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DEVELOPMENT OF STRENGTH PROPERTIES OF SELF-HEALING CONCRETE BY USING ARTIFICIAL INTELLIGENCE AND MACHINE LEARNING TECHNIQUES

B. Raghava Maheedhar[1], P. Sowkarthiga[2], C. Thirupathaiah[3], Dr. S. Senthamil Kumar[4], Kailas Sekhar Banerjee[5], Festus Olutoge[6]

[1]Research scholar, Department of Civil Engineering, Andhra University, Visakhapatnam, Andhra Pradesh, India-530003and Sr. Assistant Professor, Department of Civil Engineering, Aditya College of Engineering (A), Surampalem, Kakinada district, Andhra Pradesh, India-533437.

[2]Assistant Professor, Department of Computer Science and Engineering, Akshaya College of Engineering and Technology, Kinathukadavu, Coimbatore, Tamil Nadu, India.

[3]Assistant Professor Department of Mechanical Engineering, Annamacharya Institute of Technology and Sciences, Rajampet, Andhra Pradesh, India 516126

[4]Professor, Department of Civil Engineering, Periyar Maniammai Institute of Science and Technology, Vallam, Thanjavur, Tamil Nadu, India.

[5]Associate Professor, Department of Civil and Environmental Engineering, University of the West Indies, St. Augustine Campus, Trinidad and Tobago.

[6]Professor and Head, Department of Civil and Environmental Engineering, University of the West Indies, St. Augustine Campus, Trinidad and Tobago.

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Abstract: Bacterial-based self-mending concrete (BSHC) has been perceived for its exceptional break recuperating limit, however it is frequently exorbitant and tedious, restricting its application to lab settings. AI (ML) models offer an answer by foreseeing the mending execution (HP) of BSHC, consequently saving time and expenses related with lab tests, microscopic organisms' determination, and recuperating system reception. Ureolytic bacterial healing concrete (UBHC), aerobic bacterial healing concrete (ABHC), and nitrifying bacterial healing concrete (NBHC) are the three types of BSHC that are the subject of this investigation. Support vector regression, decision tree regression, deep neural network, gradient boosting regression, and random forest are the five ML algorithms used. These models employ 22 influencing factors as variables. A dataset of 797 BSHC tests from writing (2000-2021) approves the ML models. The grid search algorithm (GSA) is used for parameter tuning. The coefficient of determination (R2) and the root mean square error (RMSE) are used to evaluate the performance of the model. The GBR model exhibits unrivaled forecast capacity (R^2 = 0.956, RMSE = 6.756%) contrasted with different models. Awareness examination inside the GBR model further looks at the effect of factors on HP.

Keywords: machine learning-aided prediction; self-healing concrete; bacterial-based self-healing concrete; K-fold cross validation; autonomous healing concrete

1 . Introduction

Due to its low cost, high compressive strength, excellent workability, adaptability to environmental changes, and widespread use in construction, concrete is widely used. Nonetheless, concrete is inclined to break development, fundamentally because of biological impacts that outcome in low elasticity, which is just 10-15% of its compressive strength. Temperature vacillations and outrageous weather conditions can likewise prompt dampness changes and inside drying shrinkage in concrete. Most of the time, cracks smaller than 0.2 millimeters aren't too bad; however, larger cracks have a big impact on durability, and internal cracks are often hard to see during inspections. Manual fix of substantial breaks is trying because of natural effects and restricted functional space, making it expensive, frequently representing half of the development spending plan [2]. Self-healing concrete (SHC) has been proposed as an alternative to manual repairs to cut down on costs and increase efficiency. SHC can naturally fix breaks, upgrading strength and decreasing ecological effect. Autogenous healing concrete and agent-based healing concrete are the two types of SHC. Autogenous mending happens through the continuous hydration of unhydrated concrete particles and the carbonation of calcium hydroxide, however it is viable just for breaks less than 300 µm. Specialist based mending, thought about cutting edge innovation, can fix laughs uncontrollably to 970 µm utilizing different recuperating specialists. Core materials like bacteria, polymers, and expanded materials—all of which have distinct healing mechanisms—are included in these agents. This paper centers around bacterial-based self-recuperating concrete (BSHC), a promising specialist based mending strategy for upgrading substantial solidness [2].

Artificial intelligence is a type of machine learning. The point of ML is to get the free expectation capacity by gaining from input informational indexes. Using a variety of ML algorithms, the HP of BSHC is predicted in this paper. The HP prediction of BSHC has been studied by two researchers. ML models were used to predict the percentage of non-ureolytic bacterial healing concrete with crack closure in their study. Measurements of microorganisms, the underlying breaking width and the mending time were considered as the contributions of ML models [3]. In addition, an algorithm that combined genetic and ANN algorithms was used to predict the HP of agent-based healing concrete with a lightweight aggregate (LWA). The inputs were the initial cracking width, the healing time, the weight of the LWA, and the LWA with bacteria. It is fundamental to consider more factors affecting the HP of BSHC because of the intricacy of the mending instruments. Using ML models and five different kinds of algorithms, this paper first proposes complete variables—22 influencing factors—for predicting the HP of BSHC. 797 sets of BSHC are gathered, with the 22 influencing factors serving as inputs and the HP serving as the singular output. The five types of ML models' parameters are then adjusted using the hyperparameter optimisation technique GSA. After that, the ML models are trained with five algorithms to get the R2 and RMSE, which can show how well the models can predict. The R2 and RMSE are then used to determine the best ML model for predicting BSHC's HP. Besides, the The best ML model's ability to predict is checked using a 10-fold cross validation method. The optimal ML model is also subjected to a sensitivity analysis to determine the primary influencing variables [4].

2. Materials and Methods

2.1. Machine Learning Algorithms

Five kinds of ML calculations, GBR, RF, DNN, DTR and SVR, have been widely produced for anticipating the mechanical properties of cement using experimental information. For instance, the 28-day compressive strength of concrete was predicted using ANN and MLR models. The ANN model acquired a R2 worth of 0.9226, which was decisively higher than that of the MLR model (R2MLR = 0.7456). Utilizing GBR models also demonstrated R2 values of 0.951 and 0.929 for predicting the compressive and splitting tensile strengths, respectively. The ability of the five types of ML models to predict the HP of BSHC is investigated in this paper. Here, a hyper-parameter tuning technique known as GSA is utilized to identify the ideal ML model parameters in order to achieve the highest level of prediction accuracy. GSA's ability to find the best hyper-parameter combination through thorough analysis is one of the reasons it is a dependable hyper-parameter tuning method [5].

2.2. Data Research

A sum of 797 informational indexes utilized for foreseeing the HP of BSHC were gathered from 14 articles distributed somewhere in the range of 2000 and 2021. As referenced in Segment 1, 22 factors affecting the HP of BSHC are utilized in this paper to prepare ML models with the five calculations. The amount of fine aggregate (FA), the amount of coarse aggregate (CA), the types of cement (TC), the amount of cement (CM), the water binder ratio (W/B), and the number of superplasticizers (S) are the six variables used to describe the factors that influence cementitious materials and water contents. Moreover, the eleven factors corelated with microorganisms are the kinds of transporters (C), sorts of microscopic organisms (B), doses of microbes (DB), sorts of BSHC (TBSHC), sorts of calcium particles sources (TCIS), doses of calcium particles (DCI), sorts of carbon sources (TCS), measurements of carbon (DC), sorts of supplements (TN), doses of supplements (DN) and doses of urea (DU). The concrete mass-to-weight ratio is a representation of all variables. In addition, the variables that pertain to the healing environment are the initial cracking date (CD), the initial cracking width (CW), the healing time (HT), the healing condition (HC), and the healing test methods (HTM). Last but not least, the unique output of self-healing efficiency is healing performance (HP) [6].

2.3. Data Intense

The training and testing sets of the data used in this study are randomly divided at a ratio of 8:2 each. The information in the preparation set (80%) are applied to tune the ML models. In addition, 20% of the data in the testing set are used to evaluate the ML models' generalizability; in other words, the testing data set is considered a new data set that can be used with the ML models following the training process [7].

2.4. Estimate Ability Calculation

The coefficient of determination (R2) and the root mean square error (RMSE) are used to evaluate the ML models' ability to predict the HP of BSHC using five different algorithms. The arithmetic root of the mean square error (MSE), also known as the standard error, is the RMSE. The RMSE is sensitive to prediction value extreme errors. As a result, the RMSE can accurately reflect the prediction accuracy [8].

3. Results

Prophecy Capability of ML Models

The forecast capacity (R2 and RMSE values) of the preparation and testing informational indexes by the five sorts of ML models exhibiting the connection between the anticipated and trial HP of BSHC. The ML models' accuracy and prediction performance are evaluated using R2 and RMSE values. The level and vertical tomahawks show the exploratory and anticipated HP, individually. R2 is significantly higher in the GBR model than it is in the other four ML models. GBR has R2 values of 0.956 and RMSE values of 6.756%, respectively. Additionally, the DNN, DTR, RF, and SVR R2 and RMSE values are lower than those of the GBR model at (0.870, 14.145%), (0.882, 12.766%), (0.899, 11.760%), and (0.871, 13.352%), respectively. The following can be concluded based on the findings. Right off the bat, the GBR model is the ideal model for anticipating the HP of BSHC due to the most noteworthy R2 (0.956) and least RMSE (6.756%). Second, the GBR model is reliable because the training and testing sets' R2 results are the same, indicating that there is no underfitting or overfitting issue. Thirdly, the RMSE (6.756%) of the GBR model exhibits that the expectation deviation is low and powerful.

4. Discussion

The best prediction ability results and slight differences between the experimental and predicted HP define the best ML model for predicting the relationship between the 22 variables and the HP of BSHC, GBR. The justification for why the GBR model has a preferred expectation capacity over different models can be finished up as follows. ML models with the GBR calculation, named as gathering ML models, have a brilliant relapse limit and an exceptional speculation capacity because of the applied supporting technique. Various loads are conveyed to feeble students created by the helping procedure as per the expectation capacity of powerless students. Specifically, weak learners who are better at prediction can get higher weights. When a strong learner is made up of all weak learners, the promising prediction ability of GBR models can be examined, whereas the other ML models have a lower prediction ability because they are individual algorithms [9].

4.1. K-Fold Cross Corroboration

K-overlap cross approval is a technique to approve the forecast capacity of the ideal GBR, ML model. Using 10-fold cross validation, the prediction capability of GBR is verified in this paper. The following is a description of the 10-fold cross validation method. First, there are ten sections for 797 data sets. The remaining data sets are used to validate the trained GBR models, while some of the data sets are used to train GBR models. Hence, the initial step is led multiple times with various preparation and testing informational index gatherings. Finally, by averaging the R2 and RMSE values of all GBR models, the prediction capability of the GBR model that has been confirmed by 10-fold cross validation can be generated. The forecast capacity (R2 and RMSE values) of the GBR models approved by various folds of the informational indexes. Slight contrasts in R2 and RMSE upsides of the GBR models can be taken note. For example, 0.947 is the greatest R2 worth of the GBR model at Crease 8, while 0.937 is the base R2 worth of the GBR model at Overlap 1. The remaining R2 values are held at or close to 0.944. Moreover, the RMSE esteem emphatically diminishes from 6.864% to 6.039% between Overlap 1 and Overlay 2, trailed by a slight development to 6.210% at Crease 3. Thusly, it keeps steady at 6.218% until Overlay 6. From Fold 7 to Fold 10, it then fluctuates between 6.067% and 6.218%. In addition, the typical R2 and RMSE values and the standard deviations (SDs) of the GBR models are recorded in Table 1. The GBR models with various folds of the data sets have average R2 values of 0.9438 and RMSE values of 6.2342%, respectively. Additionally, the R2 and RMSE standard deviations are 0.0029 and 0.2208, respectively, indicating that their coefficients of variation (COVs) are relatively low at 0.31 and 3.54 percent, respectively. It is possible to draw the conclusion that the GBR model's promising ability to predict the HP of BSHC is reliable in light of the R2, RMSE, and statistical results [10].

Table 1. R^2 and RMSE results of GBR models with the 10-fold cross validation.

		HP Prediction Ability
Folds	**R2**	**RMSE (%)**
Fold 1	0.935	6.86
Fold 2	0.942	6.03
Fold 3	0.941	6.20
Fold 4	0.943	6.21
Fold 5	0.946	6.22
Fold 6	0.947	6.22
Fold 7	0.945	6.06
Fold 8	0.948	6.20
Fold 9	0.947	6.08
Fold 10	0.945	6.21
Average	0.9439	6.234
SD	0.0028	0.220

4.2. Sensitivity Scrutiny

A type of interpretation based on machine learning is called sensitivity analysis (SA). In addition, it is a method of uncertainty analysis that examines the influence of variables on quantitative analysis output. In this paper, the ideal ML model for anticipating the HP of BSHC, GBR, is utilized for SA. The following is a definition of the main SA processes: First, the values of one variable are kept consistent with the experimental data that was collected at a time, while the other variables' mean values are kept constant. In this way, the new informational collections are applied to prepare the ideal ML model, GBR. The SAPs of the factors connected with cementitious materials and water, the recuperating climate and microorganisms. The greatest SAP is 8.50% of CW, while the base SAP is 0.06% of DU. It can be deduced that CW has a significant impact on BSHC's HP. Be that as it may, little impact of urea on the HP of BSHC is noticed. Compared to CW, the SAPs of FA, CM, W/B, HT, and DB are 8.44%, 8.21%, 7.92%, 7.45%, and 7.04%, respectively.

As a result, the SAP decreases dramatically between DB and C, going from 7.04 percent to 5.46 percent. Then, the SAP encounters a progressive drop from 5.10% to 3.99% among B and S. The SAPs of C, TC, DN, TN, TBSHC, TCIS and TCS are 5.10%, 4.86%, 4.30%, 4.11%, 4.05%, 4.05% and 4.05%, separately. Furthermore, the other factors show a moderately lower impact on HP, i.e., 3.06%, 2.83%, 2.75%, 2.12%, 1.52% and 0.13% for CA, Cd, DCI, HTM, HC and DC, separately. As to the SAP results, the accompanying angles can be closed. First and foremost, the majority of the factors connected with cementitious materials and water, like FA, CM and W/B, show a more grounded effect on the HP of BHSC than that of the factors connected with microbes. This is because the concrete has less water and retains more unreacted cement particles for healing cracks. Additionally, because more FA can result in an increased water demand, concrete with high FA has a lower HP than concrete with low FA. It is possible to draw the conclusion that the variables related to bacteria have more of an impact on the HP of BSHC than the water contents do. Second, the healing environment-related variables, such as CW, HT, and CD, were recognized as significant HP influencing factors. Be that as it may, there was no report to show the affecting levels of the variables. This study reveals that HT's SAP is 7.45 percent lower than CWs, or 12.35 percent lower. Additionally, CW's SAP is greater than three times that of CD. Thirdly, DB has a greater impact on the HP of BSHC than any other variable on the bacteria-related variables.

5. Conclusions

In this paper, five sorts of AI (ML) models were proposed to foresee the mending execution (HP) of bacterial-based self-recuperating concrete (BSHC). The grid search algorithm (GSA) was used to optimize hyper-parameter tuning in these models, which aimed to model the non-linear relationship between HP and its 22 influencing variables. The ML models were trained on 797 data sets that were obtained through extensive experiments with various variable combinations. The following conclusions can be drawn from the results:

- The Inclination Helping Relapse (GBR) model showed the best exhibition with a R^2 worth of 0.956 and a Root Mean Square Blunder (RMSE) of 6.756%, demonstrating superb expectation precision and low deviation. When contrasted with other ML calculations like Choice Tree Relapse (DTR), Backing Vector Relapse (SVR), Profound Brain Organization (DNN), and Arbitrary Backwoods (RF), the GBR model showed predominant execution, pursuing it the ideal decision for precisely anticipating the HP of BSHC with the 22 factors.

- The robust prediction capability of the GBR model was confirmed by the results of the 10-fold cross-validation, which revealed average R2 and RMSE values of 6.2342 percent and 0.9438 percent, respectively.
- The impact of every variable on the HP of BSHC was examined utilizing the GBR model. The initial cracking width (CW), the quantity of fine aggregate (FA), the quantity of cement (CM), the water binder ratio (W/B), the healing time (HT), and the dosages of bacteria (DB) were found to be significant factors that influence HP. In ML-aided self-healing concrete design, these variables are crucial and should not be overlooked.

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