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Estimating Rice Husk Ash Concrete Compressive Strength Using Hybrid Machine Learning Methodology

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Abstract

The earth's temperature is gradually increasing due to greenhouse gases (GHGs), which have caused the global warming phenomenon. Carbon dioxide (CO_2) has accounted for a large majority of such greenhouse gases. Due to the high CO_2 emissions caused by cement production, several alternative cementitious materials have been discovered, such as Rice Husk Ash (RHA). This study suggests a hybrid data-driven machine learning framework approach for predicting RHA concrete compressive strength. The framework utilizes Bayesian Regularization-based artificial neural network (ANN) and genetic expression programming (GEP) to develop a generalized prediction mathematical model that avoids overfitting. The model included six compressive strength prediction parameters: age, cement content, rice husk ash content, water, superplasticizer, and aggregate. Based on the literature's 192 compressive strength-tested specimens, the proposed framework has been trained. The proposed model resulted in average calculated-to-measured ratios of 1.00, a standard deviation of 0.15, and a COV of 15%. In addition, a parametric study has been conducted to evaluate the effect of each contributing parameter. The analysis shows that varying the RHA content from 0 to 200 kg/m^3 will increase the compressive strength by up to 50%.

Keywords: Rice husk ash; Artificial neural network; Genetic expression programming; Overfitting; Data-driven machine learning.
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1. Introduction

In recent years, the world has witnessed dramatic climate change, including melting polar ice caps and glaciers in the Antarctic regions and increasing floods and hurricanes. This can be attributed to greenhouse gases (GHGs) and their effects. GHGs are responsible for the witnessed global warming. During the day, the sun shines through the atmosphere and increases the earth's temperature. The earth's surface cools down at night, releasing the heat back into the air. However, some of the heat is trapped by the GHGs. GHGs include carbon dioxide (CO_2), methane (CH_4), nitrogen oxide (N_2O), and fluorinated gases.[1] Carbon dioxide (CO_2) is the primary greenhouse gas emitted through human activities. In 2021, CO_2 accounted for 79% of all U.S. greenhouse gas emissions from human activities.[2]

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Consequently, there has been an increase in research studies on the triggers of climate change and the increased greenhouse gases (GHGs)[3] due to the construction and transportation of building materials, which are recognized as major contributors to carbon emissions (Fig. 1). Particularly, the cement production industry is responsible for 8% of global CO_2 emissions[4] and is expected to increase. Cement is also reported to be the third-largest CO_2 producer in the world.[2] Therefore, there is an increasing focus on integrating alternative materials into the production of cementitious components using agricultural waste such as rice husk ash (RHA), olive oil ash (OOA), sugarcane bagasse ash (SBA), palm oil fuel ash (POFA), industrial waste such as fly ash (FA), and silica fume (SF) as supplementary cementitious materials (SCMs) to reduce the usage of Ordinary Portland Cement (OPC).[5]

One of the potential SCMs is rice husk ash (RHA), which is obtained from burning rice husk. The rice husk is the outer layer of paddy grain, which is the by-product of rice milling. It is estimated that 1,000 kg of rice grain produces 200 kg of rice husk; after the rice husk is burnt, about 20 percent of the rice husk becomes RHA.[6] RHA is considered an effective, eco-friendly, and cost-effective SCM (Fig. 2).[7-8] It contains

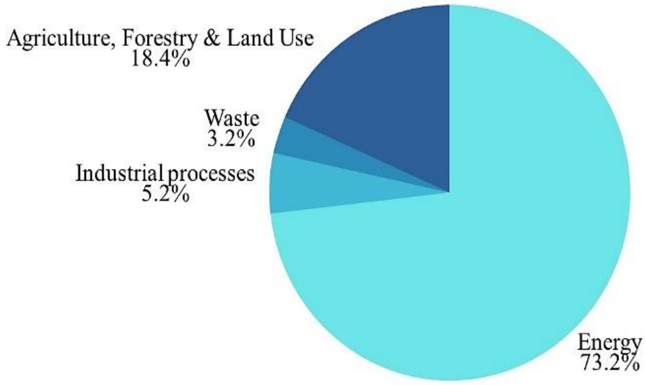

Fig. 1 Factors contributing to carbon emissions.

more than 75% silica by weight (after incineration),[9] has an amorphous nature, and has a high surface area. RHA is compatible with OPC concrete, which exhibits pozzolanic properties,[9] making it an attractive candidate for enhancing the performance of cementitious materials without sacrificing strength and durability. The incorporation of RHA into cement decreases industrial demand for OPC, lowering the expense of producing concrete and leading to mitigating the negative impacts of CO_2 discharges during the OPC production process.

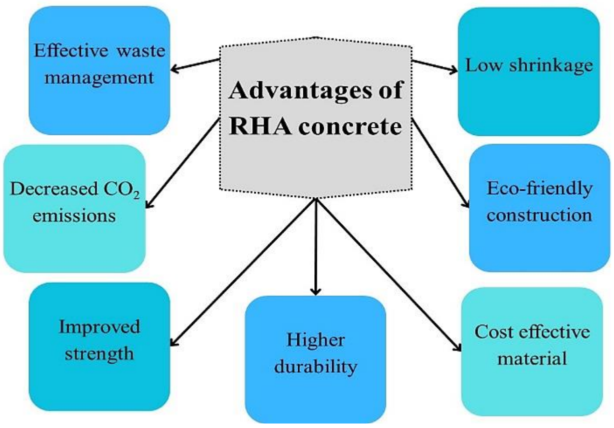

Fig. 2 Benefits of RHA concrete.

Research studies showed that concrete mixtures containing up to 50% rice husk ash by weight showed compressive strengths that were higher than the normal Portland cement mixture even at the early ages of 3-7 days and good resistance to the dilution of organic and mineral acids.[10-12] However, the increase in RHA content led to an increase in water demand for normal consistency, but this can be corrected by the utilization of water-reducing admixtures. Silica is produced when silicon is burned in the presence of oxygen. After cement hydrates, calcium hydroxide is produced, and this highly reactive Silica interacts with it to form calcium silicates, which are what give cement its strength.[13] The reactions that take place in the preparation of rice husk ash concrete are shown in Eqs. (1), (2), and (3).

$$Si + O_2 \rightarrow SiO_2 \quad (1)$$

$$C_3S\ (Cement) + H_2O \rightarrow CSH + Ca\ (OH)_2 \quad (2)$$

$$SiO_2 + Ca\ (OH)_2 \rightarrow CSH + SiO_2 \quad (3)$$

The Alkali-silica reaction (ASR) is one of the most common causes of concrete distress. ASR is a chemical reaction between alkali hydroxide and Silica that occurs in the presence of moisture. An ASR gel is formed and causes volumetric expansion of concrete, resulting in cracking and spalling of concrete structures. During the pozzolanic reaction of SCMs, the anion of C-S-H is formed with a low Ca/SiO_2. This C-S-H absorbs the alkali cations ($Na+$ and $K+$) and reduces the abundance of alkali compounds in concrete. In this way, the incorporation of SCMs reduces the ASR expansion in concrete. Research studies showed that 12–15% partial replacement of cement by RHA can mitigate ASR expansion in concrete. Eqs. (4) and (5).

Alkali hydroxide (from cement) + Silica (from aggregate) → Alkali-silica gel (4)

Alkali -silica gel + moisture → Concrete expansion and cracking (5)

Mehta, P.K., conducted investigations on rice husk ash cements with up to 50% ash, which showed higher compressive strength than the control Portland cement at early 3 days.[10] Mehta, P.K., and D. Pirtz, have shown that when 30% rice husk ash by weight of the total cementing material was present, the 7 and 28-day compressive strengths were higher than that of normal concrete.[11] S. James, J. and Subba Rao, M., studied the reaction product of lime and silicate from rice husk ash and showed that it is Calcium Silicate Hydrate (C-S-H) that accounts for the strength of lime rice husk ash cement.[12]

RHA has been employed in recent studies as a partial replacement for OPC as well as fine aggregate in concrete mixes.[14] The properties of RHA concrete change with the amount of OPC or fine aggregate, the RHA grain size, the water-cement ratio, and the aggregate size/shape in the matrix.[15] However, for optimum strength growth, a replacement of 10 to 25 percent of OPC is recommended.[16] Over the last decade, data-driven machine learning (ML) and artificial intelligence (AI) have been widely implemented in different fields of structural engineering due to their superior capabilities in pattern recognition and classification and the ability to provide accurate prediction models.[17-19] The concept of data-driven ML relies on learning and identifying behavior from experimental data through algorithms, which include performance measures to assess the model's accuracy level. One major concern in ML and AI is overfitting and the inability to generalize the developed model, especially when limited experimental data is available.

This study proposes a hybrid ML framework utilizing artificial neural networks (ANN), genetic expression programming (GEP), and a compiled experimental database to develop a generalized compressive strength model for RHA concrete. The proposed framework ensures avoiding overfitting and reflects the effect of each of the contributing variables. Variables included in the proposed compressive strength model are age, cement weight, rice husk ash weight, water amount, superplasticizer amount, and aggregate weight.[5] In addition, the study utilizes the developed ML model to conduct a parametric study to evaluate the effect of each of the included variables.

The manuscript begins by explaining the fundamentals of machine learning methods utilized in the analysis and providing a description of the database utilized. Then, a detailed description of developing a Bayesian Regularization-based ANN prediction model is presented. The ANN model is then utilized to create a new dataset with a different combination of variables (within the ranges of the variables in the dataset). The new dataset takes the form of a parametric study, where all variables are fixed, and the investigated variable is changed. Finally, the created dataset is combined with the experimental dataset to force the generalization and fed into GEP algorithm to develop a mathematical expression.

2. Machine learning overview: ANN and GEP

2.1 Artificial Neural Network, ANN

As mentioned earlier, machine learning has been utilized in different fields of civil engineering to develop prediction models and investigate the effect of input variables on the output. In this study, an artificial neural network (ANN) was selected to assess the effect of age, cement, rice husk ash, water, superplasticizer, and aggregate on the compressive strength of RHA concrete. ANN has been selected for its ability to generalize and avoid overfitting.[20]

ANN is a multi-layer framework; the first layer is an input layer representing the parameters, and the last layer is an output layer containing the output. Between the input and output layers, one or more hidden layers can exist that control the data's recognizing (learning) patterns. Each layer consists of simple processing units (PUs) that are fully connected to other PUs in the next layer (Fig. 3a).[21]

Each signal or input x_i arrives, and then the PU is multiplied by a calibrated weight w_{ji} that governs the behavior and importance of the signal. At each PU, the calibrated signals are summed, and a calibrated bias value B_{ji} is added as given in Eq. (6). The combined input I_j is then passed through a nonlinear transfer function $f_{(Ij)}$ to create the PU output, which will form the input for PUs in the next layer (Fig. 3b). A Hyperbolic tangent sigmoid transfer function is utilized in this study.

$$I_j = \sum w_{ji}\, x_i + B_{ji} \tag{6}$$

A training algorithm updates the inputs' weights and bias values in the training process according to Levenberg-Marquardt optimization. It minimizes a combination of squared errors and weights and then determines the correct combination in order to produce a network that generalizes well. The process is called Bayesian regularization. The error is expressed by the Mean Square Error (MSE), which is also known as the performance function (Eq. (7)). The training process continues until the MSE converges, and no improvement can be made.[22]

$$MSE = \frac{1}{N}\sum_{k=1}^{N}(Actual - Predicted)^2 \tag{7}$$

It should be noted that the input variables need to be normalized as a first step according to Eq. (8), where the input value is multiplied by the gain value a_{in} and shifted by the offset value of_{in}. Similarly, at the output layer, the signal needs to be denormalized by subtracting the offset of_{on} and dividing the results by the gain a_{on}.

$$x_i = X_i\, a_{in} + of_{in} \tag{8}$$

Selecting the required number of PUs in the hidden layer to express and approximate the complex behavior is done through experimentation (trial). Usually, in ANN modeling, the number of hidden layers should be restricted to avoid overfitting. However, in the current application, overfitting was not a concern due to the use of Bayesian regularization.

2.2 Gene Expression Programming, GEP

GEP is another type of artificial inelegance technique that is currently used in many engineering applications.[23] It is an algorithm that concentrates on understanding connections

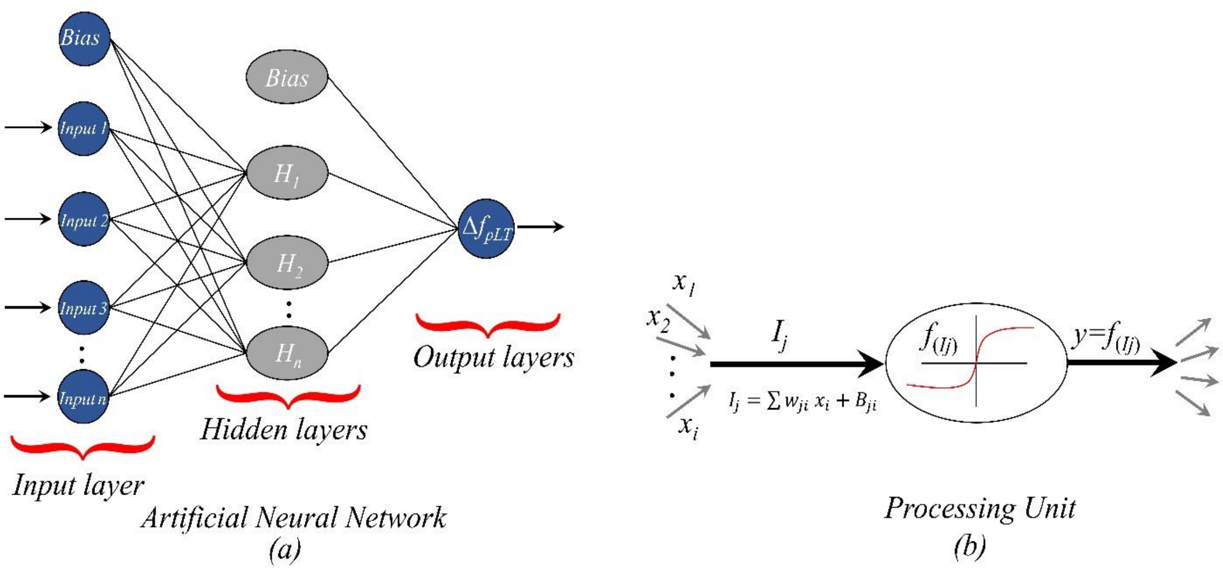

Fig. 3 General structure and processing unit of ANNs.

between variables in data sets and then devises models to clarify these associations. Ferreira[24] proposed GEP as an extension of gene programming (GP). The GEP process involves five parts: (1) the function shape, which holds the required mathematical triggers; (2) a group of changeable symbolic characterization; (3) a fitness function that measures the chromosome squared mean root error (RMSE) against the rest of the population (chromosomes); (4) controlling variables; and (5) the stopping criteria. Fig. 4 shows the GEP technique used to create the expression tree. The first step in the algorithm is selecting the five items previously mentioned. Random initial functions are generated using the provided function form and terminals. The process continues for a set number of generations or until a satisfactory categorization rate is achieved. The constructed functions are executed and converted into a tree structure. After that, the fitness function assesses the function results, and if acceptable, the process stops. The final outcome is displayed in the form of tree structures called GEP Expression trees, which provide an easily understandable representation of the mathematical functions created, as demonstrated in Fig. 5.

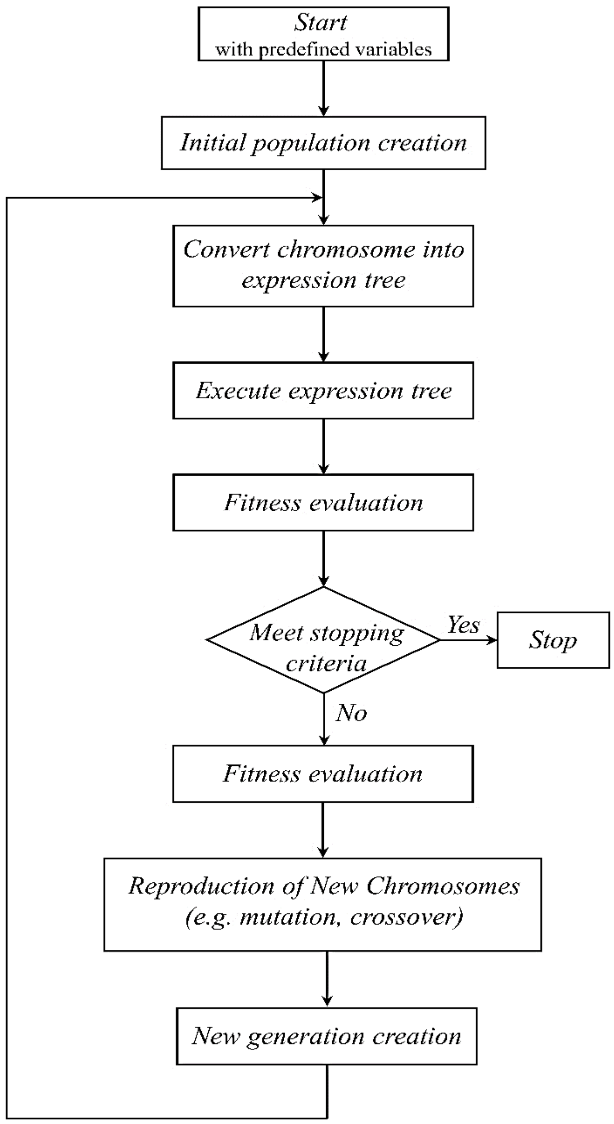

Fig. 4 Gene expression evolution algorithm.

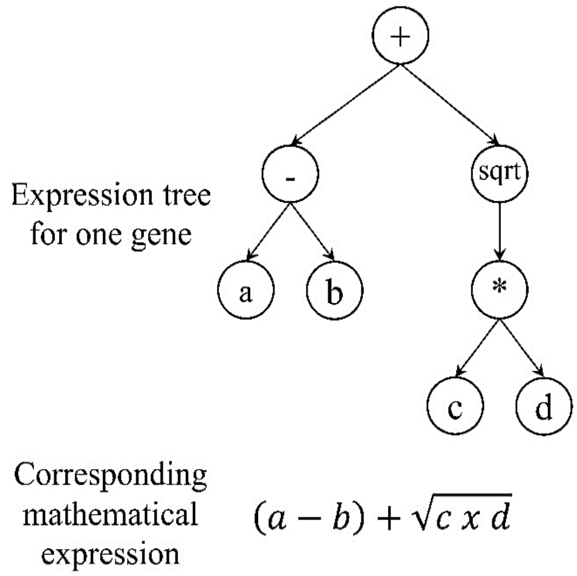

Fig. 5 Expression tree and corresponding mathematical expression

2.3 Surveyed database

In order to utilize the mentioned machine learning methodologies described earlier to estimate and understand the behavior of RHA concrete, an extensive experimental database is needed. Accordingly, experimentally measured compressive strengths of 192 RHA concrete beams from different studies have been collected in reference[25] and are utilized in this study. Variables surveyed are concrete age (days), cement (kg/m^3), rice husk ash (kg/m^3), water (kg/m^3), superplasticizer (kg/m^3) and aggregate (kg/m^3). The range and distribution of variables are shown in Fig. 6.

2.4 Model development procedure

Gene expression programming (GEP) is a machine learning approach that has been implemented recently in different applications in structural engineering to develop prediction models based on experimental databases. GEP algorithm imitates Darwinian natural selection in the evolution of mathematical expressions. As mentioned earlier, the GEP algorithm can develop prediction models expressed in mathematical formulas, making it suitable for creating prediction models (equations) for different problems. However, developing GEP models based on limited training data is susceptible to overfitting. This is a major concern in machine learning (ML) applications since the algorithms try to reduce errors between actual and predicted data. Overfitting can be defined as detecting the noise and random fluctuation in training data as general behavior. Overfitting can result in a significant error when predicting new data points.

On the other hand, various algorithms are available for training in ANN, such as Levenberg-Marquardt, Bayesian Regularization, and Scaled Conjugate Gradient. In particular, Bayesian Regularization is an appropriate algorithm for training small and noisy datasets to avoid overfitting.[21]

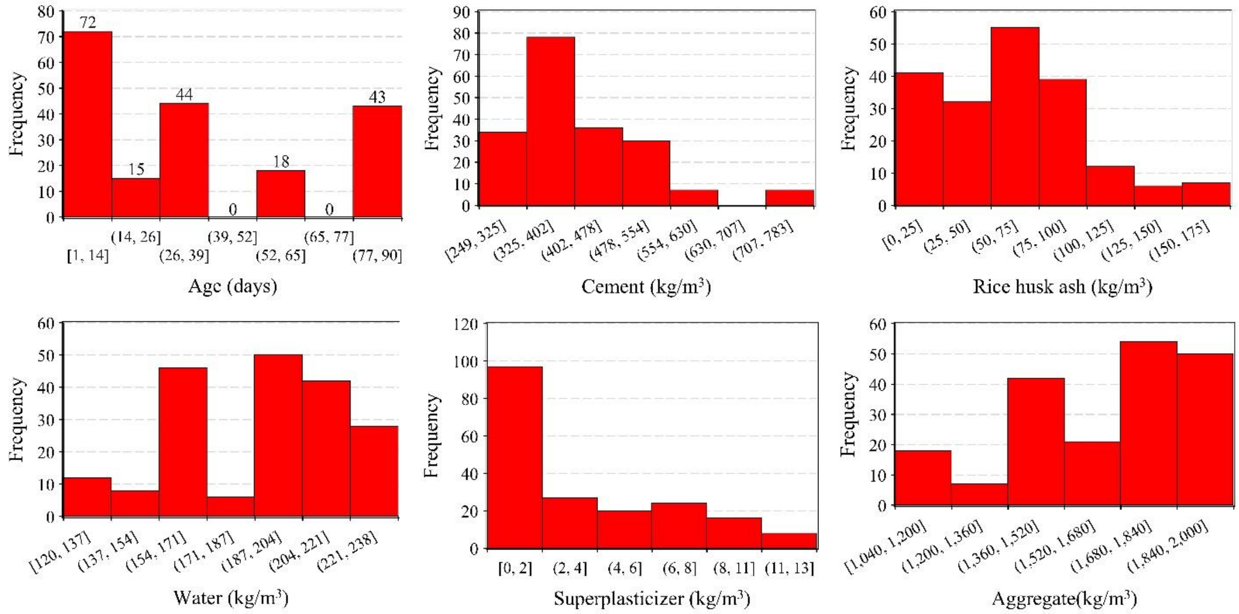

Fig. 6 Distribution of variables.

Although ANN is a powerful tool for developing accurate and generalized prediction models, the developed prediction model has the form of programming code, not a mathematical equation. This increases the difficulty of adopting and implementing the developed model. This paper proposes a framework to establish a generalized prediction for RHA concrete compressive strength with mathematical expression with a limited number of experimental data. The concept of the framework is summarized in the following steps:

1-Data collection and preparation. This step is conducted by compiling the database from reference.[25]

2-Developing a Bayesian Regularization-based ANN prediction model.

3-Creating a new dataset with a different combination of variables (within the ranges of the variables in the dataset) using the developed ANN model. The new dataset takes the form of a parametric study, where all variables are fixed, and the investigated variable is changed.

4-The created dataset is combined with an experimental dataset to force the generalization.

5-The combined dataset is trained using the GEP algorithm to develop a mathematical expression.

The procedure is summarized in Fig. 7 and discussed in detail in the following subsections.

2.5 Bayesian regularization-based ANN model

The Bayesian Regularization-based ANN model was developed using the ANN toolbox of MATLAB R2018b. To select the optimal PUs in the hidden layer, PUs from 1 to 10 were tested while monitoring the MSE, and the optimal number of layers was found to be 3. The Bayesian Regularization algorithms automatically determine the appropriate weight for each signal (hyperparameter tuning). Unlike other training algorithms, the Bayesian Regularization algorithm does not require a validation database. In this study, the input layer includes concrete age (days), cement (kg/m^3), rice husk ash (kg/m^3), water (kg/m^3), superplasticizer (kg/m^3) and aggregate (kg/m^3). The experimental versus the ANN-predicted data are shown in Fig. 8. The ANN model resulted in an average (tested-to-predicted) of 1.00, a coefficient of variation (COV) of 9.4%, and an RMSE of 4.7 MPa. The low COV and RMSE indicate the accuracy of the ANN model.

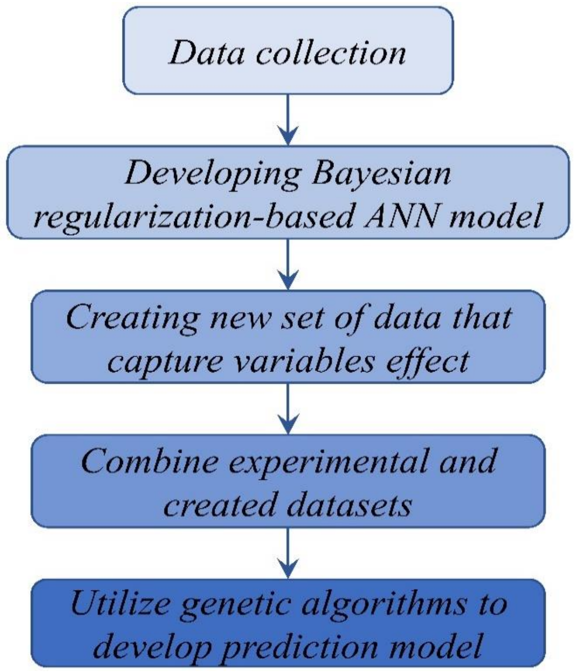

Fig. 7 Model development procedure utilized.

These performance metrics (average, COV, and RMSE) have been selected for their informativeness, and researchers are familiar with them. The average gives an insight into the conservatism of the results and their deviation from the actual value. At the same time, COV provides insight into the scatteredness of the results. In addition, RMSE provides a measure of error with the same units of the data (MPa in this case), which makes it more meaningful.

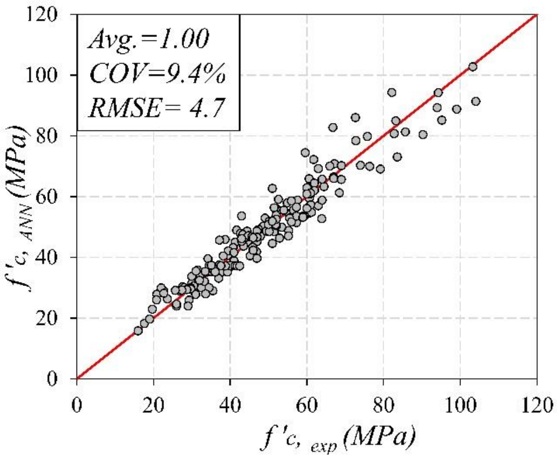

Fig. 8 Experimental vs. ANN-predicted compressive strength.

2.6 New dataset using ANN model

The developed ANN model is used to create a new dataset with new combinations of variables other than the combinations existing in the experimental database. The development of the new dataset is taking the form of a parametric study, where all variables are fixed at their average values, and the investigated variable is changed. It should be noted that the investigated is only varied within its range in the database. This procedure is repeated for each variable. The new dataset has 73 new combinations of variables. It is important to note that variables should not be varied outside the training (original or experimental) range. The compressive strength for each combination is estimated using the trained ANN model.

Figure 9 shows the generated data points in the form of a parametric study. The results have been interpreted in terms of the percentage of change in the compressive strength to clearly identify the effect of each of the variables. It can be seen that the compressive strength is positively correlated with all of the variables except the water content, as expected. Also, more than 50% of the compressive strength is gained in the first 10 days. These two behaviors can help in validating the ANN model. It can be seen that age has the highest effect on compressive strength, followed by the cement content then the superplasticizer. Varying the RHA content from 0 to 200 kg/m^3 will increase the compressive strength by up to 50%. It should be noted that the parametric evaluation is only applicable to the range of each variable. The accuracy beyond the range of variables is not guaranteed.

2.7 Combine created and experimental datasets

Both the created and experimental datasets are combined. The created dataset will force the training algorithm to recognize each variable's patterns (effects) and avoid overfitting or false generalization.

3. Proposed GEP model

The combined database is utilized in GEP to develop a generalized model in mathematical form using the evolutionary algorithm. The combined database will force the generalization of the model and avoid overfitting. Different parameters are utilized in developing the GEP prediction model; these parameters control the prediction model and the generalization capability. The utilized parameters for developing the GEP model are shown in Table 1. The selection of the parameters was based on multiple trials. In each trial, one variable varied while the others remained constant. Trials were compared based on the coefficient of variation (COV) of the calculated-to-measured ratio. In addition, basic mathematical operations were selected in the function set to produce a simple model.

Table 1. GEP selected parameters.

Parameter	Selected value
Dependent variable (shear stress)	1
Independent variables	5
Genes	6
Function set	$-, +, \times, \div, \sqrt{\square}, \sqrt[3]{\square}$, $\ln \square$, power, exp, Atan, Tanh
Head size	7
Linking function between ETs	Multiplication

Following the procedure discussed in the previous sections, the developed GEP model is shown in Fig. 10 in expression tree (ET) format. The GEP expression tree is divided into 6 sub-ETs linked by multiplication, as shown in Table 1. The factors d0, d1, d2, d3, d4, and d5 are the input variables: age, cement, RHA, water, superplasticizer, and fine aggregate, respectively. Constants are denoted by the "c" letter. Constants in each sub-ET are tabulated in Table 2.

Table 2. Constants used in the ET.

Sub-ET	Constant	Value
1	C1	8.345
2	C4	3.099
	C9	5.589
3	C6	-15.117
4	C7	0.182
	C1	-2.707
5	C8	4.167
6	C0	3.128
	C1	-3.126

The proposed model resulted in average calculated-to-measured ratios of 1.00, a standard deviation of 0.15, and a COV of 15%. It is expected that the GEP model will result in slightly higher COV due to the different algorithms used. To assess the accuracy of the proposed model and the consistency of the prediction with respect to other variables, the ratios of the calculated-to-measured were plotted with respect to

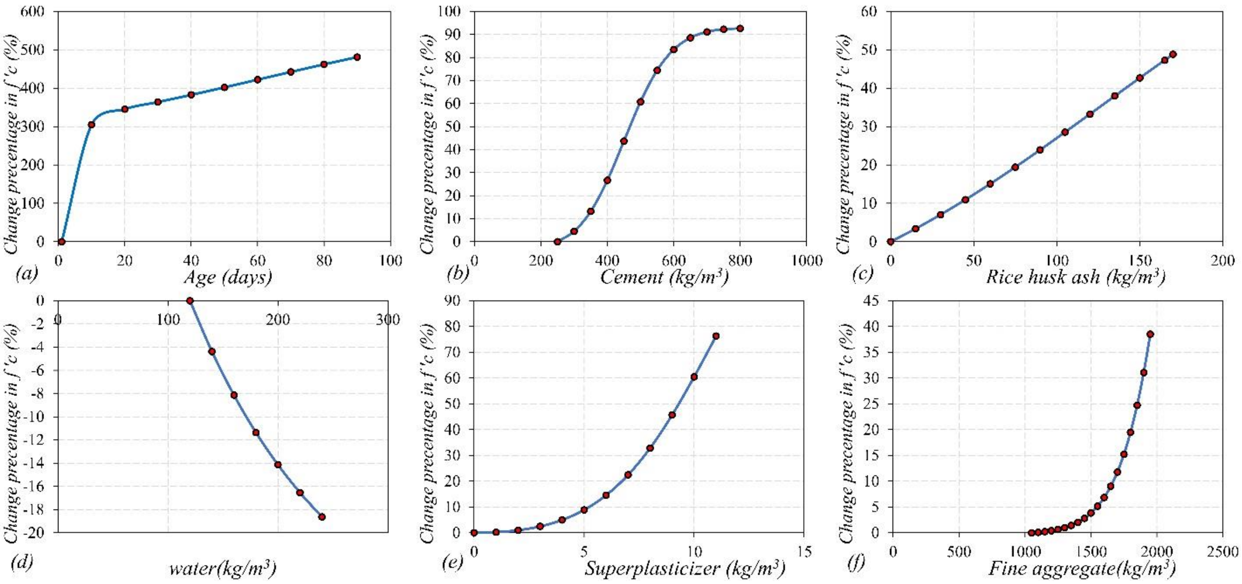

Fig. 9 Percentage increase in RHA concrete compressive strength with respect to (a) age, (b) cement content, (c) RHA content, (d) water content, (e) superplasticizer, (f) fine aggregate.

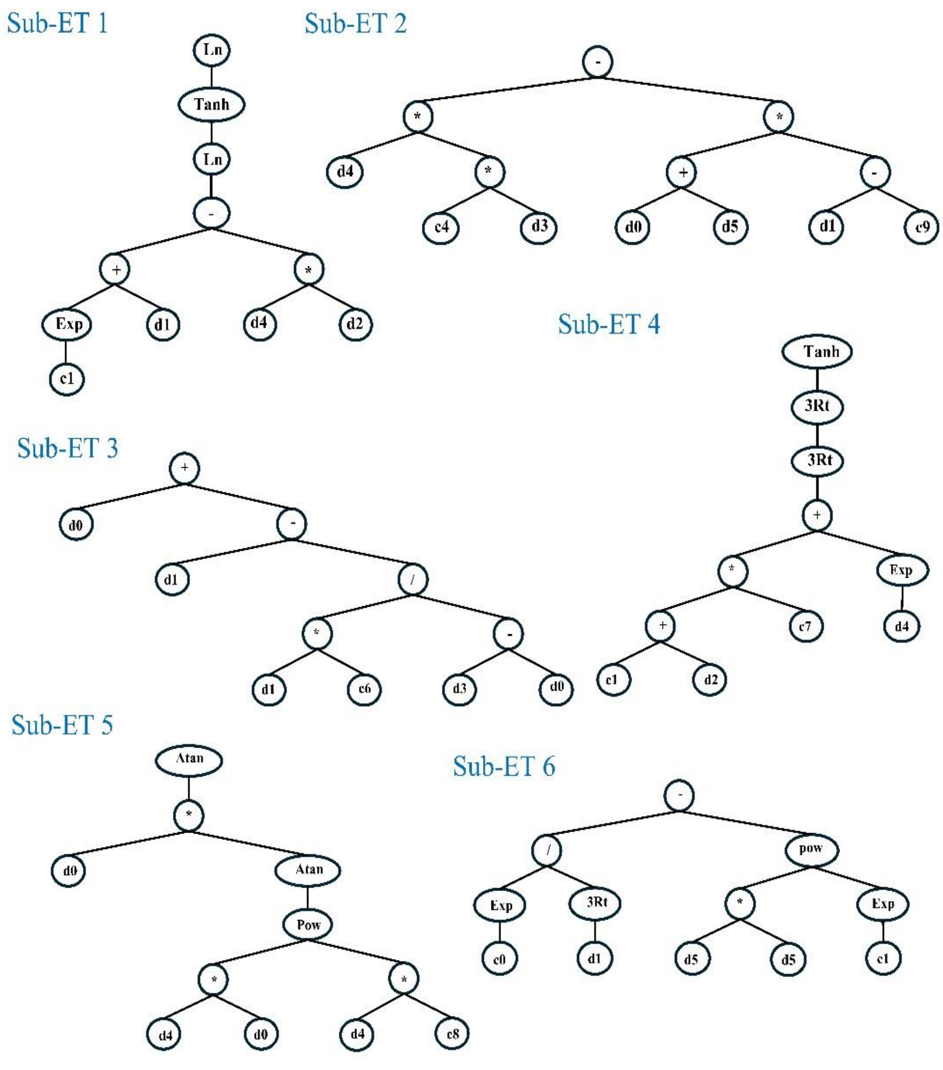

Fig. 10 GEP expression tree for the proposed model.

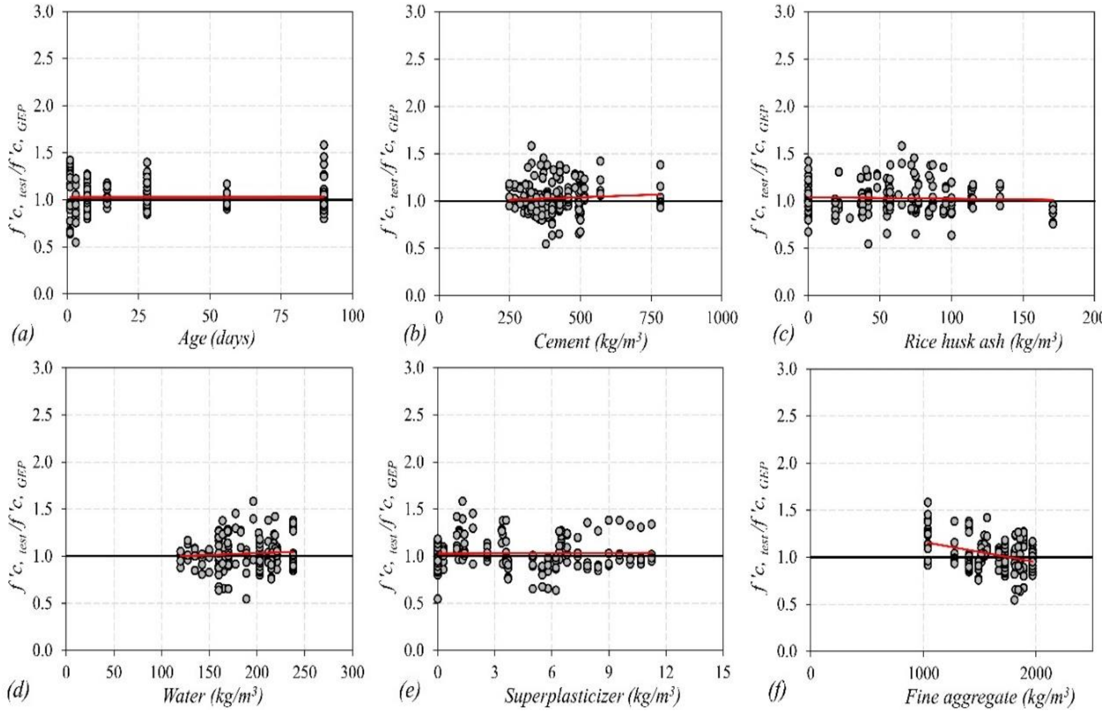

Fig. 11 Prediction accuracy (estimated-to-measured) of the proposed model with respect to: (a) Age; (b) Cement content; (c) RHA content; (d) water, (e) superplasticizer, (f) fine aggregate.

different variables in Fig. 11. The horizontal trendlines in Fig. 11 indicate a consistent prediction across all variable ranges.

4. Conclusions

The study suggests a hybrid machine learning (ML) framework that combines genetic expression programming (GEP) and artificial neural networks (ANN) with a compiled experimental database of 192 data points to create a generalized compressive strength model for RHA concrete. A parametric study has also been conducted to evaluate the contribution of each of the parameters included. The following conclusions are drawn from the study:

1- Due to the limited number of experimental measurements of RHA compressive strength and the need for an accurate mathematical prediction model, a hybrid data-driven machine learning framework utilizing artificial neural network (ANN) and genetic expression programming (GEP) is presented to develop a robust mathematical model. The general concept of the adopted framework is based on creating an additional synthetic database using Bayesian Regularization-based ANN and then combining both databases into GEP to develop the model.

2- The ANN model resulted in an average tested-to-predicted of 1.00, a coefficient of variation (COV) of 9.4%, and an RMSE of 4.7 MPa. The trained ANN model is used to create an additional database in the form of a parametric study.

3- According to the ANN parametric study, age has the biggest impact on the compressive strength of the RHA where more than 50% if it is obtained in the first 10 days, and, which is surpassed by cement content and superplasticizer. Furthermore, there will be a 50% improvement in compressive strength when the RHA content fluctuates from 0 to 200 kg/m^3.

4- The combined database from the experimental database and the ANN parametric study were then used to train the GEP model. The purpose of the combined database is to force the generalization of the model and to avoid overfitting. The proposed model resulted in average calculated-to-measured ratios of 1.00; a standard deviation of 0.15, and a COV of 15%.

Conflict of Interest

There is no conflict of interest.

Supporting Information

Not applicable.

References

[1] D. Kweku, O. Bismark, A. Maxwell, K. Desmond, K. Danso, E. Oti-Mensah, A. Quachie, B. Adormaa, Greenhouse effect: greenhouse gases and their impact on global warming, *Journal of Scientific Research and Reports*, 2018, **17**, 1-9, doi: 10.9734/jsrr/2017/39630.

[2] A. B. Rao, E. S. Rubin, A technical, economic, and environmental assessment of amine-based CO_2 capture technology for power plant greenhouse gas control, *Environmental Science & Technology*, 2002, **36**, 4467-4475, doi: 10.1021/es0158861.

[3] Y. L. Li, M. Y. Han, S. Y. Liu, G. Q. Chen, Energy consumption and greenhouse gas emissions by buildings: a

multi-scale perspective, *Building and Environment*, 2019, **151**, 240-250, doi: 10.1016/j.buildenv.2018.11.003.
[4] Jirang, C.U.I. and Roven, H.J., 2010. Recycling of automotive aluminum. *Transactions of Nonferrous Metals Society of China*, 20(11), pp.2057-2063, doi: 10.1016/S1003-6326(09)60417-9.
[5] B. Iftikhar, S. C. Alih, M. Vafaei, M. A. Elkotb, M. Shutaywi, M. F. Javed, W. Deebani, M. I. Khan, F. Aslam, Predictive modeling of compressive strength of sustainable rice husk ash concrete: ensemble learner optimization and comparison, *Journal of Cleaner Production*, 2022, **348**, 131285, doi: 10.1016/j.jclepro.2022.131285.
[6] R. Kishore, V. Bhikshma, P. J. Prakash, Study on strength characteristics of high strength rice husk ash concrete, *Procedia Engineering*, 2011, **14**, 2666-2672, doi: 10.1016/j.proeng.2011.07.335.
[7] Z. Syahida Adnan, N. F. Ariffin, S. M. Syed Mohsin, N. H. Abdul Shukor Lim, Review paper: performance of rice husk ash as a material for partial cement replacement in concrete, *Materials Today: Proceedings*, 2022, **48**, 842-848, doi: 10.1016/j.matpr.2021.02.400.
[8] H. Chao-Lung, B. Le Anh-Tuan, C. Chun-Tsun, Effect of rice husk ash on the strength and durability characteristics of concrete, *Construction and Building Materials*, 2011, **25**, 3768-3772, doi: 10.1016/j.conbuildmat.2011.04.009.
[9] M. N. Amin, S. Hissan, K. Shahzada, K. Khan, T. Bibi, Pozzolanic reactivity and the influence of rice husk ash on early-age autogenous shrinkage of concrete, *Frontiers in Materials*, 2019, **6**, 150, doi: 10.3389/fmats.2019.00150.
[10] P. K. Mehta, September. Properties of blended cement made from rice husk ash, In Journal Proceedings, 1977, **74**, 440-442, doi:
[11] P. K. Mehta, D. Pirtz, Use of rice hull ash to reduce temperature in high-strength mass concrete, *ACI Journal Proceedings*, 1978, **75**, 60-63, doi: 10.14359/10477.
[12] Antiohos, S.K., Papadakis, V.G. and Tsimas, S., 2014. Rice husk ash (RHA) effectiveness in cement and concrete as a function of reactive Silica and fineness. *Cement and concrete research*, 2014, **61**, 20-27, doi: 10.1016/j.cemconres.2014.04.001.
[13] M. B. Ahsan, Z. Hossain, Supplemental use of rice husk ash (RHA) as a cementitious material in concrete industry, *Construction and Building Materials*, 2018, **178**, 1-9, doi: 10.1016/j.conbuildmat.2018.05.101.
[14] S. Das, R. K. Patra, B. B. Mukharjee, Feasibility study of utilisation of ferrochrome slag as fine aggregate and rice husk ash as cement replacement for developing sustainable concrete, *Innovative Infrastructure Solutions*, 2021, **6**, 85, doi: 10.1007/s41062-021-00461-9.
[15] V. Ramasamy, Compressive strength and durability properties of Rice Husk Ash concrete, *KSCE Journal of Civil Engineering*, 2012, **16**, 93-102, doi: 10.1007/s12205-012-0779-2.
[16] R. K. Sandhu, R. Siddique, Influence of rice husk ash (RHA) on the properties of self-compacting concrete: a review, *Construction and Building Materials*, 2017, **153**, 751-764, doi: 10.1016/j.conbuildmat.2017.07.165.
[17] F. Liu, W. Ding, Y. Qiao, L. Wang, An artificial neural network model on tensile behavior of hybrid steel-PVA fiber reinforced concrete containing fly ash and slag power, *Frontiers of Structural and Civil Engineering*, 2020, **14**, 1299-1315, doi: 10.1007/s11709-020-0712-6.
[18] P. Deb, S. K. Pal, Interaction behavior and load sharing pattern of piled raft using nonlinear regression and LM algorithm-based artificial neural network, *Frontiers of Structural and Civil Engineering*, 2021, **15**, 1181-1198, doi: 10.1007/s11709-021-0744-6.
[19] F. Khademi, M. Akbari, S. M. Jamal, M. Nikoo, Multiple linear regression, artificial neural network, and fuzzy logic prediction of 28 days compressive strength of concrete, *Frontiers of Structural and Civil Engineering*, 2017, **11**, 90-99, doi: 10.1007/s11709-016-0363-9.
[20] A. Tarawneh, G. Almasabha, E. Saleh, A. Alghossoon, O. Alajarmeh, November. Data-driven machine learning methodology for designing slender FRP-RC columns. In Structures, Elsevier. Tarawneh ANN, 2023, **57**,105207.
[21] A. Tarawneh, E. Saleh, G. Almasabha, A. Alghossoon, Hybrid data-driven machine learning framework for determining prestressed concrete losses, *Arabian Journal for Science and Engineering*, 2023, **48**, 13179-13193, doi: 10.1007/s13369-023-07714-y.
[22] A. Tarawneh, G. Almasabha, Y. Murad, ColumnsNet: neural network model for constructing interaction diagrams and slenderness limit for FRP-RC columns, *Journal of Structural Engineering*, 2022, **148**, 04022089, doi: 10.1061/(ASCE)ST.1943-541X.0003389.
[23] A. N. Tarawneh, E. F. Saleh, Machine learning framework for predicting failure mode and flexural capacity of FRP-reinforced beams. Leveraging Artificial Intelligence in Engineering, Management, and Safety of Infrastructure, Boca Raton: CRC Press, 2022.
[24] C. Ferreira, Gene expression programming in problem solving. Soft Computing and Industry. London: Springer London, 2002, 635-653, doi: 10.1007/978-1-4471-0123-9_54.
[25] B. Iftikhar, S. C. Alih, M. Vafaei, M. A. Elkotb, M. Shutaywi, M. F. Javed, W. Deebani, M. I. Khan, F. Aslam, Predictive modeling of compressive strength of sustainable rice husk ash concrete: Ensemble learner optimization and comparison, *Journal of Cleaner Production*, 2022, **348**, 131285, doi: 10.1016/j.jclepro.2022.131285.

