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A NOVEL AI TECHNIQUE FOR FORECASTING THE COMPRESSIBLE STRENGTH OF PAVEMENT WITH ASH PARTICLES

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A B S T R A C T

Understanding cementitious composites' mechanical properties, particularly compressive strength (CS), is crucial for safety, with AI approaches being particularly useful for forecasting CS with ash particles.In this study, we proposed the ensemble honeybee mating optimized dynamic artificial neural network (EHBMO-DANN) for forecasting the CS of pavement. 7 characteristic Fly ash (FA), coarse aggregate, cement, super plasticizer, fine aggregate, days, and water were used as inputs in the experimental technique to forecast the output or the CS variable. Measured at 7 and 28 days, the CS of the concrete specimens without FA of the same age is compared to those with replacement rates of 15%, 30%, and 45%. The experimental evaluation metrics using the high degree of predictive accuracy are shown by its high Coefficient determination R2, MAE, MSE, and RMSE.The construction and engineering sectors may benefit greatly from our research on the CS of pavement comprising ash particles.

1. INTRODUCTION

An important strategic priority for many industrialized and developing countries is sustainable infrastructure. Research on the usage of sustainable alternative materials is being aggressively pursued by governments, academic institutions, and the worldwide pavement sector. This entails substituting waste by-products for conventional materials extracted from quarries. By doing this, projects involving civil infrastructure may save natural resources, cut down on greenhouse gas emissions, and utilize less energy and materials. The transition towards sustainable practices is consistent with wider environmental objectives and fosters the adoption of more environmentally conscious and resource-efficient construction methods within the civil engineering domain.The employment of green technologies in pavement building has increased the efficiency with which natural resources and recycled materials are used as a consequence of comprehensive research efforts on creative and ecologically friendly solutions in recent years (Hoy, M., et al., (2017)). An essential component of civil engineering work is building roads, which need a lot of conventional and natural resources, including gravel, crushed aggregate, and sand. On the other hand, getting rid of trash and

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by-products is a problem for many manufacturing and processing facilities. These industrial wastes often have advantageous technical qualities that make it easier to use them in the road industry. Pond ash, which is produced in coal-burning thermal power plants and dumped into ash ponds or landfills after being mixed with an appropriate amount of water, is one kind of industrial waste (Mogili, S., et al., (2020)).200 million metric tonnes of coal-based combustible residual (CCRs) in the form of fly ash, bottom ash, or a mix of each of them were produced over approximately 250 million square kilometers of land. The subgrade, which supports further layers in pavement construction, is either natural or compacted dirt. Poor subgrade soil conditions shorten a pavement's lifespan, particularly if the subgrade includes expansive clay since the subgrade serves as the pavement's base (Lam, M. N. T., et al., (2018)). The minerals montmorillonite, smectite, and bentonite are among the several expansive minerals found in expansive clays. Expanding clays undergo volumetric contraction as a result of severe droughts occurring more often and rising global temperatures brought on by climate change. Cracks gradually start to develop as a consequence of the soil shrinking during the drying process, which deteriorates the soil's hydraulic and mechanical qualities (Lam, N. T. M., et al., (2020)).In the process of creating geopolymer concrete (GPC), the use of FA or steel slag significantly decreased CO_2 emissions by as much as 5-7 times compared to cement. Experts from all around the globe are now closely monitoring this cement-free alternative because of its possible advantages for the economy and ecology (Wang, D., et al., (2019)).For a very long time, FA has been taken into consideration as a means of stabilization in a variety of presentations, including base and sub-base materials, building materials, and problematic soils. There aren't many researches that evaluate its qualities as a building material when FA is a major component of the combination (Deboucha, S., et al., (2020).Due to its self-cementing qualities, Class C FA was the only consideration in the majority of these experiments. Utilizing fly ashes from coal (class F) together with various other waste materials such as lime made of calcium carbide and recycled asphalt pavement, and NaOH leftovers has been a prevalent practice since the 1960s. Water entry may cause the compacted mixtures of coal wash and FA to collapse. One method to prevent these kinds of issues would be to stabilize the residues using other residue-containing alkali activators, like NaOH leftovers or carbide lime. Nonetheless, Class F FA does not self-cement. Therefore, it has not been given much thought as a possible addition to other aggregates in earlier research. Class F FA is the category that includes most coal combustion products (CCPs) generated in coal-fired power plants in Australia. Using this waste material would assist in lowering the amount of waste streams and landfills needed (Kang, S., et al., (2020)). In this study, we forecast the compressible pavement's strength with ash particles. The contribution of the paper is as follows:

- The proposed study introduces an innovative approach, the Ensemble Honeybee Mating Optimized Dynamic Artificial Neural Network (EHBMO-DANN), to forecast the CS of pavement incorporating ash particles.
- Water, cement, superplasticizer, fly ash, fine aggregate, days, and coarse aggregate are the seven characteristics that are used in the research as input variables to predict CS.
- When concrete specimens without FA are compared at 7 and 28 days, the replacement ratios of FA at 15%, 30%, and 45% are examined.

The rest of the paper is as follows: The current literature analysis is presented in Part 2, the methodology is explained in Part 3, the results and comments are shown in Part 4, and the conclusion of the paper is explained in Part 5.

2. LITERATURE REVIEW

2.1 ML-based compressible strength of the pavement

Khursheed, S., et al., (2021) used "machine learning (ML) techniques, including resonance vector machine (RVM), genetic programming (GP), extreme learning machine (ELM), minimax probability machine regression (MPMR), and emotional neural network (ENN),"to forecast the pavement's 30-day CS using FA. Different statistical parameters can be used to assess the models' performances that are given.Nguyen, K. T., et al., (2020) used two different machine learning approaches for calculating the CS of geopolymer concrete that was by applying FA. To provide the data needed for process training and validation, a total of 335 mix proportions were tested.Jiang, Y., et al., (2022) discovered that determining the strength qualities of FA concrete by traditional compression tests is both time-consuming and unfeasible. The original "support vector regression (SVR), the random forest(RT) model," the ELM and the SVR model improved by the grid search approach were the four ML models that were presented in order to predict the CS of FA concrete using 270 datasets for each group.To completely remove this flaw, FA concrete, or FAC, must be used. However, cementitious composites exhibit a range of characteristics, and it is essential for security to comprehend these properties' mechanical aspects. On the other hand, ML techniques and Concrete's mechanical characteristics may be predicted using a variety of techniques. Barkhordari, M. S., et al., (2022) compared separate, super learner models, stacking ensemble models, weighted averaging, super learner algorithm, integrated stacking, and simple averaging in an effort to create a precise method for calculating the CS of FA concrete and lowering large variance of the prediction models. To overcome the aforementioned difficulties, this technique uses pavement surface distresses to estimate the RSL.A total of 105 flexible pavement segments are taken into consideration to apply the suggested theory. The kind, degree, and quantity of asphalt's surface degradation have been determined for each component of sidewalk, along with to the pavement condition index (PCI) (Nabipour, N.,et al., 2019). Suthar, M. (2020) assessed the ability of lime and lime sludge stabilized pond ashes to forecast unconfined CS using five different modeling techniques: ANN, SVM, RT, M5 model trees, and Gaussian processes.

2.2 Deep learning-based compressible strength of the pavement

A revolutionary method for creating a Deep Neural Network (DNN) model for rubber concrete CS prediction was presented by Ly, H. B., et al., in 2021. With a set of aggregate, binder, and various further relevant concrete factors as the limitations for input and the CS as an output, a rubber concrete dataset is meticulously built to achieve this aim. The number of neurons inside each layer's hidden layers is carefully examined during the construction of the DNN model, in conjunction with statistical analysis of the predictions of the models' projected outputs. Information from pavement condition assessments can be used to manage the pavement network more consistently and economically. Pavement distress assessments are often carried out by foot-on-the-ground surveys or advanced data-gathering vehicles. Distress detection is a labor-intensive, costly, ineffective, and hazardous procedure in both cases. Majidifard, H., et al., (2020) examined the earlier research, which provided a pavement dataset with labels as a first stage toward a more reliable, user-friendly pavement condition assessment system. One of the biggest issues lately has been the building and upkeep of road pavement. As a result, roller-compacted concrete pavement (RCCP) is often used to solve traffic-related issues. Gene expression programming (GEP), an evolutionary-based technique, was used by Ashrafian, A., et al., (2020) to develop a novel prediction formula for the RCCP.The mechanical characteristics of cement composites enhanced with carbon nanotube (CNTs) are first predicted by (Huang, J. S., et al., (2021))using ML. To do this, predictive models are trained using experimental data that has already been published. The results show that ML models outperform classic response surface methodologies in terms of generalization and prediction. The degradation modelling procedure and results for the three kinds in Iowa, pavement made of asphalt and composite materialsare discussed (Hosseini, S. A., et al., (2020)). The Iowa collects and keeps data on the state of the pavement in a Pavement-Management Information System (PMIS).

3. METHODOLOGY

The modeling technique used to anticipate the CS of pavement containing ash particles is described in this section.

3.1 Material selection and characters

The preparation of concrete mixtures using Fly Ash (FA), cement, coarse aggregate, and fine aggregate coarse aggregate is the main objective of the study. The cement from Portland cement used in the demonstration was regular. The research follows ASTM guidelines, particularly ASTM C150, which specifies requirements for cement made from Portland cement. The experiments and findings are guaranteed to be reliable and consistent by the aforementioned requirements.The plastic containers have been covered with airtight polythene covering to keep dampness against affecting the cement's integrity. This keeps humidity against adversely altering the characteristics of cemented and compromising the functionality of the concrete construction.The first and second tables of the information in the presentations provide a description of the physical as well as chemical properties of the mineral limestone and fly ash used in the experiment. For knowledge of the material's characteristics and its influence on concrete performance, this information is essential.ASTM-recommended testing was used to determine the properties of fine aggregates, a component of concrete. Fine aggregate features are important because they affect how well concrete performs as a whole. Testing aids in understanding and managing these qualities. Adherence to ASTM standards, moisture-resistant material protection, andcomprehensive component testing are stressed in the study to guarantee the study's dependability and caliber. Table 1 presents the physical characteristics of cement followed by the cement and FA chemical composition shown in Table 2.

Table 1. The physical characteristics of cement

Physical Characteristic	Content
Specific gravity ($g/cm3$)	3.15
Specific surface area ($cm2\ /g$)	8300
Insoluble residue (% mass)	0.49
Particle size ($d50$) (cm)	1.649
Loss on ignition (% mass)	2.21

Table 2. Cement and FA's chemical composition

Details of compound	FA	Cement
Alumina (Al_2o_3)	6.96	4.26
Potassium Oxide (l_2o)	0.45	1.47
Silica (Sio_2)	18.97	52.1
Sodium Oxide (Na_2o)	0.12	0.120
Iron Oxide (Fe_2o_3)	3.62	26.9
Calcium Oxide (CaO)	64.82	2.23
Ignition Loss	-	1
Magnesium Oxide (MgO)	1.95	1.52

The concrete mix was prepared in accordance with ASTM requirements using a locally accessible coarse particle that has a nominal maximum size of 25.4 mm. Following ASTM guidelines, the coarse aggregate's (CA) mechanical properties and sieve analysis were assessed. Table 3 presents the findings. The physical properties of coarse and fine aggregate are also shown in Table 4.

Table 3. The physical characteristics of fly ash

Qualities	Range of values
Soundness by Expanded Autoclave, %	0.05
Lime Reactivity, N/mm^2	6
Drying Shrinkage, %	0.06
Retention on 45 µm Sieve, %	< 35
CS, %	80

Table 4. The fine and coarse aggregate's physical properties

Resources	Standards Followed	Coarse Aggregate	Fine Aggregate
Moisture Content, %	ASTM C566	0.62	1.127
Specific Gravity in Bulk	ASTM C128/ C127	2.70	2.64
Modulus of Fineness	ASTM C136	-	2.42
Absorption of Moisture, %	ASTM C128/ C127	1.33	1.03
Weight of Rodded Unit, kg/m^3	ASTM C29	1551.6	-
Maximum Nominal Size,mm	-	25.3	-

3.2 Procedure for Experimentation

3.2.1 Specimen preparation and materials

The present study examines the effects of age and FA ratio by a series of methodical trials. Measured and compared to the same ages, concrete examples without FA are the CSs of sample ratios of 15%, 30%, and 45% in replacement that were aged 7 and 28 days.Each and every component was obtained locally. It included coarse sand, fine sand, coarse aggregate, and 10 mm aggregate, while Cement Australia provided the FAand GP cement. For concrete mixes, 15%, 30%, and 45% replacement rates of cement are employed to investigate the impact of the FAratio on the characteristics of the concrete. Following a meticulous examination of sieve data and other factors, the concrete mixtures selected for the trials are determined and are shown in Table 5.

Table 5. Various FAfractions used in concrete mixtures to partially replace cement (https://www.researchgate.net/publication/258582817_On_Effects_of_Fly_Ash_as_a_Partial_Replacement_of_Cement_on_Concrete_Strength)

Capacity	Cement (kg)	Coarse sand (kg)	Fine sand (kg)	Water (kg)	20mm agg (kg)	10mm agg (kg)	FA(kg)
R1: 0% FA Replacement	405.377	445.798	132.681	239.157	560.422	525.565	0.000
R2: 15% Cement Replacement	472.715	445.798	132.681	239.157	560.422	525.565	70.90
R3 : 30% Cement Replacement	367.505	445.798	132.681	239.157	560.422	525.565	109.351
R4 : 45% Cement Replacement	270.615	445.798	132.681	239.157	560.422	525.565	121.776

3.2.2 Compressive Tests

Testing was done on the specimens at 7 and 28 days. A frame that loads with a 3,000 kN capacity, the CONTR 50-C3122, was used to test the cylinder specimens. To guarantee a flat surface for testing, the specimen's two ends were sealed with a sulfur mixture prior to the tests. The rate of loading was kept constant at 20 MPa/min while the load was delivered using a load-control mode. The curves for load times were captured by the device's control panel, although the samples were being gradually loaded until they failed. The peak load is divided by the regions of the specimen cross-section, and the CSs are computed.

3.3 Dataset

The dataset has one output, concrete CS, and seven inputs: FA, cement, super plasticizers, water, fine aggregate, coarse aggregate, and days. Table 6 depicts the range of variables for input and output.

Table 6. Input and output variable.

Parameters	Maximum value	Minimum value
FA($kg/m3$)	168.3	92.1
Cement ($kg/m3$)	376	136.1
Water ($kg/m3$)	220.5	141.1
Superplasticizer($kg/m3$)	18	0
Age ($kg/m3$)	90	3
Coarse aggregate ($kg/m3$)	1118	801
Fine aggregate ($kg/m3$)	905.4	687
Compressive Strength (MPa)	72.11	9.49

3.4 Ensemble Honeybee Mating optimized dynamic artificial neural network (EHBMO-DANN)

An advanced and specialised method for assessing the California Bearing Ratio (CBR) of pavement including ash particles is the "Ensemble Honeybee Mating Optimised Dynamic Artificial Neural Network" (EHBMO-DANN). The use of a specialized optimization method motivated by honeybee mating behaviour, resistance to complex data patterns, flexibility to changing conditions with dynamic neural networks, and greater accuracy through ensemble learning are just a few of the model's potential advantages.By merging the projections of several models, the word "Ensemble" suggests the algorithm can make use of numerous artificial neural networks or other machine learning models, thereby improving precision. The term "Honeybee Mating Optimized" suggests that the algorithm makes use a particular optimization method that draws inspiration from honeybee breeding behaviors. This method can help the model identify the best possible solutions and increase correctness.The dynamic nature of the model implies that it is flexible and adaptive to fluctuating roadway under certain circumstances, since it can adjust to changing conditions or emerging data. The model's ability to withstand complicated patterns in the data, especially when ash particles are included, is probably built to manage such complexity.With regard to assessing the California Bearing Ratio of pavement containing ash particulates, the EHBMO-DANN model is especially designed to handle the peculiarities and difficulties associated with this kind of pavement. All of these characteristics work together to make the model more efficient at managing the difficulties involved in assessing concrete conditions.

3.4.1 Dynamic Artificial Neural Network (DANN)

Artificial neural networks that are capable of adapting and changing their parameters or structure over time are known as dynamic artificial neural networks, or DANNs. This feature enables DANNs to learn from new data and enhance their performance. Because of their adaptable nature, they can update their knowledge or incorporate new information without needing to be completely retrained.

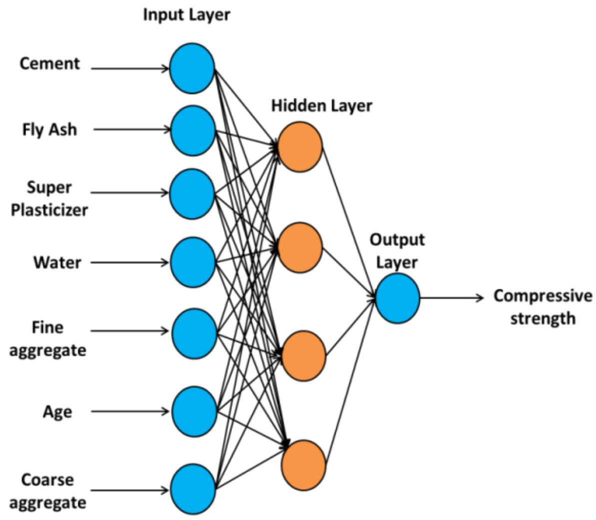

Figure 1. Architecture of DANN

DANNs are useful in fields like financial modeling, adaptive control systems, and time-series prediction, where real-time adjustments are necessary. In addition, their design may be changed to accommodate changing job needs by adding, deleting, or modifying weights. DANNs can in very handy when handling non-stationary and complicated data. This research suggests DANNusing the forecast the compressive strength of pavement. We use one hidden layer network as well. We have seven materials inside the layer of input and 1 in the output layer, based on the database of the actual concrete mix proportioning. Figure 1 depicts the structure of the DANN in use.

It is possible to represent the normalized input-output relation formula quantitatively.

$$\eta = \omega_0^{(2)} + \sum_{i=1}^{m} \left[\frac{\omega_j^{(2)}}{1+exp(-\alpha v_e)}\right] \tag{1}$$

$$v_I = \omega_{0,i}^{(1)} + \sum_{j=1}^{7} \left(\omega_{j,i}^{(1)} \zeta_j^{S}\right) \tag{2}$$

Where, in equations (1) and (2), $\omega_{0,i}^{(1)}$and $\omega_0^{(2)}$are referred to as thresholds, $\omega_{j,i}^{(1)}$ and $\omega_j^{(2)}$are The weights in synapses, αrepresents the activation function's shape parameter, j signifies A neuron's index inside the input layer, $i$denotes a neuron's index in the layer of hidden, and i depicts the total quantity of neurons in the layer of hidden signals. Finding the right amount of neurons for the buried layer is essential.

Using the database, M records used to train the ANN are selected at random.The definition of the error residual is

$$F = \sum_{j=1}^{M} \left(\eta_l^{(p)} - \eta_l^{(c)}\right)^2 \quad (3)$$

Where,$\eta_l^{(c)}$is the intended value that, in the data, reflects the normalized CS, $\eta_l^{(p)}$is the ANN's output, and $k$is the consecutive number. The underline is employed for$l$note that the samples have new numbers as we chose them at random from the database. The goal of the training procedure is to determine a range of acceptable threshold and synaptic weight values. Initially, modest random integers are used to build up all of the threshold and synaptic weight values. The error residual F now depends on the synaptic weights and thresholds. They may revise their estimate values and progress toward a better answer by using the steepest descendent approach.

$$\omega_{j,i}^{(1),new} = \omega_{j,i}^{(1),old} - \mu \frac{\partial F}{\partial \omega_{j,i}^{(1)}} \quad (4)$$

$$\omega_{i}^{(2),new} = \omega_{i}^{(1),old} - \mu \frac{\partial F}{\partial \omega_{,i}^{(2)}} \quad (5)$$

3.4.2 Ensemble Honeybee mating optimization

The study of honey bee colonies mating behaviour led to the development of a zero-order optimization method known as the ensemble Honey Bee Mating Optimization (EHBMO). Essentially, mating is modelled as the development of offspring between drones and the colony queen. In contrast to traditional evolutionary optimization techniques, the queen may be able to increase brood production by storing its sperm theca's spectrum of drone sperm. However, the initial brood generation models have a convergence problem since it may get caught in a few local optima. In an attempt to increase brood production, the modified version, on the other hand, considers three sperms chosen at random from the queen's sperm theca to create fresh, enhanced drones. The EHBMO procedure is a strong search-based technique because of this characteristic, and it has been used as an optimization tool for many different water resources applications. Figure 2 shows the EHBMO algorithm.

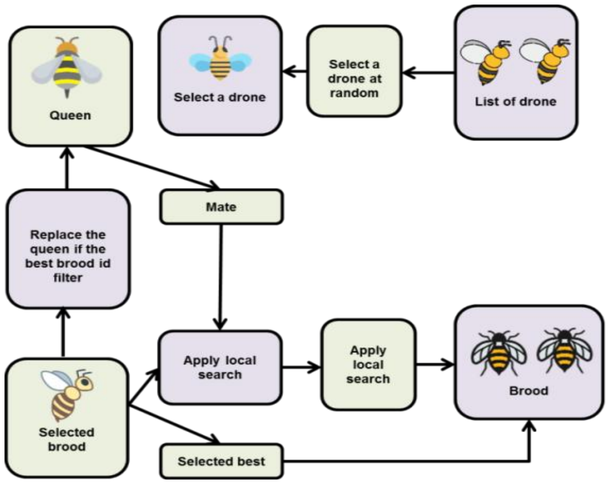

Figure 2. Structure of EHBMO (https://onlinelibrary.wiley.com/doi/abs/10.1002/dac.4259)

4. RESULT AND DISCUSSION

In this section, we discuss estimating the pavement's compressible strength using ash particles. A Windows 11 operating system with Pytorch 2.0, compatible with Python 3.11, is part of the system configuration. The validation of the model was conducted using the following performance metrics: R^2, MAE, RMSE, and MAPE.For calculating MSE, RMSE, and R^2we compare the existing methodsare Gaussian Process Regression (GPR), artificial neural network (ANN), and Support Vector Regression (SVR) (Paixao, R. C. F. D., et al., (2022)). For calculating MAE, we compare the existing methods are Random Forest (RF), Regression Trees (RT), and K-nearest neighbours (KNN) (Hadzima-Nyarko, M., et al., (2020)).

4.1 Prediction of CS

Table 7 presents the findings of the compressive testing, indicating that two specimens were examined at the 28-day mark and one specimen at the 7-day mark for each concrete mix.The findings are shown in Figure 3, where it is evident how the FAratio and age affect CS.

Table 7. Concrete's Strength after Seven and Twenty-Eight Days at Varying FA Ratios

Description	CS
7 days	
0 % Fly Ash	43.78
15% FA in replace of cement.	35.42
30% FA in replace of cement	37.47
45% FA in replace of cement	33.38
28 days	
0 % Fly Ash	52.73
15% FA in replace of cement	43.84
30% FA in replace of cement	57.91
45% FA in replace of cement	50.87

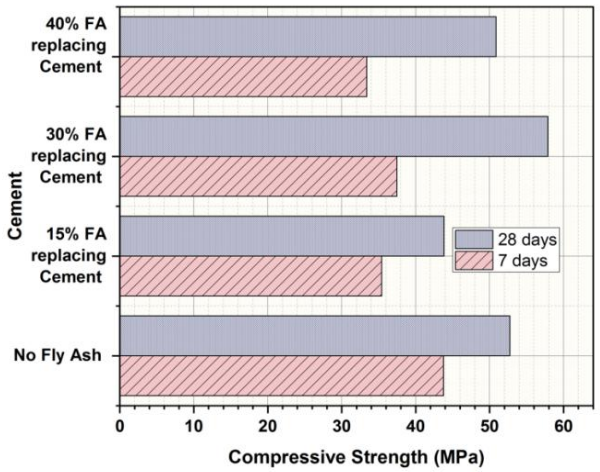

Figure 3. CS of partial cement replacement

As demonstrated in Figure 2, strength increases gradually as predicted. In particular, concrete with FAgets stronger more slowly than concrete without fly ash. If we compare the strength of concrete throughFAto concrete lacking fly ash, this trait becomes very evident. It has been observed that due to a little variation in their compositions, the hydration process between FAand water is noticeably slower than the reaction between water and cement.The maximal CScan be attained at an ideal FAreplacement ratio, which is another significant finding. This discovery has implications for the design of concrete mixes, especially for structural purposes. The united impacts of the interactions between cement and fly ash and aggregate, as well as the varying strengths of FA and cement, might be the physics behind this occurrence. Although FA have been said to have a stronger interface than cement and aggregate, fly ash's strength may actually be lower than cement's. The concrete fracture may be readily triggered at the interface when the FA replacement ratio is below the optimal value. Additionally, the concrete with higher FA content may fail due to the poor strength of fly ash. Table 8 presents the result of CS.

Table 8. Experimental and predicted value of CS.

S.NO	Experimental value	Predicted value	Error
R1	27.78	27.45	0.33
R2	29.57	29.15	0.42
R3	30.25	29.97	0.28
R4	30.85	30.58	0.27

The Mean Squared Error is a measurement of the mean squared differences among observed and predicted values. However, it's not clear how it specifically relates to CS and ash particles in the study. With the existing ANN (2.78), SVR (2.65), and GPR (1.75), the proposed EHBMO-DANN achieves less (1.68).

$$MSE = \frac{1}{m}\sum_{j=1}^{m} \left(v_j - \hat{v}_j\right)^2 \tag{7}$$

Where $m$the number of data points is$j$,$v_j$is the data-point actual compressive strength$j$, $\hat{v}_j$is the data-point predicted compressive strength$j$.

This measure, which is comparable to MSE, assesses the accuracy of a prediction model. Because RMSE is expressed in the same unit as the objective variable, it offers a more understandable assessment of the model's performance. It is the square root of MSE. When compared to the existing methods ANN (3.41), SVR (3.73), and GPR (3.43), the proposed EHBMO-DANN method indicates a lower error rate (2.78).

$$RMSE = \sqrt{\frac{1}{m}\sum_{j=1}^{m} \left(v_j - \hat{v}_j\right)^2} \tag{8}$$

In the regression model, the goodness of fit is assessed using a statistic called the coefficient of determination. It provides an indication of how well the particles explain the variation in the CS.Greater R^2 specifies that the strength levels in the experiment were quite close to the strength anticipated by the model. Table 9 denotes the outputs of MSE, RMSE, and R^2.

$$R^2 = 1 - \frac{\sum_{j=1}^{m} \left(v_j - \hat{v}_j\right)^2}{\sum_{j=1}^{m} \left(v_j - \hat{v}_j\right)^2} \tag{9}$$

It is verified by the analysis of these findings that the suggested EHBMO-DANN (0.87) model more precisely and effectively calculates the concrete's strength than SVR (0.79), ANN (0.83), and GPR (0.82). Figure 4 denotes the coefficient determination of the proposed and existing methods.

Table 9. Outputs of MSE, RMSE, and R^2.

Methods	R^2	RMSE (MPa)	MSE (MPa)
ANN (Paixao, R. et al., (2022))	0.83	3.41	2.78
SVR (Paixao, R.et al., (2022))	0.79	3.73	2.65
GPR (Paixao, R.et al., (2022))	0.82	3.43	1.75
EHBMO-DANN [Proposed]	0.87	2.78	1.68

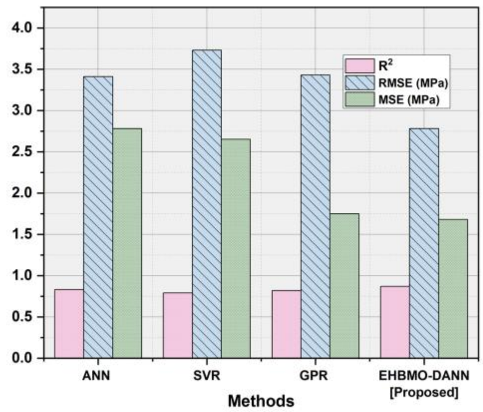

Figure 4. MSE, RMSE, and R^2 of the proposed and existing method

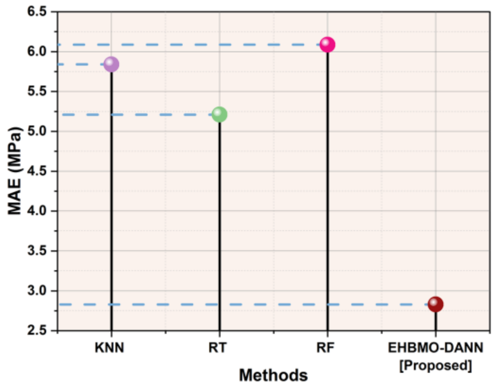

Figure 5. MAE of the proposed and existing methods

The Mean Absolute Error (MAE) is an additional metric commonly used to assess a prediction model's accuracy. The average percentage discrepancies among the actual and projected outcomes are taken into consideration. Figure 5 presents the MAE of the proposed reduced error rate (2.83) when compared to the existing and existing methods. Table 10 depicts the outputs of the MAE. The suggested EHBMO-DANN approach shows a Methods such as KNN (5.84), RF (6.08), and RT (5.21). The formula for MAE is:

$$MAE = \frac{1}{m}\sum_{j=1}^{m} \quad (v_j - \hat{v}_j) \tag{10}$$

Table 10. Outputs of the MAE.

Methods	MAE (MPa)
KNN (Hadzima-Nyarko, M., et al., (2020))	5.84
RT (Hadzima-Nyarko, M., et al., (2020))	5.21
RF (Hadzima-Nyarko, M., et al., (2020))	6.08
EHBMO-DANN [Proposed]	2.83

5. CONCLUSION

In conclusion, the investigation into the CS of pavement with ash particles provides valuable insights for the construction and engineering industry. In the context of forecasting, this research demonstrates how different ML approaches are reflected. It helps engineering researchers comprehend that running the model with correct expected outcomes is dependent on carefully choosing the input parameters. The EHBMO-DANN used in this study provides a significant correlation between the desired and anticipated outcomes. Higher levels of accuracy in the method demonstrate the value of its applications in the field of civil engineering, particularly in forecasting the

Strength qualities of concrete since it may take a long time to determine the concrete's strength in practice. Other approaches reveal higher values for comparable errors, although the errors' smaller values proposed method include MAE (3.69 MPa), MSE (24.76), and RMSE (4.97).To maximize ash particles' beneficial effects on pavement strength, further study may concentrate on optimizing their size, shape, and composition

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