and a substantial decrease in the MAPE value from 8.40 to 4.20%. Further measures that are based on errors show a consistent pattern, such as RRMSE, RSE, and RMSE. When matching both the models' efficiency, the CS-MEP model performs better with a slightly higher Nash–Sutcliffe efficiency (0.980) than the CS-GEP model (0.970), as measured by Pearson's coefficient (R). Pearson's coefficient (R) yields comparable results for both models. As shown in

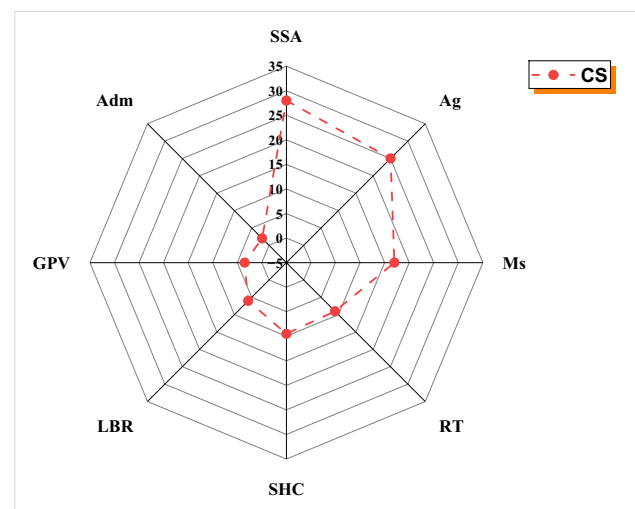


Figure 12: Radar plot for sensitivity assessments.

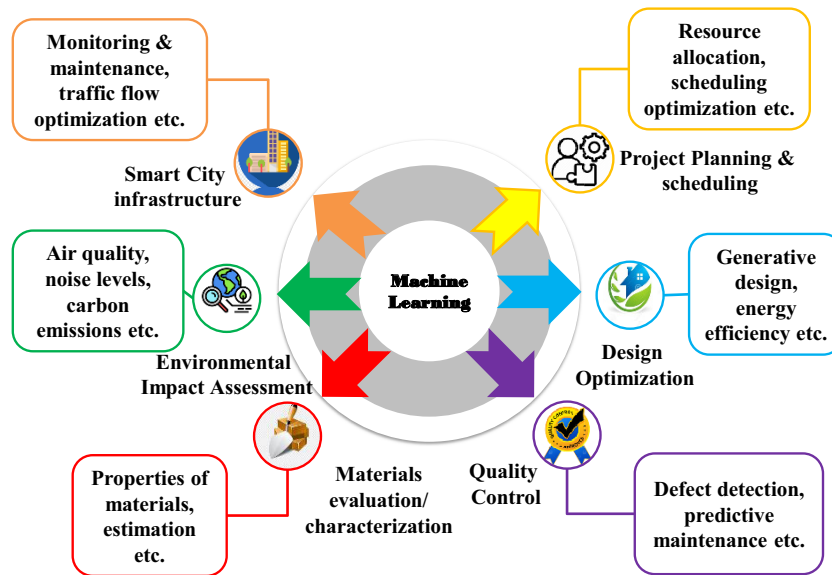


Figure 13: Civil engineering ML applications.

Figure 11, the Taylor diagram presents a comprehensive comparison of all forecasting models, highlighting MEP models' proximity in predicting the CS of AAMs, while GEP models demonstrate relatively distant predictions. With its minimal standard deviation, maximum efficiency, lowest error, and highest R^2 value, the MEP model emerges as the most accurate ML-based technique for predicting the CS of AAMs, consistent with previous research findings.

$$N_i = f_{\max}(x_i) - f_{\min}(x_i), \quad (11)$$

$$S_i = \frac{N_i}{\sum_{j=1}^n N_j}, \quad (12)$$

where $f_{\max}(x_i)$ represents the maximum value and $f_{\min}(x_i)$ represents the minimum value projected across all i th outputs.

3.4 Sensitivity investigation

This study investigates the impact of input parameters on the prediction of AAM CS. There is a significant link between the input components and the projected output [91]. A look into the future of concrete and construction materials is offered in Figure 12, which sheds light on the effect of each variable on the CS of AAMs. Among the factors examined, the SSA exerts the highest impact, accounting for 28% of the variability in forecasting the CS of AAMs, followed by the aggregate volumetric ratio at 25.0%, silicate modulus at 17.0%, SHC at 9.5%, RT at 9.0%, LBR ratio at 6.0%, geopolymers paste volume to total concrete ratio at 3.5%, and admixture volumetric ratio at 2%. The outcomes were significantly influenced by the quantity of model parameters and data points incorporated in the sensitivity analysis. Notably, when the ML technique was used, the results of the study were affected in different ways by different input parameters, such as the amounts of concrete mixes. In order to establish the weight of each input parameter to the model, we used Eqs. (11) and (12)

4 Discussions

Using the MEP and GEP models that were applied in this research, predictions that take AAMs into consideration are arrived at. A narrow range of eight input parameters is all that these models can accommodate. Consistency in unit measurements and testing techniques across all models enhances the reliability of the CS predictions they generate. By using mathematical equations, the models gain a better understanding of the mix design and the effect of every input variable. However, if there are more than eight variables in the composite assessment, the models may not perform effectively. It is crucial for the intended purpose of the models to align closely with the inputs used for their training to achieve expected results. Inconsistencies or changes in unit sizes of input parameters can lead to under- or over-predictions by the models, underscoring the importance of maintaining uniform unit measurements. ML models are highly dependent on the input parameters and the values or figures present in the dataset, which are influenced by the units used.

Altering any of these factors can lead to significant changes in the model's outcomes and performance. Consequently, even minor adjustments to the dataset can impact the accuracy and reliability of the predictions, underscoring the importance of careful data preparation and unit consistency in developing robust models. ML models have both advantages and disadvantages for the construction sector. On the one hand, they can improve energy efficiency, estimate material strength, guarantee quality, assess risk, and carry out predictive maintenance. On the other hand, they pose certain obstacles. The use of human input, which is susceptible to errors and erroneous data, is one such obstacle. Integrating Internet of Things strategies, developing cross models, employing explicable artificial intelligence approaches, considering sustainability, and tailoring data collection and dissemination for explicit industries are all potential future research topics that might be pursued in order to enhance ML-based solutions and overcome the constraints that have been identified. Modern technology has the capacity to transform the construction sector by augmenting efficiency, facilitating the comprehension and transparency of data, and enabling workers to make educated decisions. Consequently, this should result in a reduction in project delays, improved safety, and increased sustainability. More widespread use of sustainable, environmentally friendly materials and a shift toward more environmentally friendly building practices could result from the findings of this study. Figure 13 shows that ML has many real-world engineering uses.

5 Conclusions

In order to study and forecast the CS of AAMs, the purpose of this project is to make use of GEP and MEP. Using 381 different sets of CS data, the model was trained, tested, and verified, each comprising eight input parameters derived from laboratory experimental setups. The following are the primary results of the study:

- For forecasting the CS of AAMs, the GEP method exhibited a commendable level of accuracy, achieving an R^2 value of 0.953. However, the MEP method surpassed this, demonstrating even higher precision with an R^2 value of 0.970.
- The GEP approach had an average error of 3.95 MPa in predicting CS, while the MEP method had an average error of 1.97 MPa. The error rates emphasized the precision of the GEP model, while also demonstrating the greater predictive ability of the MEP technique for determining the compressible strength of AAMs.
- ML models showed gains in both R^2 values and error rates, confirming their usefulness through statistical validation. The MAPE for the GEP model was 8.40%, which is greater than the 4.20% shown by the MEP model. Furthermore, when comparing the two models, the MEP model had a better RMSE of 2.411 MPa compared to the GEP model's 5.035 MPa. These choices further reinforce the validation of the model's performance across various aspects.
- According to the sensitivity analysis, the following factors had the greatest impact on the prediction of CS of AAMs: SSA (28.0%), aggregate volumetric ratio (25.0%), silicate modulus (17.0%), SHC (9.5%), RT (9.0%), LBR (6.0%), geopolymers paste volume to total concrete ratio (3.5%), and additive volumetric ratio (2%).

To enhance the reliability and performance of ML models, programs should be developed to ensure consistent results across varying dataset units, making the models unit independent. Additionally, incorporating robust cross-validation techniques and optimizing feature selection can further improve model accuracy and generalizability.

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