Estimating the flexural strength of concrete using compressive strength as input value in a deep learning model

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Abstract. The flexural strength is a critical parameter for designing many concrete structures such as rigid pavements, beams, and bridges. The standard test for concrete is the compressive strength due to its ease of implementation. There are many proposed methods for estimating flexural strength values with enough accuracy, although it is necessary to enhance the accuracy for this estimation, and this research suggests the use of artificial intelligence methods to accomplish this goal. Artificial Intelligence has been one of the most efficient approaches for estimating material parameters because of its efficient performance. This research presents the development of a data-driven Deep Neural Network for predicting the flexural strength in concrete based on just the compressive strength test. The proposed model analyses a concrete mixture with starch and a fluidizer. The model employs a Rectified Linear Unit function and a Sigmoid function in its architecture as activation functions and a considerable perceptron's number. Results from the analysis show an excellent accuracy of over 90%, which is remarkable. This approach showed satisfactory performance in flexural strength prediction for the analysed concrete mixture.

1. Introduction

Currently, there are plenty of methods to estimate the performance of concrete structures. One approach that appears from the numerical methods is artificial intelligence. Artificial intelligence can be defined as a computer's ability to solve a problem without being explicitly programmed for that task. It is known that concrete is the most traditional material used in construction because of its broad versatility. Also, this material can be malleable compared to other materials [1]. Hence, it is necessary to have alternatives to quantify the resistance of concrete elements efficiently, that is, to obtain the most suitable characterization in the least possible time.

There are many Machine Learning applications in the construction field as the prediction of the tensile strength just with measurements of electrical resistivity, as reported in [2], or the detection of damage in high structures detailed in [3].

The rupture modulus, also known as flexural strength, is an essential value used to determine the behaviour of concrete structures such as beams, bridges, and rigid pavements. Obtaining this value may sometimes be a difficult task because the amount of material needed to perform this test is considerable; is costly, time-consuming, and requires special testing equipment. In some countries such as Mexico, this test is omitted and replaced by the compressive strength test. Under this consideration, the constructors prefer the use of the following equation:
Where $k$ is a constant value that depends on concrete properties and is estimated arbitrarily in some cases, $C_s$ represents the compressive strength of concrete, and $F_s$ is the flexural strength. This paper proposes a deep neural network (DNN) model suitable to predict the flexural strength ($F_s$) of concrete specimens. These kinds of techniques are used in forecasting tasks, particularly in this material [4]. The compressive strength ($C_s$), for short, is used as an input parameter in this research, and the $F_s$ is the outcome or also known as the target value. The concrete mixture used for this study was analysed and characterized previously in a laboratory under controlled conditions. Before the modelling process, the laboratory results were examined, and we found the correlation between the features involved in this study. In order to determine the correlation between both input and target parameters, we use the determination coefficient $r$, also known as Pearson’s correlation factor. The details of the developed model along with the validation are provided in the following sections.

2. Research significance

This paper proposes the architecture of a DNN to predict the flexural strength value only with compressive strength as a predictive variable in concrete materials. Further, a unique architecture is proposed for achieving this aim where the fine-tuning of hyperparameters for the best performance of the neural network was tested by inspection. This paper generates a robust model with the potential to analyse different data and get an accuracy close to the initial model.

3. Methodology

3.1. Concrete Mixture

For this study, the concrete mixture analysed contains starch and a fluidizer as additives. The design water-cement rate was equal to 0.35, and the mixture design was following the ACI method [5]. The cement employed in this research corresponds to CPC 40 R, which according to the Mexican cement classification standards [6], is a composite Portland cement with a compressive strength resistance of 40 MPa. The materials employed in the concrete mixtures belong to a bank placed in Morelia, Michoacán, México. The aggregates were both crushed and volcanic. The compressive strength was the critical design parameter in the concrete mixtures. The mixture was monitored in different stages; 40, 60, 90, and 120 days. In Table 1, material properties for this study are shown.

| Type of aggregates | Properties                      | Crushed aggregates | Volcanic aggregates |
|--------------------|---------------------------------|--------------------|---------------------|
| Fine aggregates (Sand) | Percent Absorption | -                  | 2.75                |
|                     | Density (g/ml)                | -                  | 2.59                |
|                     | Apparent specific gravity(g/cm³) | -                  | 1.42                |
|                     | Percent Surface Moisture       | -                  | 0.19                |
|                     | Percent Mesh #200              | -                  | 5.45                |
| Coarse aggregates (Gravel) | Percent Absorption | 3.40               | -                   |
|                     | Density (g/ml)                | 2.80               | -                   |
|                     | Apparent specific gravity(g/cm³) | 1.51               | -                   |
|                     | Percent Surface Moisture       | 1.82               | -                   |

3.2. Data collection

First, 390 specimens were tested and monitored, 195 for $C_s$ and 195 for $T_s$. Nevertheless, we removed the outliers using the standard deviation criterium, which considers the Z-score value. After the cleaning data, the final dataset keeps 183 data for each group. By convention, we segmented the dataset into two groups: training and test, and 70% and 30%, were considered respectively. In this research, the
uncertainty of data is ignored because this assumption is commonly accepted in the literature and how is detailed in [7, 8].

3.3. Deep Neural network development

In the model, each layer is assigned with the value of a variable \( a_0, a_1, a_2, ..., a_n \). The term \( a \) comes from the word axion. The axions are stated for the number of layers contained in the neural network. Each vector is known as an activation vector and is equal in size to the number of neurons that make up the previous layer. Vector \( a_0 \) looks like:

\[
a_0 = \begin{pmatrix}
a_0(0) \\
a_0(1) \\
\vdots \\
a_0(n)
\end{pmatrix}
\]

The weights generated in each connection are indicated with the \( w \) variable. These match the values of the weights that define the input of a neuron. \( w \) is known as a matrix that extends to the order of the neuron's number between the layers it is detected. This definition can be generalized by expression (3)

\[
[w]_{ij} = \begin{pmatrix}
w_{00} & \cdots & w_{0j} \\
\vdots & \ddots & \vdots \\
w_{i0} & \cdots & w_{ij}
\end{pmatrix}
\]

Additionally, the sum of a neuron in each layer known as the bias is performed. This variable allows to regulate the threshold of the neuron's behaviour and is given by the expression (4)

\[
b_0 = \begin{pmatrix}
b_0w_{b0(0)} \\
b_0w_{b0(1)} \\
\vdots \\
b_0w_{b0(n)}
\end{pmatrix}
\]

Each neuron receives the sum of the products made between the weights and the input data. Thus, it is possible to generalize the equation of a neuronal network as

\[
\sum_{i=0}^{n} f(w_{ij}a_i + b_j)
\]

and, for this study, Equation (5) can be rewritten as

\[
k_n = \sum_{i=0}^{2} f(w_{ij}a_i + b_j)
\]

where \( a_i \) corresponds to the input vector, \( k_n \) is the output or the final result of the model, \( w_{ij} \) is the weight matrix, \( b_i \) is the bias vector, and \( f \) represents the activation function. The artificial neuron is considered as a linear function with an adaptable weight matrix. The first four hidden layers operate with ReLU activation functions, and the final hidden layer works with a Sigmoid activation function.

The DNN implementation was done in Python's environment with frameworks such as TensorFlow. The values contained in the dataset were normalized to minimize the errors and minimize the computation time. The DNN is composed of four hidden layers with 200 neurons for each hidden layer. ReLU activation breaks the linearity on the hidden layers, and by inspection, we found that this activation performs adequately in this model. The final hidden layers worked with a Sigmoid activation function. The DNN contains six layers, an input layer, four hidden layers, and an output layer. The DNN presented in this study has 200 neurons in each hidden layer.

3.4. Evaluation methods

The accuracy was assessed by comparing the actual value \( y \) against the predicted \( (y_{predicted}) \). The metrics used for evaluating the DNN performance, take into consideration the weights and the loss
function and were root mean square error (RMSE), mean absolute error (MAE), and mean squared error (MSE) as follows:

\[
RMSE = \left( \frac{1}{n} \sum_{i=0}^{n} (y_i - y_{predicted})^2 \right)^{1/2}
\]

(7)

\[
MAE = \frac{1}{n} \sum_{i=0}^{n} |y_i - y_{predicted}|
\]

(8)

\[
MSE = \frac{1}{n} \sum_{i=0}^{n} (y_i - y_{predicted})^2
\]

(9)

4. Results and discussions

We observe the correlation value between the predictor variables, the histograms, and the diagram distribution of each test in Figure (1), and the correlation value is equal to 0.81. This correlation fluctuates within -1 and +1 with 0, meaning no correlation. Correlations of -1 or +1 imply an exact linear relation, according to [9].

In the modelling process, 121,201 parameters were calculated by the model. The DNN uses a regularization method called early stopping, and this hyperparameter is equal to 3 to avoid overfitting problems. The model is trained during 350 epochs using the Adam function as an optimizer with a modest learning rate of 0.001 and a batch size of 1. Each hidden layer contains 200 neurons, also known as perceptrons. Of note is that whether the number of layers is increasing, the performance model does not enhance. The accuracy in the training and test stage reaches 76.78% and 92.32%, respectively. The loss function performance in the training and test process is shown in Figure (2). The performance expected through the training and test loss considers that the losses decrease as the number of epochs increases. Finally, the values for RMSE, MAE, and MSE are equal to 0.0848, 0.0596, and 0.0072, respectively.

Figure 2. Loss performance over the number of epochs.

In this case, we can see that the model generally achieves a good fit, with train and test learning curves converging.
5. Conclusions

In this paper, a deep neural network was modelled with the capability to predict and compute the flexural strength value of concrete based on a compressive strength test with an accuracy of almost 92% in a validation dataset. This study proposed a different approach to estimate the flexural strength, which considers algorithm implementation for achieving competent results. Sigmoid and ReLU activation functions showed to reach higher accuracy compared to an individual activation function use. Thus, the combination of different activation functions had significantly improved the performance of the DNN for this study. The model architecture is determined through extensive hyperparameter fine-tuning.

This analysis and modelling can be extended to estimate other concrete features, such as tensile strength, ultrasonic pulse velocity, electrical resistivity, and other properties. This methodology might improve the optimization of the concrete mixture design due to it is possible to achieve great results with a low computational cost. It is desirable to study the application of DNN for different problems in future concrete research. Future work will focus on improving the performance of the model by increasing the performance as well as the applicability of the model to other parameters.

The approach used for the presented model in this paper achieves a satisfactory accuracy and is desirable for its use instead of the application of a theoretical equation that might not achieve the best results and depends on another unknown parameter as $k$ value.

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