Predicting 28-day compressive and flexural strengths of ironstone concrete using Gene Expression Programming (GEP)

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Abstract

The research investigated the structural performance of concrete made with ironstone as coarse aggregate. Ironstone is available in abundance in the south-eastern part of Nigeria especially Anambra and Enugu states. In view of the usual errors associated with traditional laboratory experimental procedures, a machine learning approach (Gene Expression Programming) was employed in GeneXpro Tools for the prediction of the compressive and flexural strengths of ironstone concrete. For this purpose, a database consisting of 352 data points was constructed by replacing ironstone with granite chippings and river gravel up to 50% in 1:2:4 concrete at 0.45, 0.5, and 0.55 water to cement ratios (W/C) respectively. The data set was divided into two sets called the training and validation datasets having 70% and 30% of the data respectively. The training data set was used to train the algorithm while the validation data set was used to validate the algorithm. The algorithm accuracy was checked by calculating the six commonly used errors: mean squared error (MSE), root mean squared error (RMSE), mean absolute error (MAE), and relatively root squared error (RRSE), coefficient of correlation (R) and R^2 for both data sets. The statistical evaluation shows that the R^2 Values are within range specified in the literature (greater than 0.8 and less than 1.0). At 50% replacement with granite chippings at 0.45W/C, optimum results yielding compressive strength of 32.30 N/mm² and flexural strength of 13.15 N/mm² was achieved. The accuracy of the algorithm was verified using K-Fold cross validation, plotting scatter and shapely sensitivity test. Thus the developed equation can be used to forecast the 28-day compressive and flexural strengths of ironstone concrete.

Keywords: Ironstone concrete, compressive and flexural strengths, modelling, machine learning, gene expression programming
Kulcsszavak: vasércbeton, nyomószilárdság és hajlítószilárdság, modellezés, gépi tanulás, génexpressziós programozás

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1. Introduction

Ironstone, a sedimentary rock with a high iron content, has traditionally been valued in the construction industry for its strength and durability. Due to its mineral composition, which typically includes iron oxides and silica, ironstone has the potential to improve the mechanical properties of concrete when used as an aggregate. This unique material is becoming an increasingly attractive alternative in concrete production, especially as researchers explore sustainable materials that can enhance the durability and strength of concrete. Ironstone's composition varies based on its geographic source, but it generally contains significant amounts of iron oxide, silica, and sometimes calcium carbonate. The high iron content can contribute to the concrete's compressive strength, especially in structural applications where load-bearing capabilities are essential [1]. Additionally, ironstone's durability and resistance to weathering make it suitable for environments that experience harsh climatic conditions [2].

However, the use of ironstone in concrete also comes with challenges. Its dense nature and high iron content can affect the workability of the concrete mix, potentially requiring the addition of plasticizers or other admixtures to achieve the desired consistency [3]. Despite this, the material has shown promise in studies exploring its use in concrete. Ironstone aggregates have been found to improve various mechanical properties of concrete, particularly compressive and tensile strength. Studies indicate that the high density and hardness of ironstone contribute to a stronger interfacial bond with the cement matrix. In a study by [4], concrete containing ironstone aggregates demonstrated a 20% increase in compressive strength compared to concrete with traditional limestone aggregates. The researchers attributed this improvement to the ironstone's mineral composition, which enhances the bonding at the aggregate-cement interface. Additionally, ironstone's resistance to chemical attacks, such as sulphate and chloride ion penetration, makes it a suitable choice for concrete used in corrosive environments. This is particularly important in infrastructure exposed to marine or industrial settings, where durability is a critical concern [5]. However, due to its dark colour, ironstone may retain heat, which could impact concrete's thermal behaviour. This can be mitigated by adjusting the mix design and incorporating other materials to control temperature fluctuations.

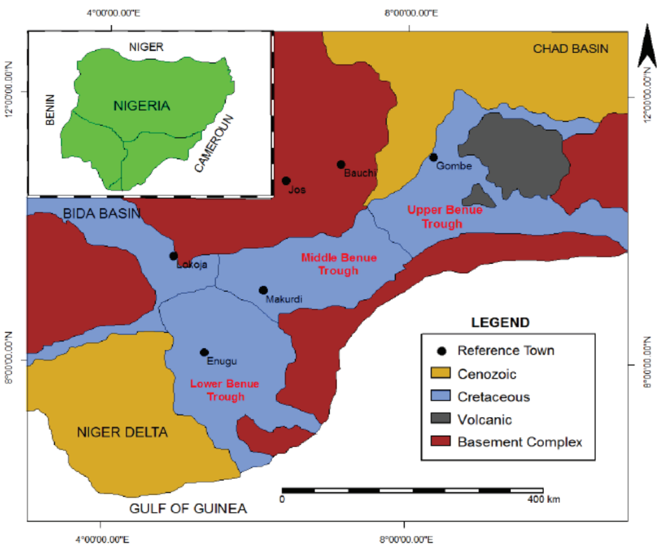


Fig. 1 Geological map of Nigeria showing the location of ironstone (sedimentary) deposit [6]
1. ábra Nigéria földtani térképe, amely a vasérc (üledékes) lelőhelyének elhelyezkedését mutatja [6]

The use of ironstone as an aggregate in concrete aligns with sustainable construction practices, as it utilizes locally sourced materials and can reduce the demand for traditional aggregates like granite and limestone. Research on sustainability in concrete production emphasizes the need to incorporate alternative materials that minimize environmental impact and promote the efficient use of resources [7]. Ironstone's availability in certain regions, especially where iron ore mining is prevalent, makes it a viable option for local sourcing and reducing transportation-related carbon emissions. Ironstone waste from mining operations can also be repurposed in concrete production. Recycling this material helps to reduce waste, contributing to a circular economy and decreasing the environmental footprint of concrete manufacturing. Studies indicate that ironstone fines can also enhance concrete's packing density, which can lead to a reduction in cement content without compromising strength [8]. Concrete produced with ironstone aggregates is suited for high-strength applications, such as foundations, bridges, and marine structures. Its resistance to environmental stressors makes it ideal for use in areas where durability is essential. However, certain limitations must be addressed to fully utilize ironstone's potential. For instance, the high density of ironstone can increase the overall weight of concrete, which may not be desirable for all applications [9]. Additionally, the need for admixtures to maintain workability can slightly increase costs, though this is often offset by the improved durability and strength of the final product. With advancements in concrete technology and mix design, there is potential for ironstone to play a more significant role in concrete production.

Finally, several studies, including [10] as well as [11], have demonstrated GEP's superior performance in predicting concrete strength compared to traditional ML techniques. [10] applied GEP to predict compressive strength and found that it outperformed other methods like ANNs and SVMs in terms of both prediction accuracy and model interpretability. The development of machine learning models, such as Gene Expression Programming (GEP), can aid in optimizing mix designs that incorporate ironstone, enabling more efficient use of this material and enhancing performance outcomes [12]. Future research should focus on exploring ironstone's long-term effects on concrete properties, particularly in diverse environmental conditions. Ironstone presents a promising alternative aggregate for concrete production, offering enhanced strength and durability. While there are challenges related to workability and density, these can be addressed through proper mix design and the use of admixtures. The sustainable aspects of using ironstone, such as local sourcing and waste reduction, further enhance its viability.

1.1 Gene expression Programming (GEP)

It has become clear that algorithms are helpful tools for reducing building waste and encouraging the use of locally abundant materials. According to [13], Gene expression programming (GEP) is a computational technique inspired by biological evolution and genetics. It is used in computer science and machine learning to evolve computer programs that solve specific problems [14]. In GEP, a population of computer programs (represented as strings of symbols) undergoes evolution through processes like mutation, crossover, and selection, similar to natural selection in biology. After which the effectiveness of these initiatives in resolving the issue at hand is assessed. GEP is a cutting-edge artificial intelligence (AI) method that makes use of evolutionary algorithms, according to [15]. It is based on Darwin's theory of natural selection and is a subtype of genetic programming (GP). A set of functions is used by GEP to generate a mathematical expression called a chromosome, which contains numerous genes [16]. A computer program is created by combining the genes that are produced by combining these functions in various ways. Many generations are needed to acquire the necessary fitness before this chromosomal creation process is completed. Individuals in the GEP are expressed as non-linear entities with varying sizes and forms (expression trees) after being encoded as symbolic strings with a fixed length (chromosomes). Because of this difference, GEP may effectively pass the phenotypic threshold and conduct unrestricted search space exploration, opening up new vistas. Furthermore, when compared to other genetic algorithms, GEP performs noticeably better because to its intricate translation mechanism between genotype (chromosomes) and phenotype (expression trees) [17]. Symbolic regression, classification, and optimization issues are just a few of the applications that employ GEP's ability to automatically identify intricate relationships and patterns in data.

1.1.2 Key features of GEP

1. Chromosome Representation: Answers are stored as fixed-length liner strings, or chromosomes.
2. Expression Trees: These depict the functional form of the solution and are translated from the liner chromosomes.
3. Genetic Operators: To evolve the population of solutions over generations, the algorithm uses genetic operators such as mutation, crossover and recombination.
4. Fitness Evaluation: A fitness function that gauges an individual's problem-solving ability is used to assess each member of the population.

For a model to be reliable, it should have R value greater than 0.8 and minimum value of other error metrics such as MAE and RMSE [17]. MAE measures the average deviation between actual and predicted values whereas RMSE indicates the presence of large errors. The errors are squared before taking mean in RMSE, so it gives more weight to larger errors. Its value is always greater than MAE. A model with high RMSE implies that the percentage of predictions with larger errors is greater and should be minimized [18]. The performance index offers the advantage of considering the values of relative root mean square error (RRMSE) and R simultaneously. Its values range from zero to infinity and the model will be reliable if its value is less than 0.2.

Fig. 2 Manually crushed and deposited ironstone [19]
2. ábra Kézzel zúzott és deponált vasérc [19]

2. Methods and material

2.1 Materials

Manually crushed and graded (18 mm – 25 mm) ironstone was obtained from Awba-Ofemili in Awka-North local government area of Anambra state (Latitude 6.8810°N and Longitude 7.5440°E), Nigeria. Crushed granite and the river gravel used were obtained from Gboko in Gboko local government area of Benue State (Latitude 7.8664°N and Longitude 7.9911°E), Nigeria. Sharp sand was obtained at Agu-Opi in Nsukka local government area of Enugu State (Latitude 7.8664°N and Longitude 7.9991°E), Nigeria. Portland cement manufactured by BUA International Ltd (CEM 1 AND 11; 42.5N) in accordance with BS EN 197-1 specification was used. The Portland cement was procured from the building material market in Nsukka community of Enugu State. The water used was supplied by the civil engineering laboratory system in the University of Nigeria, Nsukka, Enugu State, Nigeria. It was clean and free from deleterious materials and meets the requirements of ASTMC1602.

2.2 Method

2.2.1 Compressive strength test

The compressive strength of the hardened concrete cubes was determined in accordance with [20] using a 30 kN capacity electro-hydraulic testing machine in the UNN Civil Engineering Laboratory. Each specimen was loaded gradually until failure, and the maximum load at failure was recorded. The compressive strength was calculated as

$$fcs = \frac{P}{A}$$

Where F is the compressive strength, P is the maximum applied load to the specimen (in Newton, N) and A the cross sectional area of the specimen (in square millimetres mm^2). The average compressive strength of each batch was then computed.

2.2.2 Flexural strength test

Flexural strength was assessed following [21] using simply supported concrete beams (450 × 100 × 100 mm) tested under third-point loading on a universal testing machine. Failure occurred in tension at the bottom fiber, and the flexural strength was calculated as

$$ffs = \frac{FL}{bd^2}$$

where F is the maximum applied load (N), L is the span length (mm), and b and d are the breadth and depth of the beam, respectively.

2.2.3 Concrete mix design

The mix design followed the British Department of Environment (DOE) method (1975, revised 1988) with a target strength of 35 MPa at 28 days and a maximum aggregate size of 20 mm. The concrete was unreinforced, with coarse aggregates comprising ironstone, granite chippings, and river gravel. A water–cement ratio of 0.50 was adopted to achieve the desired strength.

Based on the design procedure, the final mix per cubic meter consisted of 360 kg cement, 621.2 kg fine aggregate, 1320 kg coarse aggregate, and 163.6 kg water. This composition ensured the required strength, acceptable workability (50 mm slump), and conformity with academic and industry standards.

2.2.4 Gene expression programming (GEP)

Gene Expression Programming (GEP) was used in this study to model the nonlinear relationship between concrete mix components and mechanical performance. The method was chosen for its ability to automatically generate predictive equations without predefined assumptions, unlike traditional empirical approaches. Using experimental data, the input variables were water, cement, sand, ironstone, granite chippings, and river gravel, while the outputs were the 28-day compressive strength and flexural strength. Through iterative cycles of chromosome generation, mutation, recombination, and selection, GEP evolved mathematical expressions capable of accurately predicting strength from the given mix parameters.

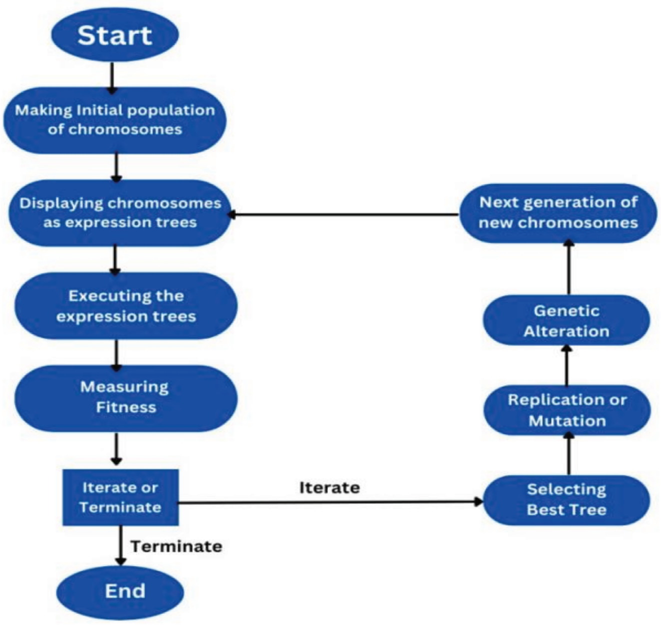


Fig. 3 Gene Expression Programming flowchart [22]
3. ábra Génexpressziós programozás folyamatábrája [22]

The GEP algorithm was implemented using a software known as GeneXpro Tools. The linking function used for the GEP model development was addition alongside other mathematical operations. The final parameters used in algorithm development are shown below in *Table 1*.

Parameter	Settings
Number of Chromosomes	30
Number of Genes	6
Head Size	8
Linking Function	Addition
Constants per Gene	10
Data Category	Floating
Lower and Upper Limit	- 10 to 10
Functions	+, -, ×, /, sqrt, cbrt, exp, ln, invrs
Training Records	687
Validation/Test Records	343

Table 1 Parameters of GEP Model.
1. táblázat A GEP modell paraméterei

2.2.3.1 Performance evaluation

The accuracy and effectiveness of the developed model was evaluated using the following five commonly utilized error metrics:

Mean squared error (MSE) $= \frac{1}{n}\sum_{i=1}^{n} (t_i - O_i)^2$

Relative root squared error (RRSE) $= \sqrt{\frac{\sum_{i=1}^{n} (y_i - \hat{y}_i)^2}{\sum_{i=1}^{n} (y_i - \underline{y})^2}}$

Root mean squared error (RMSE) $= \sqrt{\frac{1}{n}\sum_{i=1}^{n} (t_i - O_i)^2}$

Mean absolute error (MAE) $= \frac{1}{n}\sum_{i=1}^{n} (y_i - \hat{y}_i)$

Coeff. Of correlation (R) $= \frac{\sum_{i=1}^{n} (y_i - \underline{y})(\hat{y}_i - \underline{\hat{y}})}{\sqrt{\sum_{i=1}^{n} (\hat{y}_i - \underline{\hat{y}})^2}\sqrt{\sum_{i=1}^{n} (y_i - \underline{y})^2}}$

3. Results and discussion

This section presents and interprets the results obtained from the experimental investigation and predictive modeling of the concrete mixes.

Replacements (%)	28 Days					
	Compressive Strength (N/mm²)			Flexural Strength (N/mm²)		
	0.45W/C	0.5W/C	0.55W/C	0.45W/C	0.5W/C	0.55W/C
0%I 100%G 0%R	37.98	34.65	33.00	15.55	12.32	10.15
0%I 0%G 100%R	33.80	32.88	30.88	10.89	8.88	7.81
90%I 10%G 0%R	19.15	19.11	16.58	4.95	3.81	2.35
80%I 20%G 0%R	18.17	17.79	16.45	4.69	3.44	2.70
70%I 30%G 0%R	17.96	17.94	16.56	5.53	5.18	5.18
60%I 40%G 0%R	18.97	17.94	17.81	7.20	6.92	5.75
50%I 50%G 0%R	32.30	27.04	22.38	13.15	10.79	7.30
90%I 0%G 10%R	15.86	15.38	14.01	3.99	2.35	2.23
80%I 0%G 20%R	15.32	14.90	13.56	4.12	3.10	2.37
70%I 0%G 30%R	15.50	16.50	15.38	4.28	4.99	4.25
60%I 0%G 40%R	21.93	19.81	17.02	6.98	6.79	5.50
50%I 0%G 50%R	28.11	21.00	22.02	9.87	8.34	7.30
90%I 5%G 5%R	18.69	21.00	17.10	3.10	2.93	2.45
80%I 5%G 15%R	16.31	15.89	15.10	3.42	3.15	2.78
70%I 5%G 25%R	17.77	15.99	15.78	5.10	4.85	5.08
60%I 5%G 35%R	18.64	17.67	17.51	5.99	5.99	6.69
50%I 5%G 45%R	22.31	20.32	20.51	8.51	8.10	7.95
80%I 15%G 5%R	18.32	17.10	15.19	3.18	2.40	3.51
70%I 25%G 5%R	19.11	16.93	15.98	5.32	4.85	4.52
60%I 35%G 5%R	22.45	21.33	17.65	7.41	6.82	5.45
50%I 45%G 5%R	30.04	25.22	20.15	12.50	10.85	9.12
100%I 0%G 0%R	17.50	16.54	14.30	4.52	2.94	2.18

Hint: I=Ironstone, G= Granite, R=River-gravel

Table 2 Average Compressive strength and Flexural strength tests results at 0.45W/C, 0.5 W/C, 0.55W/C. (values represent the arithmetic mean of three specimens)
2. táblázat Átlagos nyomószilárdság- és hajlítószilárdság-vizsgálati eredmények 0,45 W/C, 0,5 W/C, 0,55 W/C arány mellett. (Az értékek három próbatest számtani átlagát jelentik.)

3.1 Experimental results

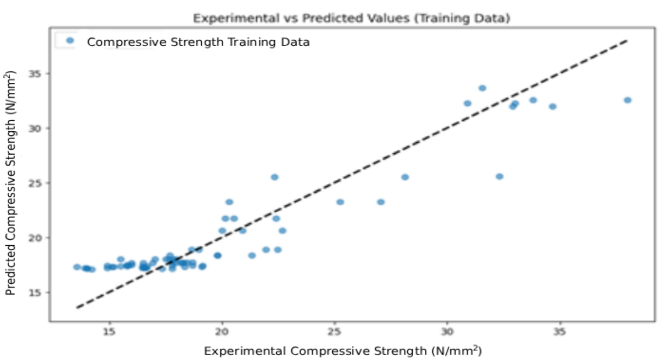
To obtain the reported values, the compressive strength for each mix was determined from three cube specimens, and the arithmetic mean was calculated. The same approach was applied to flexural strength, ensuring that *Table 2* reflects average values rather than individual test results. In *Table 2*, at a 50% replacement level with granite chippings and a 0.45 water–cement ratio, the concrete achieved a compressive strength of 32.30 N/mm² and a flexural strength of 13.15 N/mm² at 28 days. In comparison, the control mix without granite chippings at the same W/C ratio recorded 22.38 N/mm² compressive strength and 7.30 N/mm² flexural strength. These results indicate that the inclusion of granite chippings significantly enhanced both compressive and flexural strength, likely due to their higher hardness and better interlocking properties compared to the control aggregates.

3.2 Statistical analysis

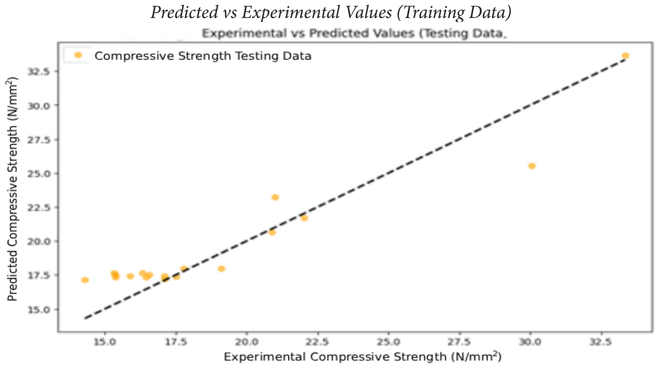
The statistical analysis comparing the predicted and experimental outcomes for the 28-day compressive and flexural strengths of ironstone concrete using GEP models is represented. The different errors, including Mean Squared Error (MSE), Relative Root Squared Error (RRSE), R-squared (R^2), Root Mean Squared Error (RMSE), and Mean Absolute Error (MAE), are detailed in *Tables 3* and *4*.

3.2.2 Scatter plots

The scatter plots displaying the comparison between the predicted and experimental values for the GEP model's training and testing of 28-day compressive and flexural strengths, are shown in *Fig. 4* and *5*;

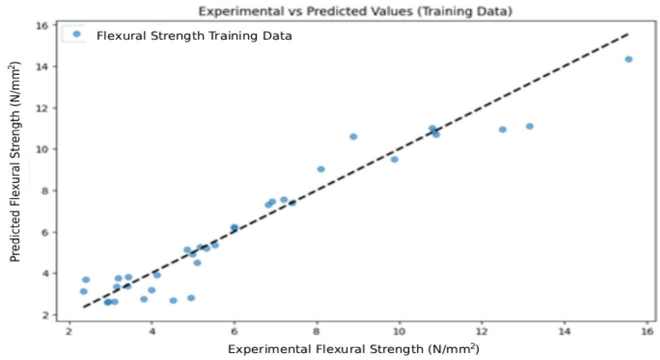


Predicted vs Experimental Values (Training Data)



Predicted vs Experimental Values (Testing Data)

Fig. 4 Scatter plots for both Training and Testing for 28 – days Compressive Strength
4. ábra Szórásdiagramok a 28 napos nyomószilárdság tanítási és tesztelési eredményeihez



Predicted vs Experimental Values (Testing Data)

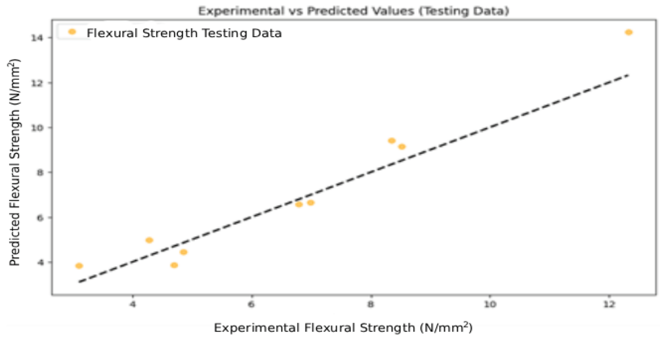


Fig. 5 Scatter plots for both Training and Testing for 28 – days Flexural Strength
5. ábra Szórásdiagramok a 28 napos hajlítószilárdság tanítási és tesztelési eredményeihez

3.2.3 Performance metrics

To evaluate the model's performance, we analysed several metrics: Mean Squared Error (MSE), Relative Root Squared Error (RRSE), R-squared (R^2), Root Mean Squared Error (RMSE), and Mean Absolute Error (MAE) for both training and validation sets for the compressive and flexural strength of various mixtures of concrete made with the aggregates (ironstone) using GEP. The results are shown in *Table 8–9* below.

Description	28 – days	
	Training	Validation
MSE	2.139	4.608
RMSE	1.463	2.147
MAE	1.079	1.405
RRSE	0.243	0.510
Correlation	0.970	0.926
R-Square	0.941	0.858
Best Fitness	406.077	317.81
Max Fitness	1000	1000

Table 3 Performance metrics for 28 days compressive strength.
3. táblázat Teljesítménymutatók a 28 napos nyomószilárdságra

The model for compressive strength shows strong performance on the training data with high R-Square of 0.974, 0.958, 0.94. Low MSE, RMSE, and MAE reflect minimal errors and precise predictions, while a very low RRSE underscores its superiority over a simple mean model in capturing data variability. However, validation metrics reveal challenges: a lower R-Square suggests reduced generalization, and higher MSE, RMSE, MAE, and RRSE indicate larger errors and decreased performance on unseen data, highlighting the need for model refinement to enhance robustness across diverse datasets.

Description	Training	Validation
MSE	0.37492654333821	0.2345183629688
RMSE	0.61231245564517	0.48427096027823
MAE	0.49275211756318	0.40005377626368
RRSE	0.1774017225576	0.27245396561304
Correlation	0.98413929700399	0.97566600817749
R-Square	0.968530153907514	0.951924159513003
Best Fitness	620.227175259184	673.73143230704
Max Fitness	1000	1000

Table 4 Performance metrics for 28 days flexural strength
4. táblázat Teljesítménymutatók a 28 napos hajlítószilárdságra

3.3 GEP expression tree

The hierarchical structure used to represent the mathematical expressions for predicting the 7-, 14- and 28-days compressive strength and the 28 days flexural strength is shown below. It consists of nodes and branches where each node represents an operator or operand, and branches connect nodes to form a complete expression or program (*Fig. 6* and *7*).

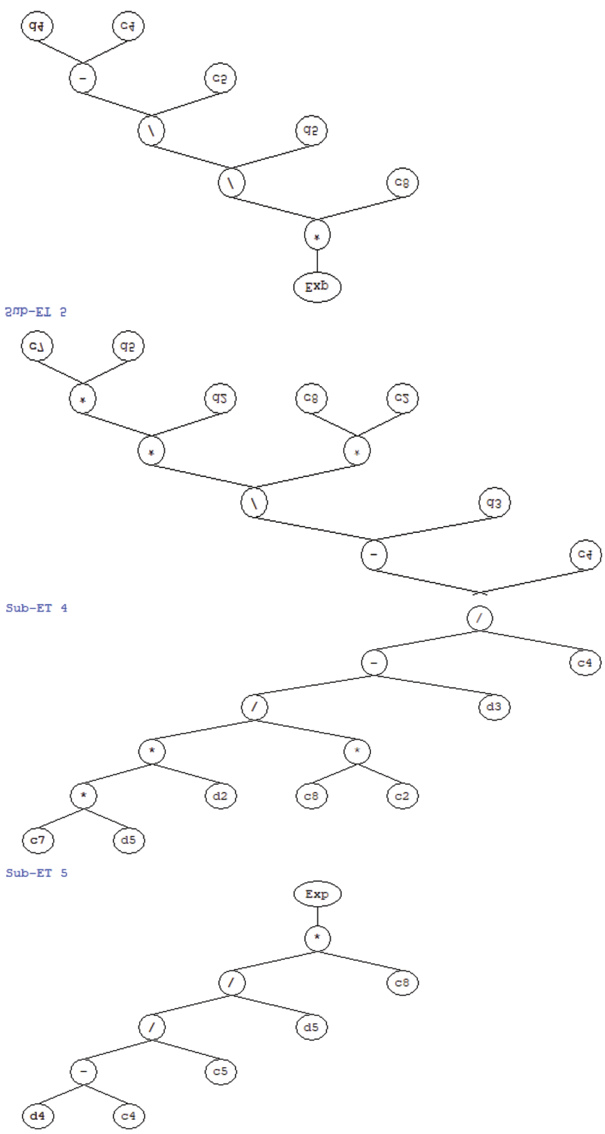


Fig. 6 Expression tree for 28 days compressive strength
6. ábra A 28 napos nyomószilárdság kifejezési fája

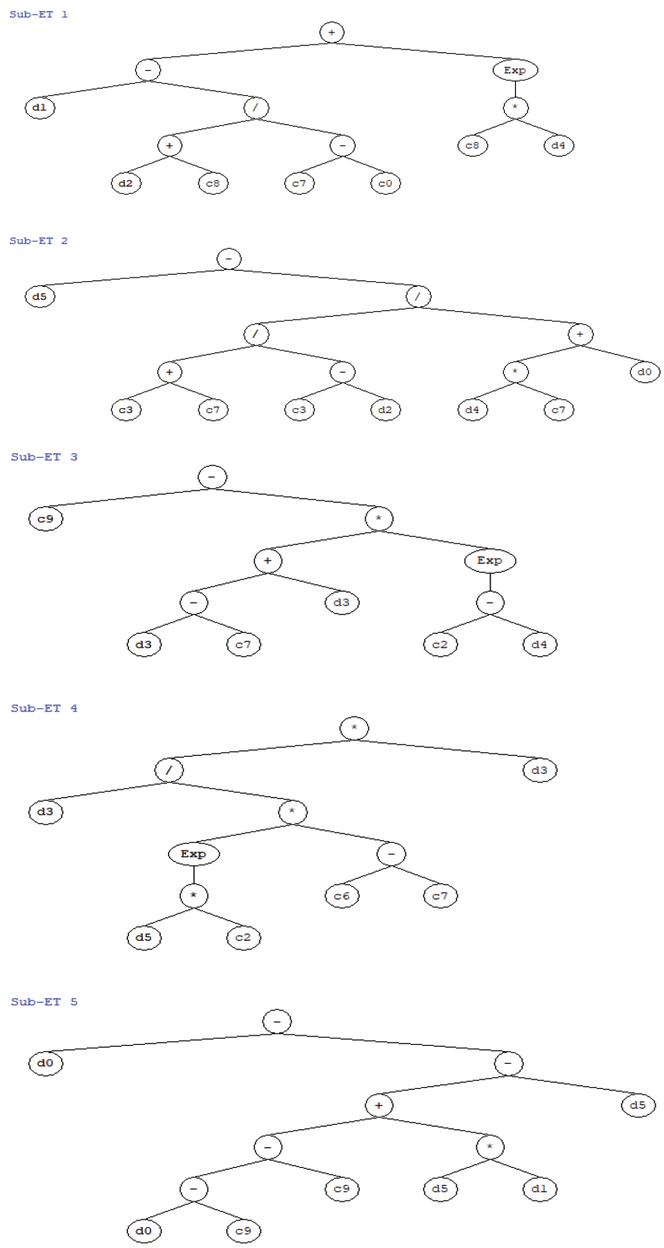


Fig. 7 Expression tree for 28 days flexural strength
7. ábra A 28 napos hajlítószilárdság kifejezési fája

3.3.1 GEP generated equations

The mathematical equations derived from the expression trees described above are crucial for predicting the compressive strength at 28 days, as well as the flexural strength at 28 days. These equations encapsulate the complex relationships between concrete constituents – cement, water, sand, ironstone, granite chippings, and river gravel, providing a structured framework to forecast these critical properties over different time period. The most crucial step in developing a GEP model is determining which parameters have the greatest influence on the final product. To achieve this, a comprehensive analysis was conducted, and multiple trial runs were made in order to determine the most important factors. The GEP method produces an equation that depends on the input parameters listed below.

$f_{Cs} = (d_0, d_1, d_2, d_3, d_4, d_5, c_0, c_2, c_4, c_5, c_6, c_7, c_8, c_9)$

where f_{Cs} is a function of the input parameters of compressive strength for the resulting equations from the GEP algorithm, $d_0, d_1, d_2, d_3, d_4, d_5$ are water, cement, sand, ironstone, granite chippings and river gravel while $c_0, c_2, c_3, c_6, c_7, c_8, c_9$ are strength, 28day strength, 0.45W/C, 0.5W/C, 0.55W/C, 28 day respectively.

$f_{fs} = (d_0, d_1, d_2, d_3, d_4, d_5, c_0, c_2, c_3, c_6, c_7, c_8, c_9)$

where is a function of the input parameters of flexural strength for the resulting equations from the GEP algorithm, are water, cement, sand, ironstone, granite chippings and river gravel while are 28 day strength, 0.45W/C, 0.5W/C, 0.55W/C, and 28 day respectively.

The expression tree provided by the GEP technique is shown in *Fig. 6* and *7*, and it is decoded to yield the mathematical equation for the compressive strength of 28 day and flexural strength estimate of 28 day as well. The resultant equations are provided below;

$f_{Cs} = (A + B + C + D + E)$

$f_{fs} = (A + B + C + D + E)$

3.3.2 Compressive Strength GEP Equations (28 Days)

$$A = exp\left[\frac{\left[\frac{\left(\frac{d_2}{c_6}\right)-(d_2-d_1)}{d_5 \times c_0}\right]}{d_0}\right]$$

$$B = d_1 + \left[\frac{exp\left(\frac{d_5}{d_5}\right)}{(d_1-c_2)(d_0-d_3)}\right]$$

$$C = exp\left[\left(\frac{d_2}{(c_9-d_4)}\right) - \left[\left(\frac{d_3}{d_0}\right) + (c_2 \times c_9)\right]\right]$$

$$D = \frac{\left(\left(\frac{d_2(c_7 \times d_5)}{(c_8 \times c_2)}\right)-d_3\right)}{c_4}$$

$$E = exp\left[c_8\left[\frac{\left[\frac{(d_4-c_4)}{c_5}\right]}{d_5}\right]\right]$$

3.3.3 Flexural Strength GEP Equations (28 Day)

$$A = \left[d_1 - \left(\frac{(d_2+c_8)}{c_7-c_0}\right)\right] + (exp(c_8 \times d_4))$$

$$B = d_5 - \left[\frac{\left(\frac{(c_3+c_7)}{(c_3-d_2)}\right)}{(d_4-c_7)+d_0}\right]$$

$$C = c_9 - [((d_3 - c_7) + d_3)(exp(c_2 - d_4)]$$

$$D = d_3\left[\frac{d_3}{(exp(d_5 \times c_2))(c_6-c_7)}\right]$$

$$E = d_0 - ((d_0 - c_9) - c_9 + (d_5 \times d_1) - d_5)$$

3.3.4 K-FOLD cross-validation

The model's reliability for predicting 28-day compressive strength, as well as 28-day flexural strength, was assessed using the k-fold cross-validation method. This method involves randomly partitioning the data into ten groups, using nine for training and one for validation in each iteration. The entire process is repeated ten times to derive an average performance measure. This rigorous k-fold cross-validation procedure ensures that the models achieve high accuracy. Furthermore, comprehensive statistical evaluations including MAE, MSE, RMSE, RRSE, and R-square were conducted and are depicted in *Fig. 8* and *9*. The models' predictive capabilities were further analysed through statistical calculations, as detailed in the equations below.

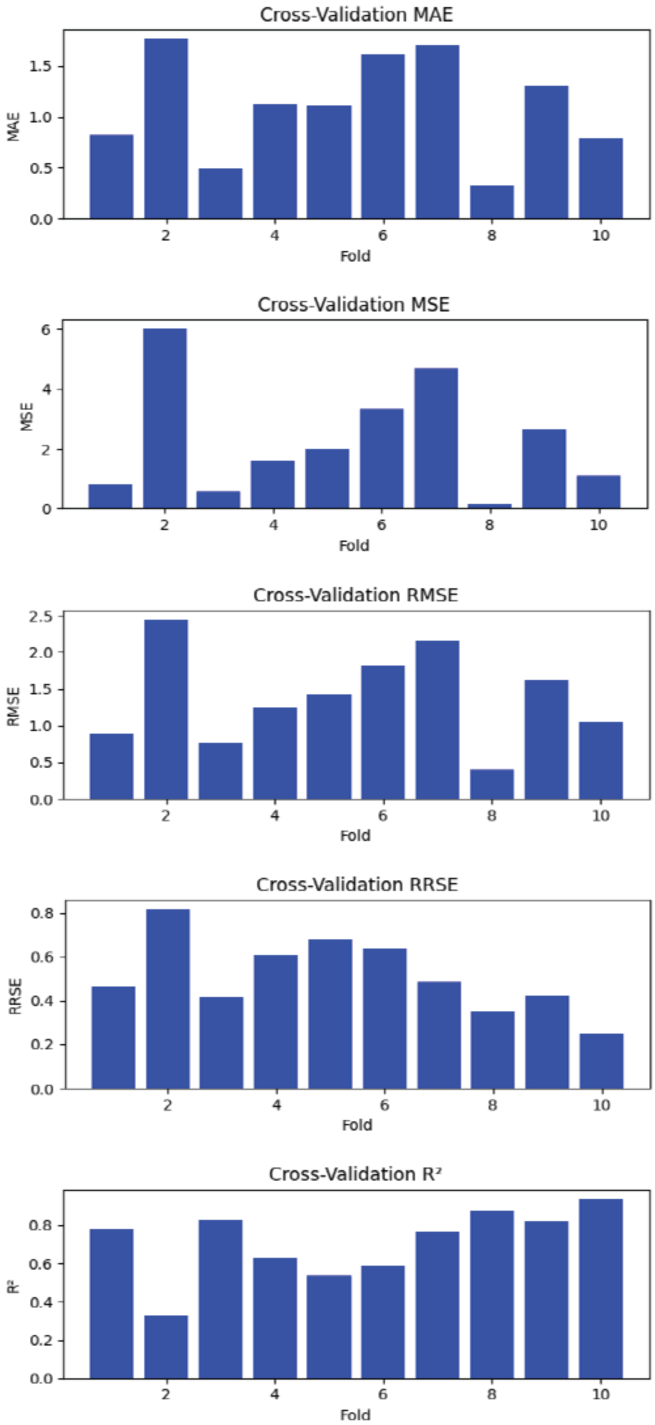


Fig. 8 *28 day Compressive Strength K-fold cross validation for MAE, MSE, RMSE, RRSE and R-square*

8. ábra *A 28 napos nyomószilárdság K-szörös keresztvalidációja MAE, MSE, RMSE, RRSE és R-négyzet értékekre*

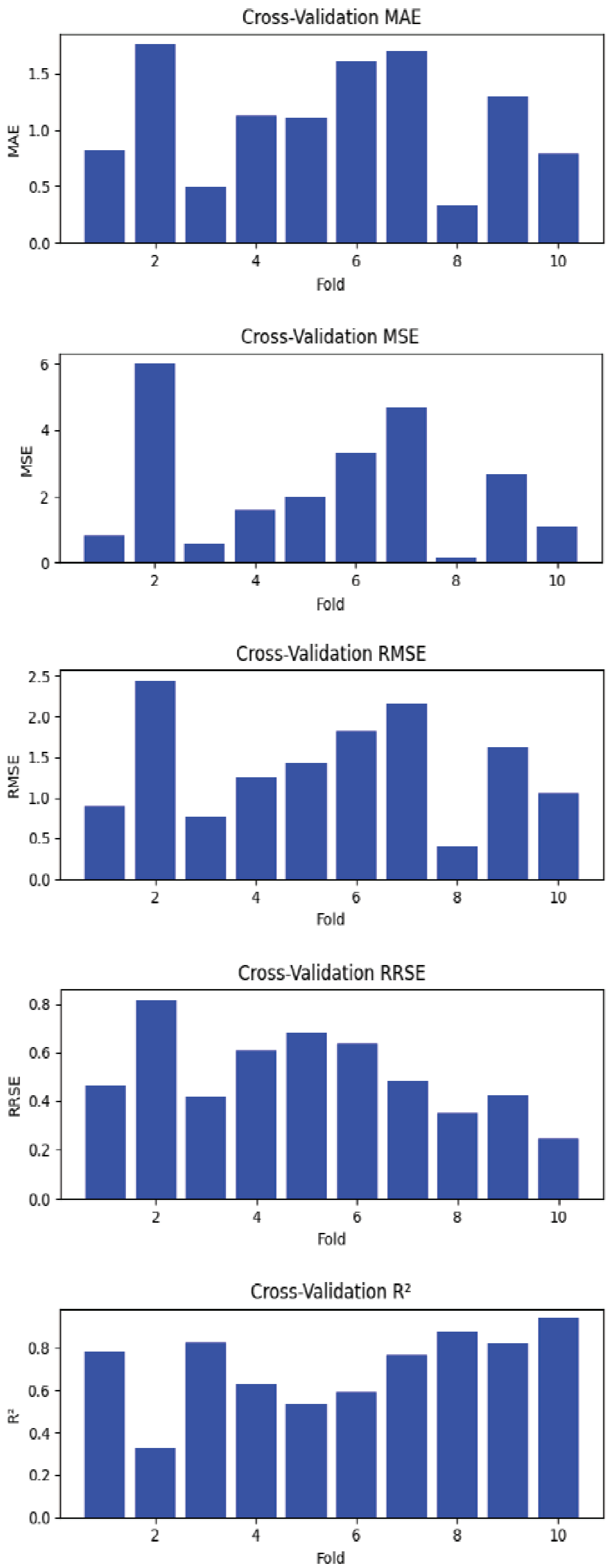


Fig. 9 *28 day Flexural Strength K-fold cross validation for MAE, MSE, RMSE, RRSE and R-square*
9. ábra *A 28 napos hajlítószilárdság K-szörös keresztvalidációja MAE, MSE, RMSE, RRSE és R-négyzet értékekre*

3.3.5 Sensitivity analysis

Predicting 28-days compressive strength showed iron stone maintaining dominance, with the water-cement ratio also playing a significant role as shown in *Fig. 10*. Regarding 28-days flexural strength prediction, iron stone was the primary influencer, followed by crushed granite and the water-cement ratio as shown in *Fig. 11*. Overall, iron stone consistently demonstrated the greatest influence across all assessed strengths, highlighting its crucial role in determining concrete's mechanical properties. The water-cement ratio consistently ranked among the top contributors, underscoring its significant impact on concrete performance. This analysis offers valuable insights for optimizing concrete mix designs and improving structural performance.

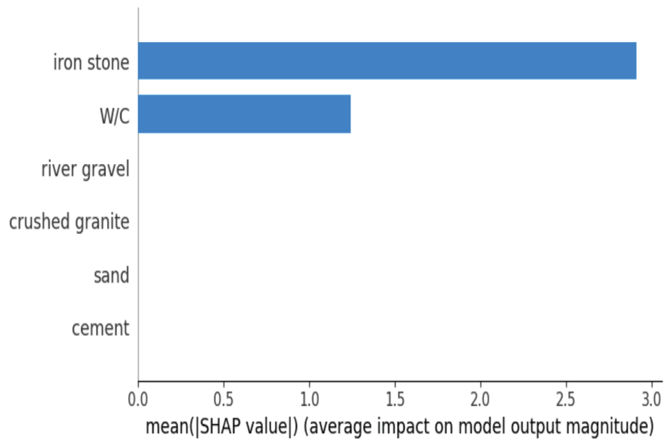


Fig. 10 *28 day Compressive Strength Shapley average impact value*
10. ábra *A 28 napos nyomószilárdság Shapley-átlagos hatás értéke*

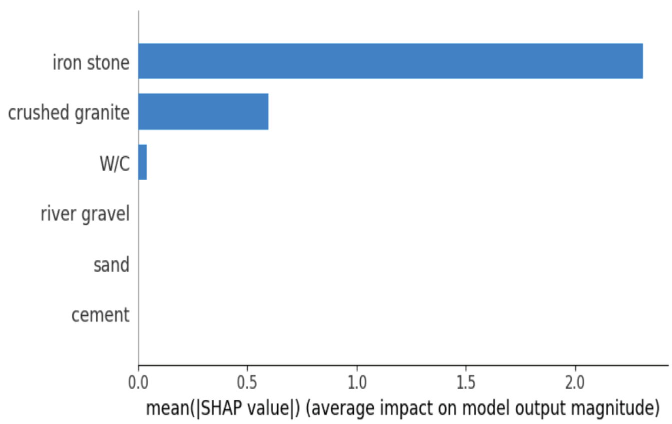


Fig. 11 *28 day Flexural Strength Shapley average impact value*
11. ábra *A 28 napos hajlítószilárdság Shapley-átlagos hatás értéke*

4. Conclusions

In this study, we applied a supervised machine learning approach to predict the compressive strength of concrete containing sedimentary aggregates. Gene Expression Programming (GEP) was employed for forecasting the compressive strength, demonstrating exceptional effectiveness through a high linear correlation coefficient (R^2) and minimal error values:

1. The GEP model effectively predicted compressive strengths at 7, 14, and 28 days with R-squared values exceeding 0.7 for both training and testing phases, indicating high precision and minimal errors. However, lower R-squared values for validation and higher error metrics suggest the need for model refinement to enhance generalization and performance on unseen data.
2. The model's reliability was confirmed through k-fold cross-validation for predicting compressive and flexural strengths, affirming its potential for practical applications in concrete strength prediction.
3. Iron stone significantly influenced all assessed strengths, highlighting its critical role in concrete's mechanical properties. The water-cement ratio and crushed granite also emerged as important factors, impacting compressive and flexural strengths. These insights are crucial for optimizing concrete mix designs and improving structural performance.
4. Ironstone shows potential for use as a coarse aggregate in concrete production, provided its physical characteristics such as high water absorption capacity, moisture content porosity, void ratio, poor grading, bulk density and specific gravity is adequately managed.

The application of GEP for predicting the compressive strength of concrete with sedimentary aggregates has proven effective and reliable, providing a foundation for further refinement and broader application of machine learning models in construction materials engineering.

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