

Concrete compressive strength prediction using machine learning algorithm

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ABSTRACT

In this study, the machine-learning system to predict the compressive strength of concrete was built using Tensorflow. In order to build the system, six variables were used: water, cement, fly ash, GGBS, sand, and coarse aggregate as well as a linear regression method where the slope of weight (w) and bias (b) converges to zero for deciding a reasonable straight line. In order to obtain an accurate predicted value as an analysis result, verified and undistributed data were needed.

1. INTRODUCTION

Compressive strength, one of the physical properties of concrete, is one of the factors needed to design concrete structures. Concrete's compressive strength is affected by various mixing materials such as aggregates, admixture, cement, and water. In order to obtain compressive strength, we properly adjusted the mixing materials, prepared a mixing table, mixed them based on the mixing table, and verified compressive strength through experiments. It takes much time and money to verify the compressive strength of concrete. Also, it is not easy to make a prediction based solely on mixing tables. However, empirical evidence has already been presented based on large amounts of experimental data. Given the experimental data already presented in previous studies, this study aims to build a system that can predict concrete's compressive strength by utilizing the Python open-source library, TensorFlow.

2. BUILDING A SYSTEM

2.1 Basic theory

Linear regression is a technique that assumes an arbitrary straight line based on a number of variables and then moves closer to the most reasonable straight line while

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reducing the difference between the value of the arbitrary straight line and the actual value. Gradient descent, one of the techniques for performing linear regression, is a technique that iterates to zero by causing the absolute value of the slope to move toward a smaller absolute value while moving by the learning rate at some point. (Figure 1)

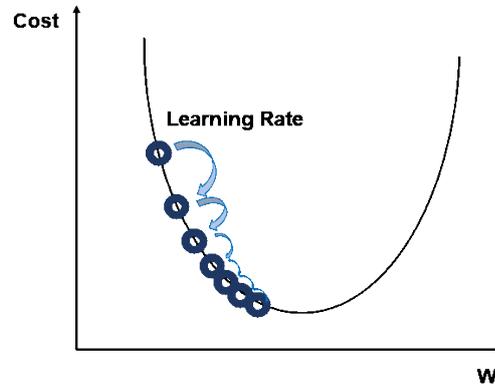


Fig. 1 Gradient descent

2.2 Building a predictive model

Water, cement, GGBS, fly ash, sand, coarse aggregate, and compressive strength are set as variables, and these seven variables are applied to Eq. (1) to (4) to create optimal virtual straight lines. Subsequently, gradient descent was applied to the slopes of a (weight) and b (bias) to obtain values a and b , respectively, by converging the slopes to zero. Consequently, the compressive strength can be predicted by determining the most reasonable straight line.

$$y = a_1x_1 + a_2x_2 + a_3x_3 + a_4x_4 + a_5x_5 + a_6x_6 + a_7x_7 \quad (1)$$

$$Cost(a, b) = \frac{1}{n} \sum_i^n (y_i - w_i)^2 \quad (2)$$

$$a \text{ Gradient} = \frac{\partial Cost(a, b)}{\partial a} \quad (3)$$

$$b \text{ Gradient} = \frac{\partial Cost(a, b)}{\partial b} \quad (4)$$

3. RESULT

3.1 Data separation

First, we obtained a compressive strength mix table owned by Kyonggi University. This table has a compressive strength range of 7 MPa to 100 MPa and varies in number

by section. The obtained experimental data were divided into two methods to learn predictive programs. One is to train experimental data ranging from 7 MPa to 100 MPa at once, and the other is to train by section (Table 1).

Table 1. Number of experimental data by compressive strength interval

	Total Data	Range of $f'_{c,meas}$					
		7 ~ 20 MPa	20 ~ 30 MPa	30 ~ 40 MPa	40 ~ 60 MPa	60 ~ 80 MPa	80 ~ 100 MPa
	4279						
Training data	2991	189	675	680	842	420	185
Validation data	1288	86	297	282	348	183	92

3.2 Evaluation method

To determine the reliability of the predicted values according to the range, the reliability evaluation indexes RMSE, MAE, and MAPE were used. RMSE is a measure of the difference between the predicted value and the actual value; MAE is the mean of the absolute error of the predicted value and the actual value, and MAPE is the value converted MAE into a percentage. Since these three evaluation indexes represent the error of the predicted value and the actual value, then the smaller the value, the higher the reliability will be.

$$RMSE = \sqrt{\frac{\sum_{i=1}^m (f_{c,pred}^i - f_{c,meas}^i)^2}{m}} \quad (5)$$

$$MAE = \frac{1}{n} \sum_{i=1}^m |f_{c,pred}^i - f_{c,meas}^i| \quad (6)$$

$$MAPE = \frac{1}{m} \sum_{i=1}^m \left| \frac{f_{c,pred}^i - f_{c,meas}^i}{f_{c,meas}^i} \right| \times 100 \quad (7)$$

3.3 Commentary result

if you have learned a full range of experimental data from 7 MPa to 100 MPa, you can see that RMSE is up to 25 MPa, MAE is up to 22.45 MPa, and MAPE is up to 51%. The evaluation indexes are significantly lower at 7.24 MPa, 5.99 MPa and 10.96%, respectively, when the experimental data is divided into compression intervals such as 7 MPa to 20 MPa, 30 MPa to 40 MPa, 40 MPa to 60 MPa, 60 MPa to 80 MPa, 80 MPa to 100 MPa.

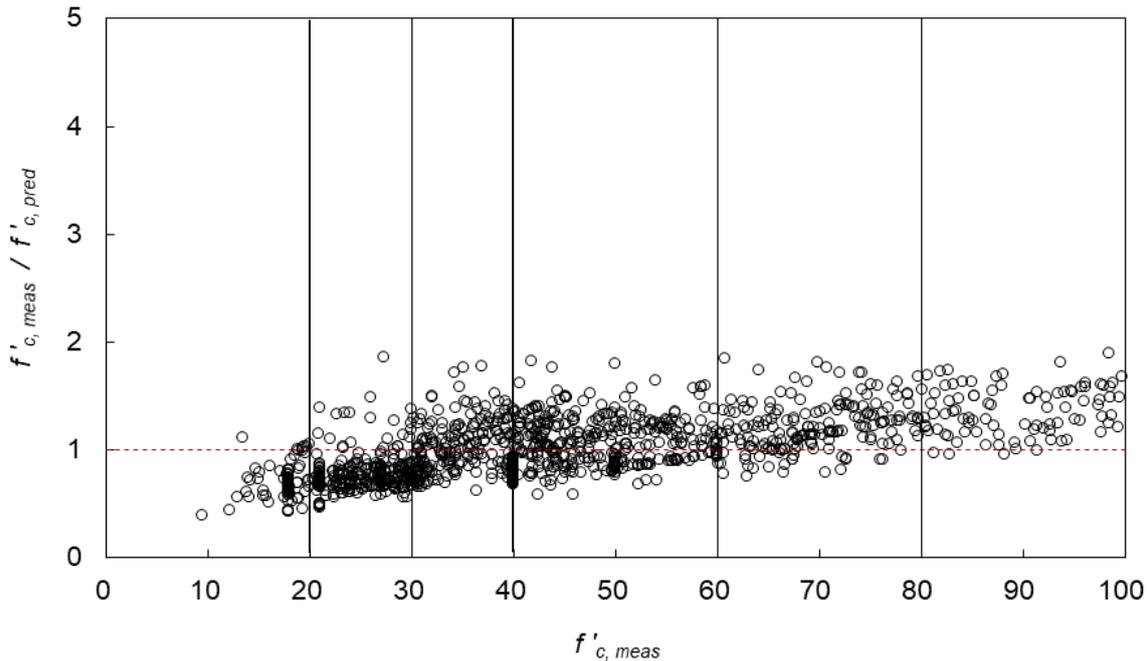


Fig. 2 Results of models that have learned all range data

4. CONCLUSIONS

This study uses TensorFlow, a Python open-source library, to predict concrete's compressive strength based on experimental data owned by Kyonggi University. If all of the experimental data is learned in all ranges and experimental data is learned in compressive strength intervals, the values of each performance indicator tend to decrease. Therefore, it can be confirmed that the wider the range of compressive strength, the higher the accuracy of the predicted value if the range is divided into sections and learned.

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REFERENCES

- Hurwitz. J., Kirsch. D., (2018), "Machine Learning for dummies", IBM Limited Edition
Huang. M.Q., Ninic. J., Zhang. Q.B., (2021), "BIM, machine learning and computer vision techniques in underground construction: Current status and future perspectives", Tunnelling and underground Space Technology, Vol. 108, Article No. 103677