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Data-driven evolutionary programming for evaluating the mechanical properties of concrete containing plastic waste

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ABSTRACT

Plastic waste (PW) has emerged as a global environmental concern due to its detrimental impact on ecosystems and human health. Traditional concrete heavily relies on natural aggregates like sand, gravel, and crushed stone, whose extraction leads to environmental degradation, including habitat destruction and resource depletion. Recently, the use of PW in concrete has gained attention as a sustainable alternative to these conventional aggregates. By incorporating PW as a partial replacement for natural aggregates, the construction industry can reduce its reliance on finite resources while also addressing the issue of PW. However, despite its potential environmental benefits, the incorporation of PW into concrete has primarily been explored through experimental studies, which are often time-consuming and resource-intensive. Therefore, this study aims to optimize the utilization of waste plastic in concrete through machine learning (ML) techniques, specifically Multi-Expression Programming (MEP) and Gene Expression Programming (GEP). A comprehensive literature review was conducted to compile a database for evaluating the compressive strength (CS) and tensile strength (TS) of PW concrete. The most influential parameters, such as plastic (P), gravel (G), water (W), cement (C), sand (S), and age (A), were considered as inputs in the models' development. The models developed were thoroughly evaluated using multiple statistical measures. Additionally, sensitivity analysis was conducted to discern and highlight influential factors that have a significant impact on the predicted outcomes. The findings indicate that both MEP (CS_R^2 = 0.88, and TS_R^2 = 0.89) and GEP (CS_R^2 = 0.87, and TS_R^2 = 0.88) models performed well, with MEP demonstrating slightly superior performance. Sensitivity analysis highlights the significant influence of cement (25.63 % and 24.53 %) and plastic (22.4 % and 23.44 %) on concrete strength properties. Furthermore, the equations provided by GEP and MEP models are simple to use from a practical perspective. Overall, this

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study contributes to sustainability efforts by promoting the incorporation of waste materials in concrete mixtures, thereby reducing reliance on cement.

1. Introduction

Plastic is considered one of the most important innovations of the 20th century. There has been a significant increase in plastic usage worldwide in recent years, leading to a comparable rise in the generation of plastic waste (PW). Plastic manufacturing in 2019 reached a total of 460 million tons, which was double the quantity manufactured in 2000 [1]. Meanwhile, PW has become a significant environmental hazard in modern society. Plastic consists of various hazardous compounds, resulting in the pollution of land, air, and water. Due to its non-biodegradable nature, dumping plastic would result in the indefinite preservation of this toxic material. Plastics present a multitude of risks. They have the potential to obstruct the municipality's water supply. The obstructed drains create ideal environments for disease-carrying insects and waterborne illnesses, in addition to producing floods [2,3]. When PW is combined with soil, it can decrease the pace at which rainwater is able to seep into the ground and also harm the fertility of the soil. Disposing of PW in waterways, lakes, and seas pollutes the water and harms marine organisms. Marine organisms have the ability to ingest plastic debris, which can have detrimental effects on their well-being. Certain marine organisms have been discovered to possess plastic fragments in their digestive systems and plastic compounds in their muscular tissues [4].

Considering the detrimental environmental effects caused by PW, it is imperative to prioritize plastic recycling to achieve sustainable development [5]. Likewise, supplementary cementitious materials are of great importance for reducing CO_2 emissions from cement consumption [6–8]. Cement manufacturing is responsible for approximately 7 % of worldwide carbon emissions, which raises the issue of climate change [9–11]. If current emission rates persist without intervention, it's projected that the cement industry will release 2.34 billion tonnes of greenhouse gases by 2050 [12]. Moreover, the process of extracting gravel during mining has a negative impact on the availability of groundwater [13–15]. A significant portion of unoccupied land was depleted during the extraction of sand from the riverbed. According to Shiuly et al. [16], the amount of land wasted as a result of natural aggregates has risen from 14 % to 112.9 % between 2013 and 2017. Further, the use of aggregates contributes to 13–20 % of the overall CO_2 emissions produced during the production of concrete.

Prior discussions have highlighted the pressing need to recycle PW in a sustainable manner and explore substitute materials for cement in the manufacturing of concrete [17–19]. In recent times, scientists have achieved significant advancements by utilizing PW as a feasible substitute for traditional cement and aggregates in concrete mixtures. For example, Schaefer et al. [20] studied the use of PW treated with gamma radiation as a replacement for cement. They found that integrating 100 kilograys of IPW with substituting 1.25 % of the weight of binder resulted in a 1 % improvement in CS. He et al. [21] assessed the utilization of PW as a replacement for cement in

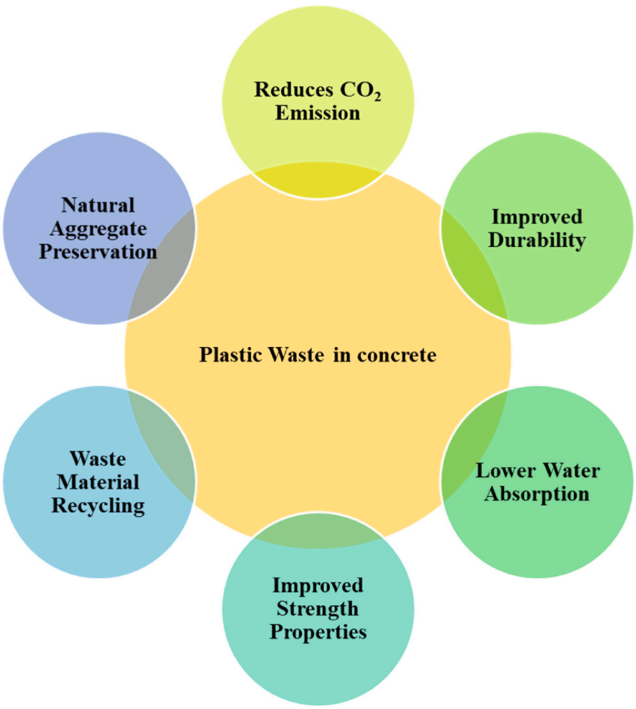

Fig. 1. Benefits of PW in concrete.

mortars. They discovered that this substitution increased the initial strength of the mortar, improved the process of cement hydration, and decreased both electrical flux and permeability. Lee et al. [22] demonstrated that substituting sand with irradiated plastic waste (IPW) up to 5 % leads to a 23 % enhancement in CS. In addition, Marzouk et al. [23] used PET PW as aggregates in concrete and discovered that replacing up to 50 % of the particles produced similar outcomes as traditional concrete. However, over this limit resulted in notable decreases in mechanical characteristics. In a similar manner, Rahmani et al. [24] noticed a 9 % enhancement in CS by substituting 5 % of the fine aggregate with PW. Several other studies demonstrated the economic and ecological benefits of PW in concrete, including cost reduction, decreased energy and water usage, reduced greenhouse gas emissions, and preservation of natural resources.

For example, Javadabadi [25] conducted a comprehensive analysis to evaluate the environmental consequences of using recycled plastic as a fine aggregate in the manufacturing of concrete, from its initial creation to its final use. The study found that using recycled-based aggregates resulted in considerable reductions in environmental consequences, including global warming potential and human toxicity. Similarly, researchers such as Ersan et al. [26] investigated the environmental impacts of incorporating fly ash and recycled PW into concrete. They used a cradle-to-grave approach using SimPro software to assess the environmental implications of 1 m^3 of concrete across its entire life cycle. The results demonstrated a significant reduction of 13 % in carbon emissions when compared to traditional approaches. In addition, PW contributes to the circular economy in several ways. Firstly, since it's regarded as waste and lacks inherent value, incorporating it into construction materials enhances its utility and promotes recycling. Secondly, utilizing plastic waste reduces transportation costs associated with sourcing traditional building materials, as it is readily available. Lastly, incorporating plastic waste into construction materials reduces the energy consumption involved in cement manufacturing, thus promoting sustainability and resource efficiency [27].

According to the studies mentioned above, incorporating PW into concrete presents a sustainable alternative for concrete ingredients while preserving the desirable characteristics. The use of PW in concrete offers numerous benefits, as illustrated in Fig. 1. Due to plastic being a recent addition to concrete as a raw material, evaluating its mechanical qualities and establishing the appropriate mix ratio necessitates conducting numerous experimental tests. Moreover, conducting traditional experiments may be time-consuming and expensive. Consequently, scholars are currently dedicated to creating machine learning (ML) algorithms to assess the characteristics and enhance the composition of concrete [28–30]. Creating a robust predictive methodology would lead to the development of more efficient combinations that meet design requirements and improve the practical utilization of concrete mixtures.

In recent years, ML techniques such as Artificial Neural Networks (ANN) [31], Deep Learning (DL), Adaptive Neuro-Fuzzy Inference Systems (ANFIS), Partical Swarm Optimization (PSO), Random Forest (RF) [32], Support Vector Machines (SVM) [33], Decision Tree (DT), Extreme Gradient Boosting (XGB) and Multilayer Perceptron Neural Networks (MLPNN) have gained popularity as viable alternatives to traditional experimental testing within the realm of structural materials engineering [34–36]. These advanced

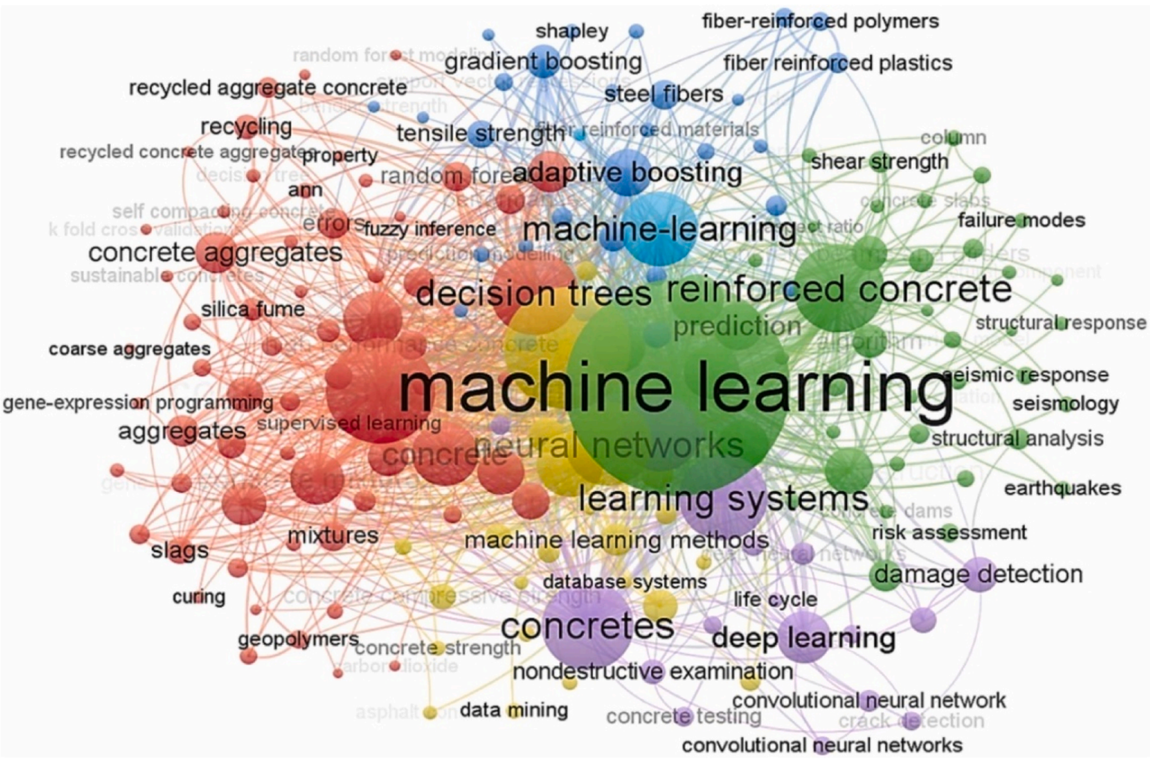

Fig. 2. Scientometric analysis of ML applications in concrete.

computational methods offer efficient and accurate solutions for predicting material properties and behaviour, thereby revolutionizing the field [37]. For instance, Dai et al. [38] utilized nine ML methods to estimate concrete electrical flux data associated with chloride ion permeability. Ensembled nonlinear models demonstrate superior accuracy compared to linear models. The article proposes an economical method of improving the mixture of concrete by utilizing machine learning techniques. Huang et al. [39] employed an innovative ML model that integrates XGB, RF, and SVM techniques. The model was developed specifically to precisely predict the bond strength of degraded reinforced concrete. The algorithm used outperforms empirical equations in terms of predictability, as demonstrated by the RF method's excellent accuracy ($R^2 = 0.963$), which was determined through the examination of 166 sets of data collected from experiments. The findings highlight the potential of ML models in accurately estimating the binding strength of concrete. Feng et al. [40] utilized the adaptive boosting method to estimate the CS of concrete. Their study employed a dataset consisting of 1030 samples. The comparative investigation demonstrated that boosting achieved superior performance compared to ANN and SVM in predicting CS. Karim et al. [41] investigated the incorporation of fly ash (FA) and rice husk ash (RHA) as an additive to the manufacturing process of sustainable concrete. The study examined these variables' combined effects on concrete properties and successfully predicted the CS using ML approaches (ANN, XGB, and GBM). The results showed that optimal strength was achieved with a higher percentage of fly ash and a lower percentage of rice husk ash. Similar results were also demonstrated by ML models, which, in XGB, had an exceptional precision of 0.84. Peng et al. [42] used standard and hybrid algorithms along with interpretable models. They found that hybrid ML models performed better as compared to simple ML models. They also identified that cement content, water content, natural fine aggregates, and water absorption were the main factors influencing the mechanical properties of concrete.

Furthermore, Fig. 2 illustrates a Scientometric study that shows the importance of ML applications in predicting the characteristics of concrete. Previous research has shown that ML algorithms can effectively support the adoption of novel and environmentally friendly materials in the production of concrete. Notably, only a few investigations have been undertaken on the utilization of PW in concrete through the application of ML models. For example, Nafees et al. [43] employed ML techniques such as DT, SVM, RF, and MLP and ensemble methods to estimate the CS and TS of PW concrete. The findings showed that an RF model using a modified learning approach demonstrated robust and reliable efficiency, achieving a high R^2 value of 0.94 and 0.87 for CS and TS, respectively. In addition, the sensitivity assessments highlighted key elements that have a significant impact on the mechanical properties, highlighting the potential of ML in advancing environmentally friendly building methods. Asif et al. [44] conducted a similar study using ML models to evaluate the CS and FS of concrete containing PW. They also found satisfactory results. Likewise, Han et al. [45] utilized an ML model, namely Random Forest (RF), to forecast concrete properties, such as CS and dry density, by integrating plastic aggregates. They observed that the RF model demonstrated high accuracy in predictions with low mean absolute percentage errors. Additionally, they highlighted the significance of plastic aggregate content in influencing concrete properties.

Although traditional ML methods have shown exceptional performance in different fields, they frequently fail to present simple prediction equations, instead operating as complicated systems that hide their internal mechanisms [46,47]. Moreover, these methods sometimes need substantial memory resources, which can impose constraints on their implementation [48]. In recent years, evolutionary algorithms such as genetic programming (GP) have emerged as a promising alternative to traditional methods [49,50]. GP offers a simple prediction equation, enhancing understanding of fundamental processes. GP also reduces the risk of overfitting, which is common in conventional ML models [51]. Moreover, advanced variants like multi-expression programming (MEP) demonstrate even greater potential. MEP not only provides prediction equations but also boasts improved memory capacity, offering enhanced adaptability and efficiency compared to conventional ML techniques [52].

Therefore, considering the above drawbacks of conventional ML and the benefits of evolutionary algorithms, this study employs the GEP and MEP-based models for the first time to evaluate the CS and TS of PW concrete. Initially, comprehensive data was collected for model development, followed by hyperparameter tuning to select the best settings for the models. Subsequently, the efficacy of the models was evaluated using various statistical metrics. Then, the most effective models from the GEP and MEP were utilized to develop mathematical predictive equations for CS and TS of PW concrete. Sensitivity analysis was also conducted to understand how different factors influenced the prediction models. Finally, GUI was developed using MATLAB v2024, which provides quick estimation tools for the pre-mix design of PW concrete mixtures, providing efficient alternatives to the traditional, time-consuming experimental approaches. This study considerably contributes to the eco-friendly utilization of PW and the reduction of cement usage in concrete. Additionally, it contributes to the economy by utilizing waste materials effectively.

Table 1
Statistics summary of CS dataset.

Inputs	Mean	SD	Maximum	Mode	Range	Kurtosis	Minimum	Skewness
Plastic	111.69	141.57	637.00	0.00	637.00	1.93	0.00	1.53
Sand	634.22	156.72	957.00	789.14	877.00	1.51	80.00	−0.85
Age	20.75	10.15	28.00	28.00	25.00	−1.50	3.00	−0.70
Water	189.48	27.40	241.50	197.00	141.50	0.75	100.00	−0.53
Cement	394.97	67.31	550.00	367.34	450.00	4.38	100.00	−0.84
Gravel	996.08	355.02	1867.00	865.00	1767.00	0.75	100.00	0.23
CS.	29.20	11.54	66.89	27.00	64.20	0.68	2.69	0.70

2. Methods and materials

2.1. Data collection

In this study, a comprehensive database comprising 324 data records for CS and 261 data records for TS of concrete made with PW was systematically curated from relevant literature sources [53–67]. Through an extensive literature review, only data records with complete information essential for the analysis of CS and TS were considered. In the developed database, standard-size cylindrical specimens (150 mm×300 mm) were consistently used for both CS and TS measurements to ensure uniformity and comparability of results. The selected input variables include plastic (P), gravel (G), water (W), cement (C), sand (S), and age (A). Statistical summaries, including minimum, maximum, skewness, kurtosis, and range, were calculated and presented in Table 1 and Table 2. Notably, variables such as C lie in a range of 100 and 550, and 295 and 550 kg/m^3, G has a range of 100 and 1867, and 147 and 1246 kg/m^3 in CS and TS databases, respectively. P showed values in the range of 637 kg/m^3 in both cases, while S has a range of 80 and 957, and 85.40 and 909 kg/m^3 in CS and TS. These higher values indicate the spread of the data in a wider range. Kurtosis and Skewness values that fall inside the limit of $\pm$ 3 and $\pm$ 10 are generally considered acceptable [68]. Table 1 and Table 2 indicate that these values are within the acceptable limits. Further, considering the importance of data distribution in ML analysis, frequency distribution plots (depicted in Fig. 3 and Fig. 4 for CS and TS, respectively) were employed. It can be observed that the inputs show the random distribution of data across the entire range. This visualization highlights the generalization of the databases.

Additionally, the presence of multicollinearity can adversely impact model performance [69,70]. To assess this issue, correlation metrics were developed to quantify the degree of correlation between input variables, thereby enhancing the accuracy and reliability of the predictive models. Fig. 5 and Fig. 6 display the multi-correlation matrices of the input variables and outputs utilized in this investigation. Different colors represent distinct correlations. The analysis reveals that the inputs with the strongest connection are age, water, and cement. Likewise, coarse and fine aggregates have weaker connections. These findings align with other prior investigations, as it is widely recognized that water and cement are the main factors influencing both the initial qualities and long-term attributes (such as CS and TS) of concrete [71,72]. Furthermore, there is a significant correlation between all contents and the outputs, indicating that all inputs are contributing to the efficacy of the CS and TS.

2.2. Gene-expression programming (GEP)

GEP, initially developed by Ferreira, is an evolutionary algorithm designed to evolve computer programs for solving complex problems [73,74]. The GEP approach involves the following steps:

1. **Initial Population:** GEP begins with a randomly generated population of chromosomes. These chromosomes represent computer programs as sequences of symbols encoding mathematical expressions or algorithms.
2. **Fitness Evaluation:** The performance of each chromosome is assessed by calculating its fitness, which measures how accurately it solves the problem at hand. For instance, in this study, fitness is determined by how well the chromosome predicts the CS and TS of concrete incorporating PW.
3. **Selection:** Chromosomes with higher fitness values (i.e., those with minimal prediction error) are selected to reproduce. These selected chromosomes are considered the most "fit" individuals in the population.
4. **Genetic Operations:** Genetic operators such as mutation (random changes in the chromosome's structure) and crossover (the exchange of segments between chromosomes) are applied to the selected chromosomes. These operations create new offspring with the potential to perform better than their parents.
5. **Evolution:** The process of fitness evaluation, selection, and genetic operations is repeated over several generations, allowing the population to evolve toward better solutions.
6. **Final Output:** After multiple generations, GEP produces mathematical expressions directly from the trained models' data. These expressions provide accurate predictions for the material properties being studied. The schematic representation of the GEP process is shown in Fig. 7.

2.3. Multi-expression programming (MEP)

MEP is an advanced evolutionary algorithm that extends traditional genetic programming principles, including those used in GEP

Table 2
Statistics summary of TS dataset.

Inputs	Mean	SD	Maximum	Mode	Range	Kurtosis	Minimum	Skewness
Plastic	105.75	146.97	637.00	0.00	637.00	2.09	0.00	1.61
Sand	677.54	130.80	909.00	789.14	823.60	1.60	85.40	−0.69
Age	22.05	9.48	28.00	28.00	21.00	−1.07	7.00	−0.97
Water	194.53	33.50	260.00	197.00	135.32	−0.22	124.68	−0.18
Cement	405.83	68.32	550.00	367.34	255.00	−0.71	295.00	0.32
Gravel	867.12	220.26	1246.00	865.00	1099.00	0.88	147.00	−0.65
TS.	2.85	0.97	5.56	3.10	5.11	−0.14	0.45	0.39

$$F = \left[\frac{-1.A + 0.66C + 0.348S}{3.4A + G}\right] \tag{13}$$

$$G = \left[-\frac{8.725P}{(4.84)W}\right] \tag{14}$$

$$H = \left[6.96 - \frac{12.126C(20.10 + G)}{A.S^2} - G\right] \tag{15}$$

On the other hand, in MEP, the MEPx tool was used to develop empirical predictive equations for CS and TS, as shown in Eqs. 16 and 17. The basic hyperparameters and arithmetic functions used for formulation were explained in Fig. 10.

$$CS(MPa) = \left[[-\frac{3\left(P + 2C\left(\frac{C^2}{W^3} + \frac{C}{W^2}\right) + A\left(A + C\left(\frac{C^2}{W^3} + \frac{C}{W^2}\right)\right)^2\left(\frac{C^2}{W^3} + \frac{C}{W^2}\right)^2\right)}{C} + \frac{2.12.S(A + C(\frac{C^2}{W^3} + \frac{C}{W^2}))W}{AC(A + G(\frac{C^2}{W^3} + \frac{C}{W^2}))((A + C(\frac{C^2}{W^3} + \frac{C}{W^2}))^2} - \frac{C^2(P - A(\frac{C^2}{W^3} + \frac{C}{W^2})^2)}{W^3} + \frac{0.92.(A + C(\frac{C^2}{W^3} + \frac{C}{W^2}) + \frac{C}{W})W}{C}] \right] \tag{16}$$

$$TS(MPa) = \left[\frac{-\frac{S}{W} + 3W + \frac{(W+P])^2}{3W}}{\frac{S}{G} + W + P} + 1.1\left(\frac{\left(A + P\left(\frac{C}{W^3} + \frac{C}{W^2}\right) + \frac{C}{W}\right)W}{C}\right) + 0.94\left(\frac{A}{W}\right)\right] \tag{17}$$

3.2. Regression analysis of GEP and MEP models

Fig. 11 **(a and b)** presents scatter plots illustrating the comparison between the GEP model-predicted and observed values of CS and TS for both training and testing datasets. A criterion for model efficiency suggests that both the R^2 and gradient values should surpass 0.8 [82]. Notably, GEP demonstrates superior efficiency, with slope of 0.91 and 0.86 in CS and 0.87 and 0.85 in TS for the training (learning) and testing datasets, respectively, indicating a robust correspondence between anticipated and actual values of CS and TS. Correspondingly, R^2 values of 0.87 and 0.86 in CS and 0.88 and 0.87 in TS were noted during the training and testing (evaluation) phases, reflecting an almost exact fit for the datasets and indicative of well-fitted models.

Moreover, a thorough investigation of error analysis provides valuable insights into the functioning of the GEP model, as depicted in Fig. 12 **(a-d)**. It can be noted that 77 % and 87 % of the error instances lie below 5 and 0.5 MPa in the case of CS and TS models, correspondingly. The consistently low variation seen at each level of the GEP model study indicates strong overall performance, confirming its effectiveness in forecasting CS and TS.

Similarly, the scatter plots in Fig. 13 **(a and b)** depict the comparison between the predicted values of CS and TS by the MEP model

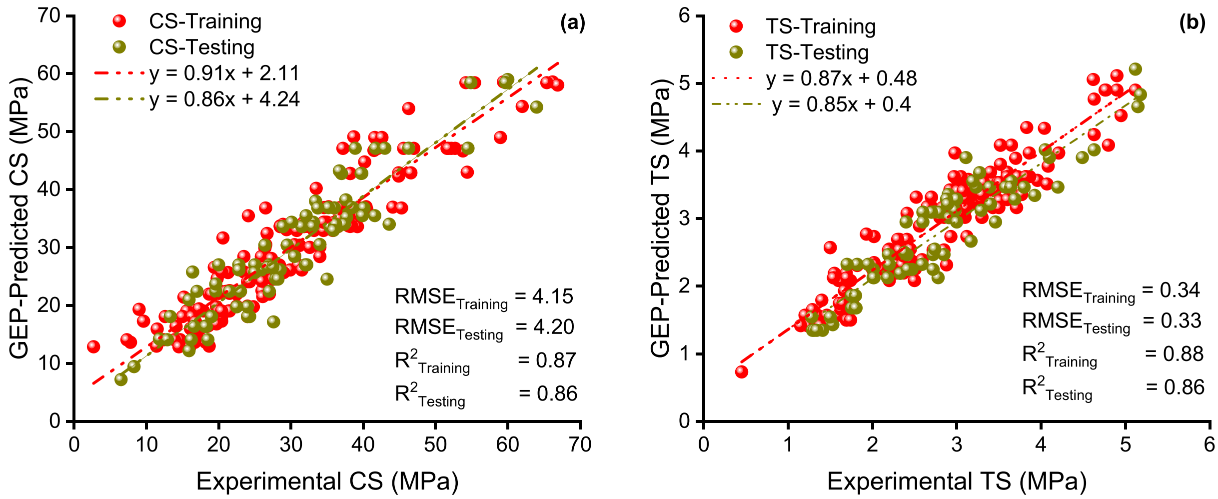

Fig. 11. Scatter plots for GEP projected and observed values for (a) CS and (b) TS models.

3.3. Comparative analysis of GEP and MEP models

The coherence of an ML algorithm is closely linked to the quantity of data used in its development. Based on established research criteria, the number of data points should exceed three times the number of independent variables [83]. In this investigation, the ratio for both CS and TS is significantly beyond the established threshold, with values of 54 (324/6) and 44 (261/6) correspondingly. As mentioned before, there is a substantial association between parameters in both CS and TS models based on GEP and MEP. It is important to mention that although R^2 can successfully identify linear relationships between inputs and outputs, it may not be enough to fully evaluate the proposed models. Therefore, in this study, additional statistical criteria were used to evaluate the strength and dependability of both models.

Fig. 15 (a and b) shows a comparison between the predicted and observed values produced by the GEP and MEP models for CS and TS. It can be seen that both models show comparable trends in their projected and actual values. The MEP-based machine learning models exhibit slightly higher accuracy in predicting CS and TS for PW concrete compared to the GEP, as demonstrated by the statistical assessments illustrated in Fig. 16 (a-d). More precisely, MEP models demonstrate a reduction of 3.22 % and 4.71 % in MAE and RMSE values, respectively, as compared to GEP models in CS models. Similarly, the MEP models exhibit a reduction of 3.12 % and 4.21 % in MAE and RMSE values, respectively, as compared to GEP models in TS models. Furthermore, the highest errors shown in MEP-based models are slightly lower than those seen in GEP models. For all instances, the PI values are below 0.2, signifying that the created model satisfies the essential conditions for approval.

Ultimately, both the MEP and GEP models demonstrate exceptional predictive capabilities, with MEP displaying a little higher accuracy. The MEP equation is also easy to implement due to its simplicity and user-friendly nature, making it a helpful tool for quick estimations. This research aims to simplify the evaluation of sustainable concrete mixtures that incorporate plastic waste, hence promoting the adoption of green construction methods.

3.4. Sensitivity analysis

In ML models, it is important to understand the influence of various features on the model's predictions. In this study, sensitivity analysis was performed to examine the relative importance of each variable in determining the CS and TS of PW concrete using the equations presented below.

$$Y_i = P_{\max}(m_i) - Q_{\min}(m_i) \tag{18}$$

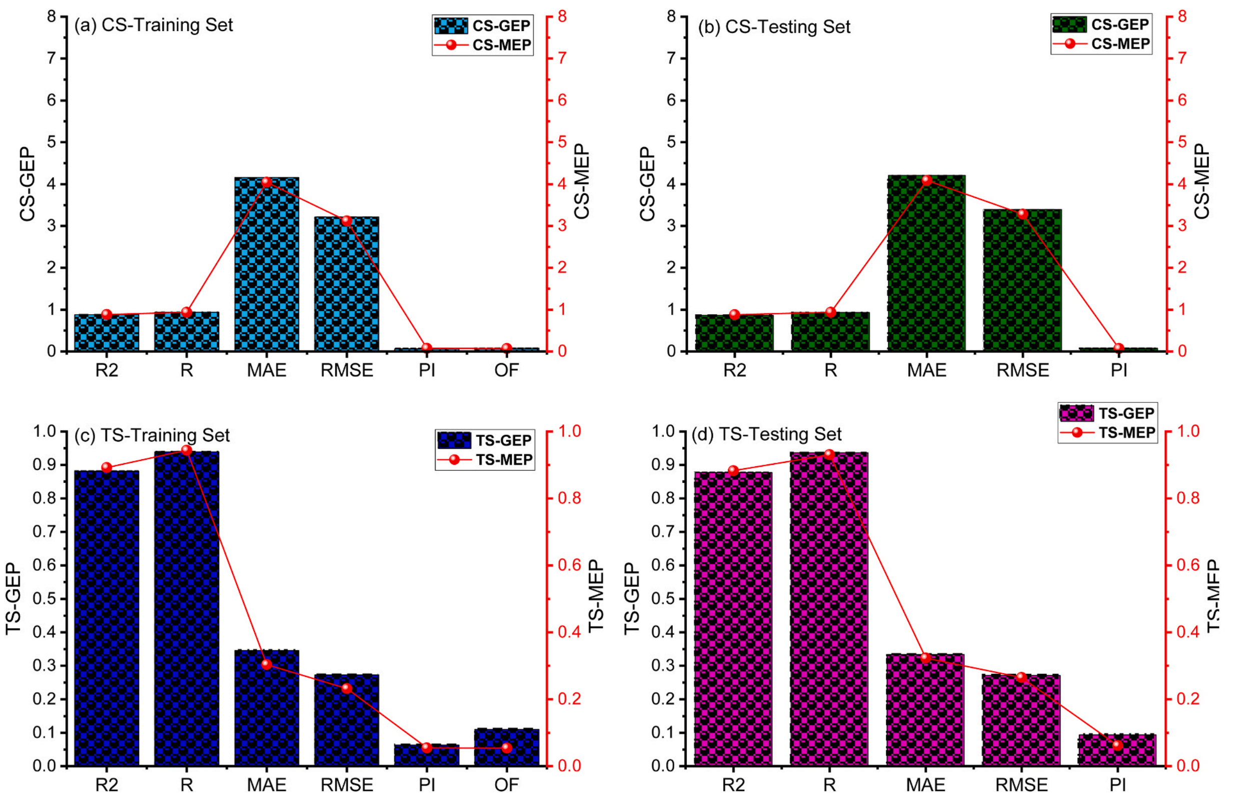

Fig. 16. GEP and MEP comparative analysis based on statistical metrics.

$$SA(\%) = \frac{Y_i}{\sum_{n}^{j=1} Y_j} \times 100 \tag{19}$$

Here, Y signifies the potential range of outcomes of the model that are connected with a particular input variable while keeping all other inputs unchanged. The acceptable range of values for SA spans from 0 % to 100 %. A figure approaching 100 % implies a major impact, whereas a value near 0 implies limited influence. It is important to mention that age was kept constant throughout the analysis as it has an obvious impact on the outputs.

Fig. 17 **(a and b)** clearly shows that cement (25.63 % and 24.53 %) and plastic (22.4 % and 23.44 %) have the greatest sensitivity in both scenarios, indicating their significant influence on the model's outputs. The contributions of water (18.7 and 19.75), sand (16.45 % and 17.33 %), and gravel (17.55 % and 15.87 %) to CS and TS are nearly equal, as indicated by the sensitivity values measured. These results align with prior studies, emphasizing the concurrence between the conclusions of this research and the existing body of literature.

3.5. Comparison of proposed models with literature

In this section, the results of this study are compared with existing literature. Recently, several studies have been conducted to examine the properties of concrete utilizing ML models. Table 3 provides an overview of prior studies conducted to evaluate the properties of concrete containing PW. It is evident that the developed models yield comparable results to those reported in the literature, as indicated by the R^2 and RMSE values. Minor differences may arise due to factors such as hyperparameters and data split in the various phases of training and testing of the models. In conclusion, it can be inferred that the proposed models can be confidently employed to estimate the CS and TS of PW concrete.

3.6. Graphical user interface (GUI)

It is essential to provide a GUI to enhance the practical implementation of predictive models for plastic concrete. In this study, MATLAB was used to develop a GUI, as shown in Fig. 18. The GUI was designed using the optimized best predictive model (MEP) estimations, ensuring accurate and reliable outputs. The interface consists of input panels where users need to enter values in kg/m^3. By clicking on the "Predict" button, users can obtain outputs such as compressive strength (CS) and tensile strength (TS). This GUI offers several advantages, including user-friendly interaction, quick predictions without requiring advanced programming knowledge, and efficient handling of data inputs and outputs, making it accessible for both researchers and practitioners.

4. Conclusion

Waste plastic poses significant hazards to the environment due to its non-biodegradable nature, requiring sustainable solutions for its management. Additionally, the use of SCMs in concrete has gained significant importance due to the greenhouse emissions of cement in the environment. Recently, various researchers investigated the integration of PW in concrete as a sustainable and cost-efficient alternative to cement and recycling waste plastic. However, most prior studies focused on traditional experimental procedures to optimize the integration of PW in concrete, which can be labor-intensive and time-consuming. Alternatively, ML-based models offer a promising solution by using the literature data to optimize and assess concrete properties. This study introduces robust predictive equations based on GEP and MEP to evaluate the CS and TS of concrete containing PW. For the development of the models, a comprehensive database comprising 276 data points for CS and 235 data records for TS of concrete made with PW was systematically curated from relevant literature sources. The models were evaluated and compared using various statistical parameters. The key findings of this study can be seen below:

1. Statistical evaluations revealed that MEP outperforms the GEP model, demonstrating higher accuracy with favourable slope values and R^2 values in both training and testing datasets.
2. The MEP models exhibit lower RMSE and MAE values compared to the GEP model, indicating superior predictive capabilities. More precisely, MEP models demonstrate a reduction of 3.22 % and 4.71 % in MAE and RMSE values, respectively, as compared to GEP models in CS models. Similarly, the MEP models exhibit a reduction of 3.1 % and 4.2 % in MAE and RMSE values, respectively, as compared to GEP models in TS models.
3. Error analysis demonstrates that the majority of anticipated values from the GEP and MEP model fall within acceptable error thresholds for CS and TS, further validating its reliability.
4. Both the MEP and GEP models demonstrate exceptional predictive capabilities, with MEP displaying a slightly higher accuracy. The MEP equation is also easy to implement due to its simplicity and user-friendly nature, making it a helpful tool for quick estimations.
5. Sensitivity analysis highlights the significant influence of variables such as cement and plastic content on the model's predictions, emphasizing their importance in accurately estimating CS and TS.

In conclusion, the GEP and MEP models can be used as reliable tools to optimize the use of PW in concrete while providing reliable predictive equations. These equations are simple to use and require only the input of various parameters associated with PW concrete. Consequently, the CS and TS of the concrete can be accurately predicted and utilized for pre-design purposes. Additionally, these

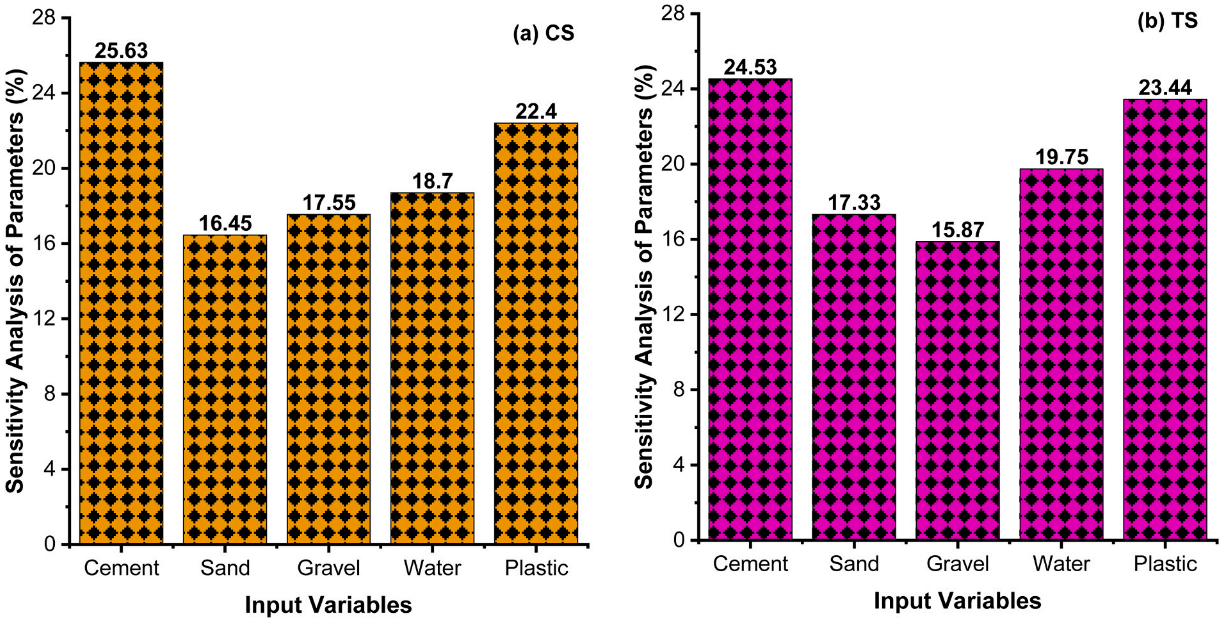

Fig. 17. Outcomes of sensitivity analysis (a) CS and (b) TS models.

Table 3
Comparison of developed models with literature.

ML model	R^2	RMSE	Output parameter	References
MEP	0.88	4.04	CS	This study
	0.89	0.3	TS	
GEP	0.87	4.15	CS	
	0.88	0.34	FS	
SVM	0.75	6.9	CS	[84]
	0.73	0.58	TS	
MLPNN	0.78	6.5	CS	
	0.74	0.59	TS	
DT	0.78	6.68	CS	
	0.77	0.54	TS	
ANN (optimized)	0.9	0.73	CS	[85]
	0.91	0.3	FS	
	0.9	0.55	TS	
	0.89	0.513	Slump	
GEP	0.92	3.88	CS	[86]
	0.88	0.82	TS	

predictive models not only aid in efficient design purposes but also contribute to the reduction and elimination of PW. However, it's important to acknowledge the limitations of this study. The range of data used in the database is restricted, which may limit the generalizability of the findings. To address this limitation, future research could focus on expanding the database with additional inputs and outputs. Furthermore, conducting SHAP (Shapley Additive Explanations) analysis could provide deeper insights into the contribution of input variables to model predictions. Additionally, while the current study focused on short-term performance, the impact of PW on the long-term durability and mechanical properties of concrete remains underexplored. Future research could benefit from long-term durability studies and assessments of environmental aging on plastic-infused concrete.

5. Challenges in the commercial use of PW in concrete

The commercial implementation of PW in concrete faces several challenges, including economic feasibility, scalability, and regulatory approval. While PW-infused concrete can reduce material costs, the collection, processing, and integration of PW into existing production systems require investment. Ensuring consistent quality, addressing the melting behavior of plastics at high temperatures, and modifying mixing processes are necessary for large-scale production. Regulatory hurdles, particularly concerning waste management and building codes, must be navigated, and environmental concerns, such as microplastic leaching, need thorough investigation. Market acceptance will depend on successful demonstrations of PW-infused concrete in real-world applications, particularly in

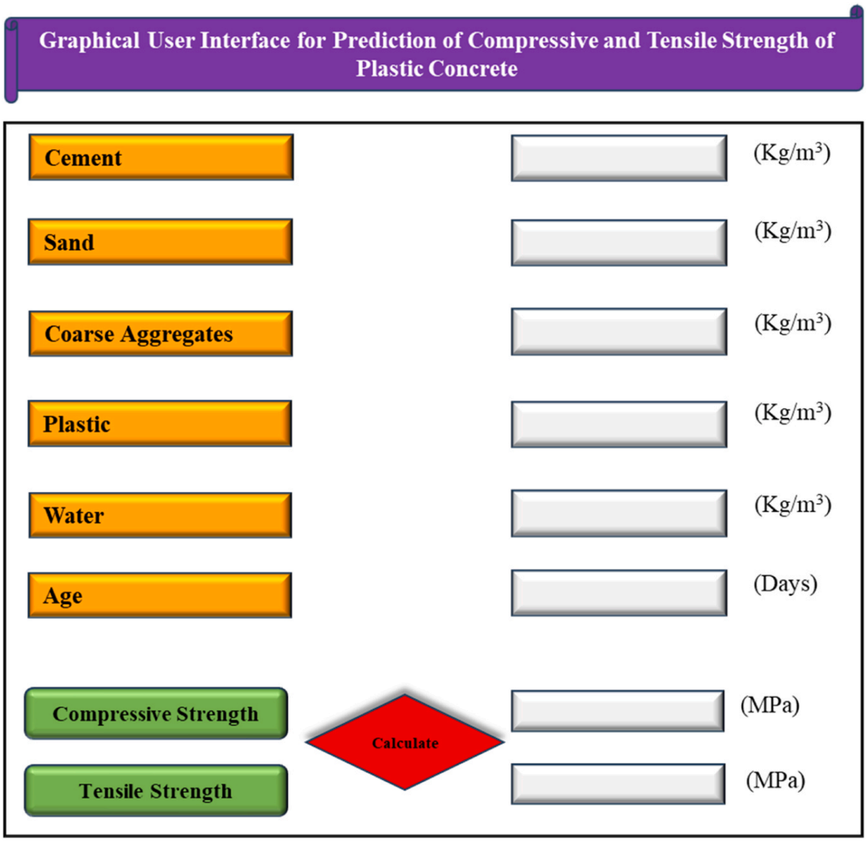

Fig. 18. GUI.

non-structural or light-traffic uses. Future work should focus on expanding the database, assessing environmental impacts, and collaborating with industrial partners to scale up production and validate the material's performance on a larger scale.

CRediT authorship contribution statement

Usama Asif: Writing – original draft, Visualization, Validation, Software, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Muhammad Faisal Javed:** Writing – review & editing, Supervision, Software, Methodology, Investigation, Conceptualization. **Diaa Salama Abd Elminaam:** Visualization, Project administration, Formal analysis. **Deema mohammed alsekait:** Supervision, Resources, Funding acquisition. **Fahid Aslam:** Resources, Project administration, Funding acquisition.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

Data will be made available on request.

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