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Artificial Intelligence and Machine Learning Techniques to Predict the Compressive Strength of Concrete at High Temperature

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Abstract: The nature of the components used to make concrete is significantly impacted by high temperatures, which in turn lessens the concrete's strength qualities. Increasing the concrete's compressive strength to the optimum level takes effort and time. However, the use of supervised machine learning (ML) techniques enables the first, very accurate prediction of the desired result. This study uses 207 data points to anticipate the compressive strength of concrete at high temperatures using a decision tree (DT), an artificial neural network (ANN), bagging, and gradient boosting (GB). The chosen models were run using Anaconda navigator programme and Python code. Both information about the input variables and the output parameter are needed by the programme. One output parameter (compressive strength) was chosen out of a total of nine input parameters (water, cement, coarse aggregate, fine aggregate, fly ash, superplasticizers, silica fume, nano silica, and temperature). Statistics such as the coefficient correlation (R2), mean absolute error (MAE), mean square error (MSE), and root mean square error (RMSE) were used to assess the effectiveness of the deployed ML algorithms. R^2 for individual models using DT and ANN was 0.83 and 0.82, respectively, but R^2 for models using the ensemble approach and gradient boosting was 0.90 and 0.88. This shows a significant link between the actual and expected results. Ensemble methods performed worse than the k-fold cross-validation, coefficient correlation (R^2), and fewer errors (MAE, MSE, and RMSE). Sensitivity studies were also performed to see how each input variable contributed to the results. It has been established that employing the ensemble machine learning method would raise the model's level of performance.

Keywords: concrete; compressive strength; high temperature; prediction; decision tree; bagging; gradient boosting

1. Introduction

Concrete technology is always being updated and improved since it is very inexpensive compared to other building materials and is frequently employed in engineering constructions throughout the globe [1]. Concrete is in great demand due to urbanization's quick and technologically sophisticated growth [2], as it has several desirable qualities such compressive strength, shape-ability, and environmental resistance [3]. The benefits of concrete are also listed as include porosity, impact resistance, fire resistance, durability, and acoustic insulation [4]. Due of its many advantages, it may be used to build infrastructure, including dams, tunnels, bridges, and reservoirs [5]. The economical factor is greatly influenced by the local availability of materials such water, binding material, coarse aggregate, and fine aggregate [6]. Compared to concrete, other construction materials like steel have many more qualities but are not as affordable. However, the techniques of adding additional materials, such as fly ash, silica fume, other cementitious material, and other fibres, are frequently used to create concrete a more favourable material with enhanced qualities [7-9]. In order to reduce environmental concerns and the price of the material, using waste materials in concrete is essential [10].

Concrete's characteristics are significantly impacted by heat and fire in both the fresh and hardened stages [11]. Chimneys, chemical factories, and buildings used in the atomic industry are a few examples of structures or structural components that are subjected to extreme temperatures. Additionally, it is difficult to cast and cure concrete in hot environments, and at high temperatures, concrete loses its mechanical qualities (compressive and flexural strength), which eventually reduces its durability [12]. Due to the rise in fire-related events, research into developing novel materials and techniques for defending against high temperatures has become increasingly important [13,14]. In addition to degrading cement composites, the action of fire is regarded as a high frequency calamity that contributes to the material's spalling [15,16].

According to the research [17], one of the important variables affecting the safety of utilising structures is a structure's ability to withstand the impact of high temperatures brought on by a fire. More study is necessary for this problem. Concrete is a material that is frequently used and is regarded as one of the greatest materials for preventing high temperatures. A prolonged exposure to heat can cause the components of concrete to dissolve (during the stages of the hydration of C-S-H and Ca(OH)2, and at the stage of the creation of calcium aluminate gels). The physicochemical characteristics of concrete may deteriorate as a result. Therefore, researchers focus on examining how increased temperature affects the mechanical characteristics of hardened concrete. When cooled in various environments (air and water), the variations in the flexural and compressive strength of both regular and high-performance concrete have also been studied [20]. The increased porosity of the cement matrix and a decline in strength characteristics cause the breakdown reaction in cement composite material (concrete). When the cement matrix is subjected to high temperatures of around 600 to 700 C, calcium hydro silicate residues may be seen there [21].

Regarding the effects of high temperature, the performance of various types of concrete, such as lightweight concrete, has also been examined [22]. The mechanical characteristics of concrete heated to temperatures of up to 800 C [23–25] or greater [26–28] have been the subject of much investigation. It has been demonstrated that the qualities of concrete, which also involve various energy projects, are significantly affected by the change in natural temperature (which relies on the climate zone).

Despite being a largely non-combustible substance, concrete's chemical, physical, and mechanical characteristics are immediately impacted by high temperatures [31]. The spilling, perforation, and cracking of concrete are brought on by thermal stresses, decomposition, and dehydration [32]. Additionally, at high temperatures, the strength characteristics of the components of concrete are diminished. For cement paste to function properly inside the concrete matrix, a defined temperature range is needed. The strength of concrete is not favourably impacted by cement paste at high temperatures. This is particularly true for high-strength concrete since it needs a normal temperature to get the necessary strength [33].

The heating rate, temperature, or circumstances of the structural elements, i.e., the application, are just a few of the causes of concrete failure due to fire. Since the aggregate, hydrated cement paste, and interfacial transition zone all undergo microstructural changes when concrete is exposed to high temperatures, it is often challenging to analyse the direct impact of high temperatures on concrete. Previous research has shown that input parameters and output outcomes are directly correlated. The beneficial element of these strategies is that supervised machine learning methods may also take the impact of temperature change into account. When taking into account the parameter of temperature change, ML algorithms perform better and with less variation. The number of parameters and the set of data used to build the model are two factors that affect how well ML techniques function. The innovative feature of the authors' study strategy is the addition of a second parameter (the temperature impact) for forecasting concrete strength. This study looked at the ML techniques and how they compared in terms of performance. In order to investigate how well the chosen ML techniques performed in predicting the compressive strength of concrete, this study incorporated the temperature impact as an input parameter.

2. Research Significance

This study used both individual and group machine learning algorithms to predict the compressive strength of concrete subjected to high temperatures. The bagging regressor and gradient boosting regressor were employed as ensemble machine learning algorithms, along with the decision tree (DT) and artificial neural network (ANN) as a system. This study is interesting in that it examines the degree to which individual and ensemble machine learning algorithms are accurate, as well as in that it rates how well each method predicts the compressive strength of concrete at high temperatures. Additionally, statistical markers that are utilised to assess the model's correctness are contrasted in this study. This study demonstrates that when compared to individual machine learning approaches, ensemble algorithms produced a strong association. Additionally, the k-fold cross-validation approach and statistical tests were used to assess the validity and accuracy of all the used models. The importance of the temperature parameter to the prediction of compressive strength is shown through sensitivity analysis, though. The comparison of the applied machine learning methodologies with the methods used in the literature is another goal of this study.

3. Methodology

3.1. Supervised Machine Learning (ML) Techniques

In civil engineering, machine learning techniques are used increasingly frequently to forecast the mechanical characteristics of concrete. Examples of their use are provided in Table 1. For concrete samples of varied ages, the hit and try method can be used to measure the compressive or flexural strength. We employed machine learning methods to predict results for input data in order to get around some limitations in this strategy. Support vector machine (SVM) and k-fold crossvalidation were used by Hao et al. to forecast the compressive strength of concrete in a maritime environment. They claimed that the SVM outperforms the artificial neural network (ANN) and decision tree (DT) in terms of performance. Using a backpropagation artificial neural network (BP-ANN), Chengyeo et al. predicted the compressive strength of concrete in a wet-dry condition. It has been demonstrated that the BP-ANN offers more accuracy for both the actual and anticipated results. In order to forecast the compressive strength of concrete with limestone filler, Hocine et al. used the ANN model. Their data's training, testing, and validation yield a good correlation (over 97%) with the actual data. To forecast the compressive strength of concrete, Behfernia et al. employed the ANN and adaptive neuro-based fuzzy inference (ANFIS). The ANN model was shown to be an effective tool for forecasting the compressive strength of concrete. Effective machine learning models were used by Hoang et al. sto forecast the strength of concrete. They claimed that when compared to the support vector regressor and multilayer perceptron (MLR), the trained models of the gradient boosting regressor (GBR) and extreme gradient boosting (XGBoost) performed better.

3.2. Description of the Obtained Data

The Appendix A contains the data points that were used to run the machine learning algorithms on the models [20]. The information from the published article describes how concrete behaves in a heated environment. Cement, water, fine and coarse aggregates, fly ash, superplasticizer, nano silica, silica fume, and temperature were used as the input factors, while compressive strength was taken as the output parameter. These settings were used in the Jupiter Python software to display the relative frequency distributions of these parameters graphically, as seen in Figure 1.

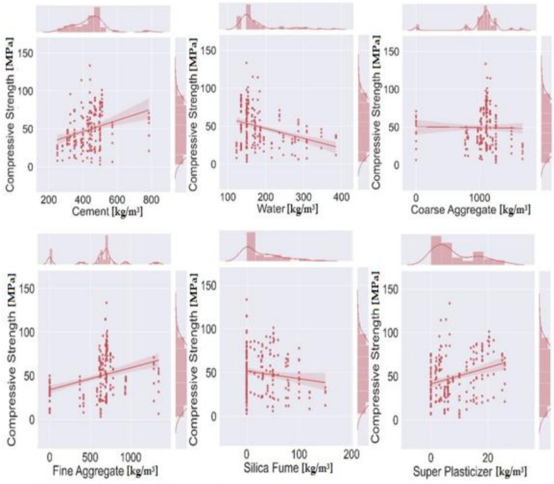

Figure 1. Contour plots showing the relative distribution of the parameters.

3.3. Machine Learning Approaches

The many methods that are employed to forecast the compressive strength of concrete at high temperatures are described in this section. Both ensemble and individual algorithms were used to predict the concrete's strength attribute (compressive strength). The models were performed using gradient boosting, bagging, and decision tree approaches. All three of the machine learning techniques that were used made use of Python coding in Anaconda software.

A supervised machine learning method called a decision tree is employed for both the distribution of regression problems and the categorization of issues. The decision tree's structure, which consists of nodes, branches, and roots, is similar to a flowchart. The core node displays a test on an attribute; each branch displays the results, and each leaf node indicates the class tag. The route taken from the root to the leaf serves as a representation of the categorization rule. There are three main types of decision tree nodes that come in triangular, square, and circular forms. In general, it may be considered a straightforward method for comprehending and interpreting. The organisation of bagging in a way that can increase the stability and accuracy of the machine learning algorithms used in regression and classification is known as bootstrap aggregating or bagging. It is often applied to lessen the differences between actual and expected results. Although bagging may be used with any sort of method, it is most frequently used with decision tree approaches. It is also regarded as one of the model averaging technique's special situations. Bagging is a parallel ensemble machine learning method that, by including supplemental data during the training phase, explains the variance of predicted models. In the new dataset, each element has an equal probability of showing up.

The widespread consensus is that one of the effective methods for developing predictive models is gradient boosting. It is an ensemble machine learning approach that is frequently used for classification and regression issues. It creates a projected model out of a collection of weak predicted models, often a decision tree. The resultant technique is therefore referred to as a gradient boosting tree when the decision tree outputs the result as a weak learner. The field of learning to rank can also benefit from the use of gradient boosting. It is also employed in data processing for high energy physics. The artificial neural network (ANN) algorithm has a network of neurons that resembles the brain. The ANN, which serves as a model of the human brain, is simply a collection of interconnected units or nodes (sometimes referred to as artificial neurons). These neural networks pick up information by analysing examples. They create probability-weighted associations between the input and result and are kept within the data structure of the net itself. They contain a known "input" and "result" Today, there is a lot of interest in using ANNs in the field of civil engineering, particularly to forecast the mechanical characteristics of concrete. This is because it can anticipate concrete's real strength values with a high degree of precision.

4. Result and Analysis

4.1. Statistical Analysis

Figure 2 displays the statistical findings for the actual and anticipated compressive strengths of concrete achieved at high temperatures (using supervised machine learning methods), as well as their error distribution. The correlation coefficient (R^2) value and the model's accuracy degree of performance were compared. As shown in Figure 3a, the DT (individual algorithm) model looked to be superior, with an R2 value of 0.83. Figure 3b depicts the error distribution of the model. At a level of 14.5 MPa and 101.4 MPa, respectively, the minimum and maximum error values of the DT model were identified. The errors had an average value of 51.2 MPa. However, only 7.1% of the data revealed errors over 100 MPa, as shown in Figure 3b, with 50% of the errors data falling between 30 and 70 MPa.

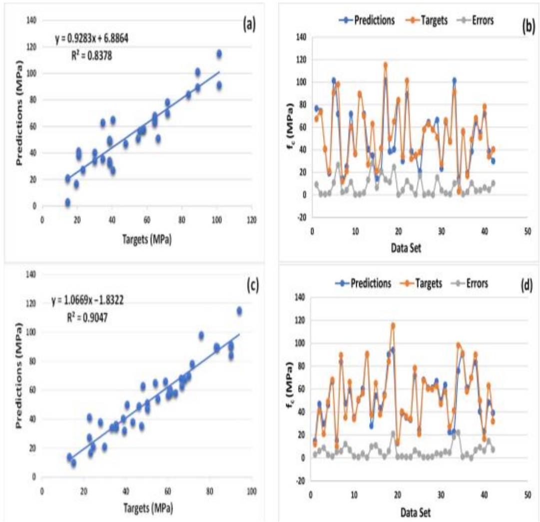

Figure 2. Numerical analysis results showing the relationship between the actual and predicted results, including the error distribution of models

The bagging (ensemble algorithm) model's prediction capability shows a significant correlation with the actual results. The bagging regressor's example yielded the greatest R^2 value (0.90). In turn, 0.82, 0.83, and 0.88 were the corresponding values of R^2 for the ANN, DT, and GB. These findings show that the forecast was quite accurate. Figure 2c and Figure 2d provide the graphical depiction of the expected and observed findings for the compressive strength of concrete at high temperatures. When predicting the strength property of concrete at raised temperatures, the bagging regressor's maximum and minimum error values were equivalent to 94.1 and 12.95 MPa, respectively. Figure 2d demonstrates that 59.92% of the erroneous data were found between 30 and 70 MPa.

The prediction and actual results for the compressive strength of concrete at high temperatures show that the gradient boosting (ensemble ML method) model is more accurate. According to Figure 3e, gradient boosting performed almost as well as the bagging regressor (with smaller margin for the bagging regressor because the R^2 value was equivalent to 0.88). In Figure 3f, the error distribution is displayed. The gradient boosting regressor had a mean value of 50.76 MPa and a maximum and minimum error of 114.5 and 6 MPa, respectively. Additionally, for the regressor, only 4.76% of the erroneous values were above 100 MPa.

The ANN model likewise shows a greater performance when compared to the DT method, according to the same statistical outcome. The ANN model generated the R2 value of 0.82, as shown in Figure 3g, and suggested a strong relationship with a lower variation between the actual and anticipated outcome. Figure 3h displays the error distribution for the ANN model. The error's greatest and minimum values, which were 24.58 and 0.29 MPa, respectively, are shown by the distribution. The average value, however, was 9.158 MPa. Additionally, it was discovered that 57.14% of the incorrect data fell between 0 and 10 MPa and 19.04% of the data fell between 10 and 15 MPa.

4.2. k-Fold Cross Validation and Statistical Checks

We used the k-fold cross validation method to assess the model's real-world performance. This approach is typically used to examine how well models really function. The data were separated into 10 groups and randomly sorted for this test. One group was designated for model validation while the other eight were used for training purposes. By carrying out the same procedure ten times, the average value was determined. To get the models' most accurate performance, the 10-fold cross validation test was applied. Applying statistical checks was crucial in order to determine the model's performance level.

the introduction of the correlation coefficient (R^2), mean absolute error (MAE), mean square error (MSE), and root mean square error (RMSE) for assessing the k-fold cross validation. All of the applied machine learning (ML) methods (DT, ANN, bagging, and gradient boosting) underwent validation. In comparison to the ANN, DT, and GB, the bagging model's modest levels of errors and concurrently increasing value of the correlation coefficient (R^2) suggested a higher degree of accuracy. Table 3 includes the specifics of the analysis utilised for the k-fold cross validation procedure. Additionally, all machine learning algorithms were assessed using the statistical tests, including mean absolute error (MAE), mean square error (MSE), and root mean square error (RMSE). The correlation coefficient (R2) grew as the error's magnitude decreased. In comparison to the MAE values of the DT (7.54 MPa), ANN (9.15 MPa), and GB (6.93 MPa), the bagging regressor generated a value of MAE equal to 5.65 MPa. In a similar vein, the ANN's MSE and RMSE were greater than those of the DT, bagging, and GB, although its R2 value was lower than those of the other regressors.

Additionally, the statistical breakdown of the k-fold cross validation, including the correlation coefficient and errors. R^2 for the DT had an average value of 0.42 and a minimum and maximum value of 0.03 and 0.82, respectively. The bagging regressor had an average R^2 value of 0.44 and a minimum and maximum R^2 value of 0.03 and 0.77, respectively (Figure 4b). Similar to this, the gradient boosting had an average R^2 value of 0.54 and a lowest and highest value of 0.11 and 0.87, respectively. The average R^2 value for the ANN was 0.42, with maximum and minimum values of 0.84 and 0.037, respectively (Figure 2d). Figure 4a shows the average error values for the DT, which were 12.96, 269.79, and 15.26 MPa, respectively. Figure 4b shows the average error values for bagging, which were 13.64, 316.80, and 16.31 MPa, respectively. The similar pattern was seen for the GB regressor as well, which had an average MAE value of 13.79 MPa and MSE and RMSE values of 282.08 and 15.72 MPa, respectively (see Figure 2c). Additionally, the ANN model's average MAE, MSE, and RMSE values were 13.44, 258.98, and 15.28 MPa, respectively.

4.3. Sensitivity Analysis of the Compressive Strength of Concrete at High Temperatures

As indicated in Figure 3, sensitivity analysis was carried out to examine the variables that have a major impact on the prediction of the compressive strength of concrete at high temperatures. The model's ability to forecast the strength of concrete depends on every variable that was used to run it. Cement, however, has the greatest impact on the strength of concrete predictions. Its impact on the outcomes was assessed to be 32%. The effects of fly ash, superplasticizers, silica fume, water, temperature, nano silica, fine aggregate, and coarse aggregate were each projected to have a respective impact of 16%, 15%, 14%, 2%, 6%, 3%, 10%, and 2%. The number of input parameters and the number of data points used to run the model affect the outcome of the sensitivity analysis. The used ML technique, however, identifies the influence of each parameter. The various amounts of the concrete mix and the inclusion of additional input parameters cause the findings of these assessments to fluctuate.

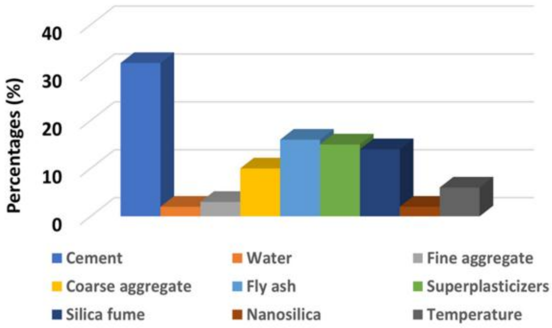

Figure 3. Bar chart indicating the performance of input parameters with regards to predicting of the compressive strength of concrete.

4.4. Discussion

In this study, the effectiveness of several models is compared to experimental data on the compressive strength of concrete subjected to high temperatures. For making predictions, supervised machine learning methods were combined (bagging, gradient boosting) and utilised alone (ANN, DT). In terms of prediction performance, the bagging regressor performed better than the ANN, DT, and GB. However, because the performance of the models is directly influenced by the input parameters and the data points used to train the model, it is challenging to analyse and suggest the optimal machine learning regressor for predicting outcomes for a variety of themes. The weak learner is typically used by ensemble machine learning approaches, though, since they create sub-models that may be trained on data and employ optimisation to get the highest possible R^2 value. Figure 3 displays the results of the 20 sub-models of the bagging and GB regressor along with their correlation coefficient (R^2) values. As a result, when compared to individual machine learning techniques, ensemble models perform better, according to the research. Previous research has demonstrated that ensemble ML techniques like bagging, boosting, and AdaBoost perform better in outcome prediction.

Additionally, it's critical to understand how well each metric performs in terms of prognostication. The sensitivity analysis gives details on how each parameter affects the ability to anticipate results. The outcome of the sensitivity analysis for this study. In addition, statistical checks, the validation procedure, and sensitivity analysis were used in this work to confirm the degree of execution of the assessed ML approaches. When it comes to cutting expenses and shortening the time needed to achieve the necessary strength of concrete using the hit-and-trial approach, this research may be helpful. The study's findings can also be used to other branches of engineering to forecast desired results.

5. Conclusions and Future Recommendations

This study offers details on supervised machine learning algorithms used individually and collectively to estimate the compressive strength of concrete at high temperatures. When compared to the actual outcome, the use of ML approaches for concrete performance prediction demonstrates a high degree of accuracy, making it a very useful strategy. The average period required to assess the strength of concrete is 28 days. In consequence, ML algorithms contribute significantly to shortening this period of time and also significantly reduce the expenses and labour necessary to carry out experimental work. The decision tree (DT) and artificial neural network (ANN) algorithms were chosen from among the individual approaches in this study, whilst the bagging and gradient boosting (GB) regressors were applied as ensemble algorithms to predict the strength of concrete at high temperatures. The most efficient method and one with the highest correlation coefficient value was bagging. Indicators of its superior performance over ANN, DT, and GB included lower values of the errors (MAE of 5.65 MPa, MSE of 61.08 MPa, and RMSE of 7.81) from the statistical tests for bagging. It is practically difficult to determine the impact of temperature on the mechanical characteristics of concrete made with different types of mixtures. To run the models and get the desired output, the temperature and other associated factors, such humidity, can also be provided as input parameters. From this research, the following findings may be made: Both at normal and high temperatures, the ensemble methods (bagging and GB) did well at estimating the compressive strength of concrete.

- Input parameters may have an impact on a model's performance. We discovered that the ensemble models exhibited less disparity between actual and anticipated results when the thermal aspect—the paper's primary consideration—was taken into account.
- The k-fold cross validation procedure was also used to check the accuracy level of the bagging and GB regressors.
- Sensitivity analysis was used to see how each parameter contributed to forecasting the outcome
- This paper outlines the beneficial effects of supervised machine learning techniques in the discipline of civil engineering. Without spending much effort on laboratory experiments, these strategies may be effectively used to forecast the mechanical characteristics of concrete. Additionally, it was shown that, when compared to individual algorithms, the ensemble machine learning algorithms show a good correlation between actual and predicted results.
  - Increasing the amount of data points can also help models attain high accuracy, as the quantity of data points has a significant impact on the model's output.
  - In order to understand the amount of variation between the actual and predicted results, the performance of the models may also be assessed using practical work done in a laboratory.
  - In the ensemble approaches, breaking the model into more than 20 sub-models for data-driven training and optimisation would result in the highest R^2 value.

It should be noted that while various approaches (such the AdaBoost Regressor) can be used to anticipate results so that comparisons can be made, it is impossible to recommend or state about any methodology directly on a few trails that would produce the best accurate result.

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