Prediction of Concrete Compressive Strength Using Artificial Intelligence Methods

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Abstract. Concrete is one of the most used materials in buildings today; yet, predicting the accurate concrete compressive strength remains challenging because of the highly complex relationship between its mixture. An accurate method of predicting concrete compressive strength can provide a significant advantage to the construction material industry, particularly within the concrete material industry. Many methods can be used to build the prediction model of concrete compressive strength. However, the traditional methods have so many shortcomings, including expensive experimental costs and the inability to formulate an accurate complex relationship between the components of a concrete mixture with the compressive strength. To overcome this issue, this study applies multiple artificial intelligence (AI) methods to find the most accurate input and output relationships within concrete mixtures. The three types of AI methods that will be used in this study are artificial neural networks (ANN), support vector machine (SVM), and linear regression (LR). This study uses 1030 data samples from concrete compressive strength tests obtained from University of California, Irvine, to demonstrate the use of AI prediction models. The obtained results of the simulation show that these artificial intelligence methods can build predictive models without conducting any expensive experiments in the laboratory with good accuracy.

Keywords: artificial intelligence, artificial neural network, concrete compressive strength, prediction, support vector machine

1. Introduction
Concrete material in recent years has become the most used material in buildings because it has proven to be able to show stable high strength characteristics. In addition to the four basic ingredients of conventional concrete, namely cement, coarse aggregate, fine aggregate, and water, a number of other cement composition materials have been used, such as fly ash, blast furnace slag, and chemical mixtures such as superplasticizer [1]. The use of additional cement composition materials also produces economic benefits because Portland cement is the most expensive component of concrete mixtures. On the other hand, the use of additives in concrete is popular because it can increase the workability, durability, and strength of the concrete. These new additions to the concrete mixture introduce new dimensions to the modeling of the concrete compressive strength, which results in increased complexity. However, traditional modeling methods that are usually used to predict concrete behavior are less able to produce accurate prediction results.

Generally, strength tests are carried out 7–28 days after the concrete casting process. The 28-day waiting period required to carry out such tests can cause the next construction process to be slightly delayed [2-3]. However, ignoring testing will limit the quality control on a large and complicated construction scale. Therefore, fast and reliable predictability of concrete compressive strength is very important for quality control, even in the early design stages [4]. If adjusting the proportion of the
mixture can be done immediately when the strength of the concrete is not compatible with the specifications, there will be savings in terms of time and construction costs. The early prediction of concrete strength is extremely important in estimating the time needed to open the concrete formwork, project scheduling, and quality control [4].

Because the relationship between components and the character of concrete is nonlinear, the modeling using a mathematical approach becomes very complicated. The empirical equation presented in the current standard code for estimating compressive strength is based on testing concrete without additional cement composition material. Understanding the relationship between the concrete composition and its strength is very important for optimizing a concrete mixture [5-6]. Significant amounts of research have done by using experimental tests that usually require a lot of time and money. For this reason, a new modeling system is needed that is not dependent on experimentation but still can predict the concrete compressive strength with good accuracy.

Recently, artificial intelligence (AI) methods are increasingly being used in solving classification and regression problems because AI methods have proven to be more accurate than conventional methods [7-12]. This research develops AI techniques to accurately predict the concrete compressive strength from various components. Experimental data were taken from a machine learning repository held at the University of California, Irvine (UCI), that was collected by Yeh [1] to predict the compressive strength at HPC. AI modeling is carried out in Clementine 12.0 using three predictive techniques, namely artificial neural networks (ANN), support vector machines (SVM), and linear regression (LR). This study uses two model construction, namely single model and ensemble model. In ensemble models, a combination of classifiers can compensate for errors made by the individual classifiers on different parts of the input space. The strategy used in ensemble systems is to create many classifiers and combine their outputs such that the combination improves upon the performance of single classifiers in isolation.

2. Artificial Intelligence Methods

2.1 Artificial Neural Network (ANN)

ANN is a computational model that tries to simulate the structure and functional aspects of biological neural networks. Various ANN applications can be categorized as classification models or regression models. The use of ANN specifically to predict the compressive strength of concrete has been intensively studied [1, 6]. The researchers also explored the use of ANN to build concrete compressive strength models that were more accurate than the regression model. The most used ANN model is the multilayer perceptron (MLP) model. In the MLP model, the input layer contains a set of sensory input nodes, one or more hidden layers that functionate to compute, and the output layer contains one computational node that represents the concrete compressive strength. The most commonly used and effective learning algorithm for training the MLP model is a back-propagation (BP) algorithm. The activation process of each neuron can be seen in Equations (1) and (2).

\[
net_k = \sum w_{kj}o_j
\]

\[
y_k = f(\text{net}_k)
\]

Where \( net_k \) is the activation of neurons to \( k \), \( j \) is the set of neurons in the previous layer. \( w_{kj} \) is the weight of the connection between neurons \( k \) and neurons \( j \). \( o_j \) is the output of neurons \( j \), and \( y_k \) represents the output that is usually calculated in sigmoid and logistical transfer functions. Illustration of ANN structure can be seen through Figure 1.
2.2 Support Vector Machine (SVM)

SVM was first introduced by Vapnik (1995) [13]. SVM has been used in many civil engineering applications, and in recent years, it has often been used to predict concrete compressive strength [14-16]. In this study, support vector regression (ε-SVR), which is a variation of SVM, is used to build an input-output model from concrete. SVM uses an objective function that allows the function estimation process to occur, as illustrated in Figure 2. When nonlinear space occurs, the kernel radial-based function (RBF) is selected as a kernel function in SVM because it can provide better results than the other kernels.

![Figure 1. Illustration of ANN structure.](image1)

The following model underlies the functional relationship between one or more independent variables with the response variable:

$$y(x) = w^T \phi(x) + b$$  \hspace{1cm} (3)

where \( x \in \mathbb{R} \), \( y \in \mathbb{R} \), and \( \phi(x) \): \( \mathbb{R}^n \) is the process of mapping to higher dimensional feature space.

In SVM for regression analysis, a data set of \( \{X_k, Y_k\}_{k=1}^N \), objective functions can be formulated as follows:

$$\text{Min. } J_p (w,e) = \frac{1}{2} w^T w \phi + c \sum_{k=1}^N e_k^2$$  \hspace{1cm} (4)

$$\text{s.t } y_k = w^T \phi(x) + b + e_k, \ k = 1, \ldots, N$$  \hspace{1cm} (5)

where \( e_k \in \mathbb{R} \) is the error variable; \( c \) indicates the regularization constant.

2.3 Linear Regression (LR)

LR, an extension of the simple regression model, determines the relationship between a numerical response variable and two or more explanatory variables [17]. It is used for the modeling mechanical properties of construction materials. This study investigated the applicability of LR. The computational problem addressed by LR is fitting a hyperplane to an \( n \)-dimensional space where \( n \) is
the number of independent variables. For a system with n inputs (or independent variables), X’s, and one output (or dependent variable), Y, the general least square problem is to determine unknown parameters of the linear regression model as illustrated in Figure 3.

![Figure 3. Illustration of linear regression.](image)

The general formula for LR models is shown in Equation 6.

\[ Y = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \ldots + \beta_n X_n + \varepsilon \]  

(6)

In the proposed model, \(\beta_i\) is a regression coefficient \((i = 1,2,3,\ldots,n)\), \(X\)’s values represent concrete attributes, \(\varepsilon\) is an error term, and \(Y\) is concrete compressive strength. Regression analysis estimates the unbiased values of the regression coefficients \(\beta_i\) against the training data set.

3. Experimental Setting

Experimental data were obtained from a machine learning repository held at the University of California, Irvine (UCI) that was collected by Yeh [1]. A total of 1030 concrete samples evaluated by various university research laboratories were used to test the prediction models of each AI method. All tests were carried out on a 15 cm cylindrical concrete specimen using standard procedures. Table 1 shows the experimental data set of nine HPC variables used in this study.

| Variables         | Unit       | Min   | Mean    | Max   | Standard deviation |
|-------------------|------------|-------|---------|-------|--------------------|
| X<sub>1</sub>: Cement | kg/m³      | 102.0 | 281.17  | 540.0 | 104.51             |
| X<sub>2</sub>: Blast-furnace slag | kg/m³    | 11.0  | 107.28  | 359.4 | 61.88              |
| X<sub>3</sub>: Fly ash       | kg/m³    | 24.5  | 83.86   | 200.1 | 39.99              |
| X<sub>4</sub>: Water        | kg/m³    | 121.8 | 181.57  | 247.0 | 24.35              |
| X<sub>5</sub>: Superplasticizer | kg/m³  | 1.7   | 8.49    | 32.2  | 4.04               |
| X<sub>6</sub>: Coarse aggregate | kg/m³  | 801.0 | 972.92  | 1,145.0 | 77.75         |
| X<sub>7</sub>: Fine aggregate | kg/m³   | 594.0 | 773.58  | 992.6 | 80.18              |
| X<sub>8</sub>: Age of testing | Day     | 1.0   | 45.66   | 365.0 | 63.17              |
| Y: HPC compressive strength | MPa     | 2.3   | 35.82   | 82.6  | 16.71              |

Table 2 shows the performance measurement model used to estimate the accuracy of each predictive method. This accuracy model is calculated based on how accurate it is between actual data and the predicted results of the output variable. These four performance measurement models include root mean square error (RMSE), mean absolute error (MAE), mean absolute percentage error (MAPE) and coefficient of correlation (R). RMSE measures the average deviation of each actual data point and the predicted results. MAE calculates the average error using the absolute difference from the actual data and the predicted results. The strength of the linear relationship between the two variables is
measured by $R$. Although it is similar to MAE which uses absolute difference in accuracy calculations, MAPE has the advantage that it is not affected by the unit and the size of the predicted and actual values, so that it can be more efficient in determining the relative differences between models. Here, the value of $R = -1$ represents a perfect negative correlation, while the value of $R = 1$ indicates a perfect positive correlation. The best model results are shown by the highest $R$ values, and the lowest RMSE, MAE, and MAPE values.

Table 2. Indicators of prediction model accuracy.

| Performance measurement          | Mathematical formula                                      |
|----------------------------------|----------------------------------------------------------|
| Correlation coefficient ($R$)    | $R = \frac{n \sum y \times y' - (\sum y)(\sum y')}{\sqrt{n(\sum y^2) - (\sum y)^2} \sqrt{n(\sum y'^2) - (\sum y')^2}}$ |
| Root mean squared error ($RMSE$) | $RMSE = \frac{1}{n} \sum_{i=1}^{n} (y - y')^2$            |
| Mean absolute percentage error ($MAPE$) | $MAPE = \frac{1}{n} \sum_{i=1}^{n} \left| \frac{y - y'}{y} \right|$ |
| Mean absolute error ($MAE$)      | $MAE = \frac{1}{n} \sum_{i=1}^{n} |y - y'|$           |

The AI model of the Clementine 12.0 software is used to form an accurate prediction model. Although this platform is relatively easy to use for the purposes of AI methods, a precise flow chart is still needed to form an accurate prediction model. The five steps of forming the AI model are described as follows.

1. Data input: This step is the first step where data collection will be taken.
2. Training and testing: Input data will be divided into 2 data groups, namely, training and testing. Training is used to create prediction models that fit the data while testing is used to test prediction models that are built. In this study, 70% of the data will be used for training, and 30% of the data will be used for testing.
3. The learning process of AI prediction models with training data.
4. The process of testing AI prediction models with data testing.
5. Prediction results: The four accuracy indicators will be used to measure the performance of the predicted results obtained for each model.

Figure 4 explains the flow diagram to building the AI prediction using a single model.

Figure 4. Flow diagram of the formation of AI prediction using a single model.
included ANN+SVM, ANN+LR, and SVM+LR. Ensemble of three different classifiers included ANN+SVM+LR. Figure 5 explains the flow diagram to build the AI prediction using ensembles model.

4. Experimental Results
This study compares the ability of two construction models, namely single models and ensemble models in predicting concrete compressive strength from 1030 concrete samples. Of the 1030 samples, 723 were used for training, and 307 were used for testing. ANN, SVM, and LR use the default parameters of Clementine 12.0. As described previously, R, RMSE, MAPE, and MAE are used to find out how accurate each prediction method is. The results of the analysis of the four indicators of each method of testing data can be seen in Table 3.

| Methods            | Testing Result |
|--------------------|----------------|
|                    | R  | RMSE (MPa) | MAPE (%) | MAE (MPa) |
| ANN                | 0.909 | 7.176       | 19.93     | 5.550      |
| SVM                | 0.779 | 10.914      | 32.59     | 8.687      |
| LR                 | 0.768 | 10.975      | 31.69     | 8.634      |
| ANN+SVM+LR         | 0.855 | 9.039       | 26.99     | 7.103      |
| ANN+SVM            | 0.883 | 8.360       | 25.29     | 6.622      |
| ANN+LR             | 0.876 | 8.319       | 24.35     | 6.504      |
| SVM+LR             | 0.774 | 10.862      | 32.32     | 8.607      |

From Table 3, it can be seen that ANN has succeeded in surpassing all existing methods in all four indicators of accuracy. ANN gets an R-value of 0.909, higher than the other methods and is close to 1. Meanwhile, ANN produces a lower error rate compared to all existing methods. ANN received 7.176 MPa, 19.93%, 5.550 MPa for RMSE, MAPE, and MAE, respectively. Meanwhile, other methods generate RMSE, MAPE, and MAE numbers that are far adrift with ANN. Furthermore, Figures 6 and 7 show the predicted results of the single model construction of ANN, SVM, and LR.
Figure 6. Comparison of prediction and actual results in testing data using (a) ANN method, and (b) SVM method.

Figure 7. Comparison of prediction and actual results in testing data using LR method.

Figures 8 and 9 show the predicted results of the ensemble model, namely ANN + SVM + LR, ANN + SVM, ANN + LR, and SVM + LR.

Figure 8. Comparison of prediction and actual results in testing data using ensemble method (a) ANN+SVM+LR and (b) ANN+SVM.
As seen in the figures above, if the prediction results get closer to the diagonal line, the prediction results can be said to have higher accuracy. From Figure 6 to Figure 9, it can be concluded that the ANN prediction results are more accurate than the other methods because the predicted results from each point of ANN are closer to the diagonal line. To support the results of this study, we compare it with the results of the previous study that has been done by Prof. Jui-Sheng Chou. Table 4 show the predicted results of the best individual and ensemble models research by Prof. Jui-Sheng Chou.

| Dataset            | Predictive technique  | MAE (MPa) | RMSE (MPa) | MAPE (%) |
|--------------------|-----------------------|-----------|------------|----------|
| Dataset 1 (Taiwan) | SVM                   | 3.75      | 5.59       | 12.03    |
|                    | CART+SVM+LR (stacking)| 3.52      | 5.08       | 11.97    |
| Dataset 2 (Chile)  | MLP                   | 4.00      | 5.40       | 6.81     |
|                    | CART (bagging)        | 3.82      | 5.13       | 6.50     |
| Dataset 3 (Hong Kong) | MLP+SVM+LR (stacking) | 4.70     | 6.02       | 11.75    |
| Dataset 4 (South Korea) | SVM                  | 1.31      | 1.73       | 2.95     |
|                    | CART+SVM+LR (stacking) | 1.09     | 1.51       | 2.11     |
| Dataset 5 (Iran)   | CART                  | 5.42      | 7.11       | 12.55    |
|                    | MLP+CART+LR (voting)  | 4.06      | 5.61       | 9.87     |

Specifically, the ensemble learning based models that performed the best, in terms of SI values, over the five datasets were stacking-based CART+SVM+LR for Datasets 1 and 4, bagging-based CART for Dataset 2, stacking-based MLP+SVM+LR for Dataset 3, and voting-based MLP+CART+LR for Dataset 5[17]. Based on the latest research this method has a good accuracy approaching the real results.

5. Conclusion

This study presents a comparative study between two construction models, namely the single model and ensemble models, in predicting the concrete compressive strength based on 1030 concrete samples. These samples were used to form a database that was used to create a prediction model as well as to test the accuracy of the prediction model formed. Four accuracy indicators are used in evaluating the performance of each method, including R, RMSE, MAPE, and MAE. Experiments were carried out using Clementine 12.0 software. The finding showed that ANN achieved the best accuracy...
for all performance measures because it can provide the most optimal performance when viewed from the four indicators. This research succeeded in proving that AI methods are able to predict concrete compressive strength without conducting experiments in the laboratory with good accuracy.

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