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CLASSIFICATION OF GEOPOLYMER CONCRETE GRADE WITH CONVOLUTIONAL NEURAL NETWORK USING LE-NET ARCHITECTURE

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ABSTRACT

Geopolymer concrete is one of the innovations in the field of construction materials, this kind of material can reduce the impact of carbon emissions on the environment. Geopolymer concrete is an environmentally friendly material, which does not use cement as a base material. Compressive strength is a quality parameter of geopolymer concrete as well as normal concrete. This study aims to model the compressive strength classification of geopolymer concrete using an artificial neural network. The classification process is based on the composition of the geopolymer concrete mixture by considering the geopolymer concrete curing process, including the temperature and duration of geopolymer concrete curing. Eight independent variables and one dependent variable were used in this modelling process. The artificial neural network model developed is a Deep Learning model, using the Convolutional Neural Network algorithm and LeNet network architecture. Three variations of hyper parameters were compared in this study, including variations in the number of epochs, learning rate values, and variations in the optimizer function. From the modelling results that have been made, the LeNet architectural model with 1000 epochs, a learning rate value of 0.001, and using the Adam optimizer function is able to produce the best model with a training accuracy rate of 86.15%, and an R-square value of 0.93. This model is able to produce a testing accuracy value of 79.80%. As an alternative, the RMSprop optimizer function is also able to produce an adequate model to classify the compressive strength of geopolymer concrete.

Keywords: geopolymer concrete, artificial neural network, deep learning, LeNet, accuracy.

INTRODUCTION

The cement production process, which has been used for many years in the construction project of buildings, bridges, and other infrastructure, contributes significantly to carbon emissions into the air. Ma et. al (2018) [1] and Gargav (2016) [2] estimated that the cement manufacturing process is capable of emitting up to 1.5 billion tons of CO_2 into the atmosphere every year, 5% of global CO_2 emissions according to Mo et. al. (2016), or 7% of the total man-made greenhouse gases (about 2.8 billion tons) according to Malhotra [3]. Geopolymer concrete is an innovative construction material, that uses fly ash as a cement substitute. Geopolymer concrete is also an environmentally friendly material, in terms of the number of CO_2 emissions released into the air. As with normal concrete, the quality of geopolymer concrete is determined based on its compressive strength value. Normally, to determine the compressive strength of concrete, a destructive test is carried out in the laboratory on cylindrical concrete specimens with a diameter of 150 mm and a height of 300 mm.

In line with the development of the Industrial Revolution 4.0, the development of artificial intelligence (AI) technology is also growing rapidly. One branch of AI science is Machine Learning (ML). ML is an intelligent system developed to carry out the learning process on the given input and produce various expected outputs. The real form of ML is the development of an artificial neural network (ANN) system to model an object. In recent years, learning algorithms with ANN have developed further with the introduction of Deep Learning (DL) learning algorithms. DL is a learning algorithm part of Machine Learning that consists of algorithms that allow the software to train itself to perform tasks, such as speech and image recognition, by exposing layered neural networks to large amounts of data.

The model created using the DL algorithm is able to model objects with a high degree of accuracy. Several machine learning models with deep learning algorithms in the construction field have been proposed by several previous researchers. Akinosho *et al*. [4] stated that some DL applications in the world of construction such as for monitoring the condition of structures, or for predicting the compressive strength of concrete as done by Nguyen *et al*. [5]. Krizhevsky *et al.* [6] proposed a Deep Learning Convolutional Neural Network (CNN) learning algorithm, to classify 1.3 million high-resolution images with a fairly good error rate of up to 15%.

This research was conducted with the aim of using the CNN algorithm model to classify the quality of geopolymer concrete based on the proportion of the mixture of its constituent materials. The weight of the geopolymer concrete constituents is used as an independent variable in the network modeling. These variables include the weight of coarse aggregate, fine aggregate, fly ash, and activator solution. In addition, the important thing in the manufacture of geopolymer concrete is the temperature and duration/time of curing of geopolymer concrete which is also included in the modeling of artificial neural networks with the CNN algorithm.

MATERIALS AND METHODS

In this research, the modeling of a non-cement geopolymer concrete mix design was carried out using the Convolutional Neural Network (CNN), which consists of the input layer, a hidden layer, and an output layer, with the addition of a convolution layer and a pooling layer and a fully connected layer. Figure-1 shows the flow chart in this study.

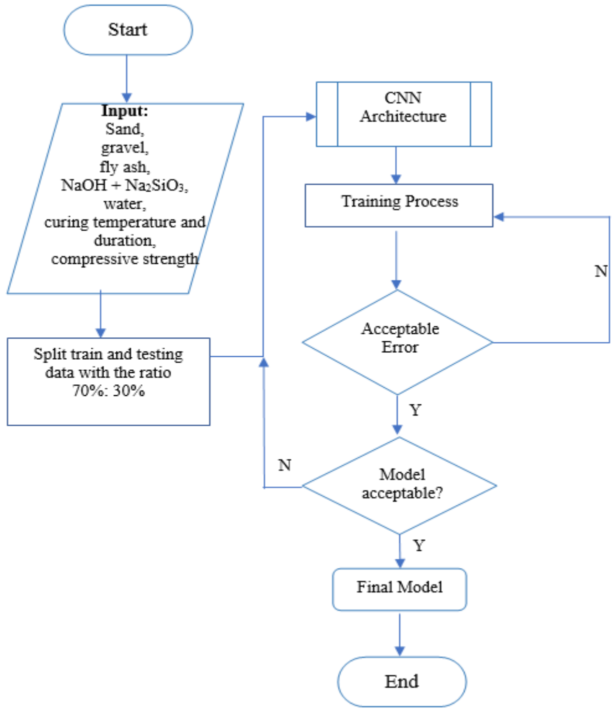

Figure-1. Research methodology flow chart.

Population and Research Instruments

There are two kinds of data used in this research, i.e. primary data and secondary data. Primary data was obtained from the results of experimental concrete compressive strength testing in the laboratory. In addition to primary data, this study requires secondary data used for the training process of the convolutional neural network (CNN) model. The Comparison of the amount of secondary data and primary data in this study is 70%: 30%. The target number of secondary data in this study is a minimum of 700 data, and a minimum of 300 primary data.

Secondary data was obtained through library searches from previous studies. In this study, the number of secondary data is targeted at 700 data. Primary data, was obtained through the manufacture of cylindrical specimens of non-cement geopolymer concrete in the laboratory. The manufacture of geopolymer concrete specimens refers to Indonesian Standard SNI 2493:2011 Procedures for Making and Maintaining Concrete Test Objects in the Laboratory.

The data used include 8 types of independent variables and 1 type of dependent variable. The forms of the independent and dependent variables are described in Table-1 below.

Table-1. The type of independent and dependent variable.

Variable's	Type	Definition	Unit
X_1	Independent variable	Weight of coarse aggregate	kg/m^3
X_2	Independent variable	Weight of fine aggregate	kg/m^3
X_3	Independent variable	Weight of fly ash	kg/m^3
X_4	Independent variable	NaOH	kg/m^3
X_5	Independent variable	Na_2SiO_3	kg/m^3
X_6	Independent variable	Weight of water	kg/m^3
X_7	Independent variable	Hot steam curing temperature	^{o}C
X_8	Independent variable	Hot steam curing duration	Hour
Y	Dependent variable	Concrete compressive strength	MPa

For classification purposes, the independent variable *Y*, which is the compressive strength of geopolymer concrete is divided into 9 classes. The nine classes are concrete compressive strength classes ranging from concrete with a compressive strength of fewer than 20 MPa, to more than 55 MPa.

Architecture of CNN

Basically, a CNN network architecture consists of 4 layers, namely the input layer, the feature extraction process layer, the classification process layer, and the output layer. In the CNN architecture, there are several hidden layers, namely the convolution layer, activation function (ReLU), and pooling. CNN works hierarchically, so the output in the first convolution layer is used as input in the next convolution layer. After going through the convolution layer, the next layer is the classification layer which consists of fully-connected activation functions (softmax). The last layer is the output layer.

Figure-2 shows the general architecture of the CNN method. There are several types of CNN network architecture, including LeNet, AlexNet, VGG, ResNet, and so on. In this study, the LeNet network architecture was chosen, with architectural details shown in Table-2. In this study, to obtain the optimal value from the process and modeling, various variations of the hyper parameters were carried out, including the epoch value, learning rate, and the optimizer function. Epoch value variations are taken 3 kinds, ranging from 250, 500 to 1000 epochs.

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While the variable learning rate varies from 0.1, 0.01, and 0.001. The optimizer functions used are Adam, SGD, and RMSprop.

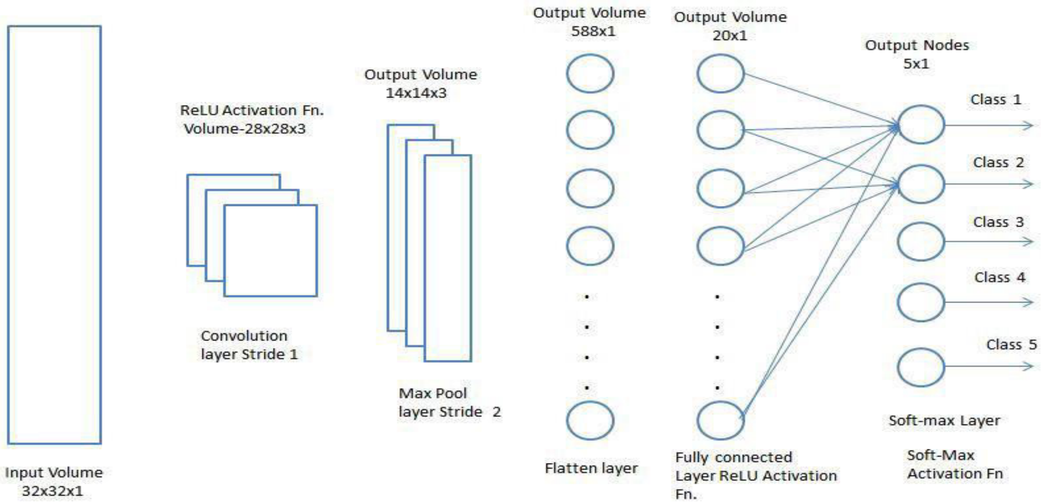

Figure-2. Architecture of Convolutional Neural Network, CNN [6].

Table-2. Architecture of LeNet algorithm.

Layer		Feature map size	Filter	Kernel Size	Stride	Pool Size	Activation
Input	**image**	**3×3**					
	resize	32×32					
1	Convolution 2D		6	5×5	1		tanh
2	Avg pooling2D				1	2×2	sigmoid
3	Convolution 2D		16	5×5	1		tanh
4	Avg pooling2D				1	2×2	sigmoid
5	Convolution 2D		120	5×5	1		tanh
6	Fully Connected						tanh
Output	Fully Connected						softmax

Validation Method

In order to validate the model, several validation methods were used in this study. The validation methods in question are mean square error (MSE), root means square error (RMSE), mean absolute error (MAE), and coefficient of determination (R2). According to Chai *et al.* [7]. This validation method is accurate enough to be used to provide quantification of error values in artificial neural network models.

Mean square error (MSE)

$$\text{MSE} = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(u_i - \hat{u}_i)^2} \qquad (1)$$

Root mean square error (RMSE)

$$\text{RMSE} = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(u_i - \hat{u}_i)^2} \qquad (2)$$

Mean absolute error (MAE)

$$\text{MAE} = \frac{1}{n}\sum_{i=1}^{n}(u_i - \hat{u}_i) \qquad (3)$$

Coefficient of determination (R-square), R^2)

$$R^2 = 1 - \frac{\sum_{i=1}^{n}(u_i - \hat{u}_i)^2}{\sum_{i=1}^{n}(u_i - \bar{u})^2} \qquad (4)$$

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Trial Environment

The software environment used to test the artificial neural network in this study is Windows as the operating system (OS). Communication with cloud servers using wi-fi or GSM data. For cloud server software use google collab (https://colab.research.google.com). The computer used is a Ryzen 5 with 16 GB of DDR4 RAM memory. On the GPU side, it uses NVIDIA GeForce GTX1650Ti. The concrete strength classification module is implemented using the Python programming language and with three source libraries, namely Keras/Tensor flow to build the architecture of CNN, Pandas for data analysis, and numpy for numerical computation.

The modeling process is carried out using a combination of primary and secondary data. Primary data was obtained through experimental results in the laboratory, there are 300 primary data. Secondary data was obtained through literature studies from several previous studies, there are 722 secondary data.

RESULTS AND DISCUSSIONS

This section contains a testing scheme to measure the success rate of the method used. There are a total of 1.022 data that will be separated into training data and test/testing data, with a ratio of 70%: 30%. While the classification class in the network training process is divided into 9 classes. In this study, to obtain the optimal value from the process and modelling, various variations of the hyper parameters were carried out, including the epoch value, learning rate, and the optimizer function. Epoch value variations are taken 3 kinds, ranging from 10, 50, 100, 250, 500, 1000 to 2000 epochs. While the variable learning rate varies from 0.1, 0.01, and 0.001. The optimizer functions used are Adam, SGD, and RMSprop.

Figure-3 shows the relationship between the number of epochs and train accuracy, for the three types of optimizer functions. From Figure-2, the Adam and RMSprop optimizers show good performance, as indicated by the higher train accuracy values as the number of epochs increases. At 1000 epochs, Adam produced a train accuracy value of 86.15%, higher than the RMSprop function which only reached 60.98%.

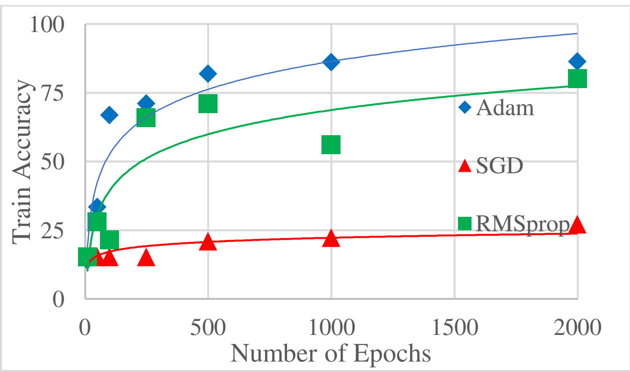

Figure-3. Number of epochs and train accuracy.

Meanwhile, the SGD optimizer has not shown good performance, only producing a train accuracy value of 22.24%. In addition, increasing the number of epochs to 2000 does not show a more significant increase in the train accuracy value. In The Adam optimizer with 2000 epochs, the train accuracy value achieved was 86.29% or only increased by 0.16% from the value generated with 1000 epochs. However, the increase in the value of train accuracy is shown by the RMSprop optimizer, where in 2000 epochs it is able to produce a train accuracy value of 89.79%, or an increase of 47.25%.

In line with the results of the train accuracy value, the same thing is also shown from the R-square value results. The R-square value also tends to increase towards 1.0. The relationship between the number of epochs and the R-square value is shown in Figure-4. With the number of epochs of 1000, the Adam optimizer produces an R-square value of 0.9323, while the RMSprop optimizer produces an R-square value of 0.86, or lower than the Adam optimizer of 7.52 %. The addition of the number of epochs up to 2000, seems to reduce the R-square value in the Adam optimizer model. With 2000 epochs, the R-square value in the Adam optimizer model reached 0.9304, or decreased by 0.204%. The opposite occurs in the model using the RMSprop optimizer, in 2000 epochs it shows an increase in the R-square value to 0.9366 or an increase of 9.27%. Meanwhile, the model that uses the SGD optimizer shows a less good performance than the R-square value, where at 1000 epochs the resulting R-square value only reaches 0.099.

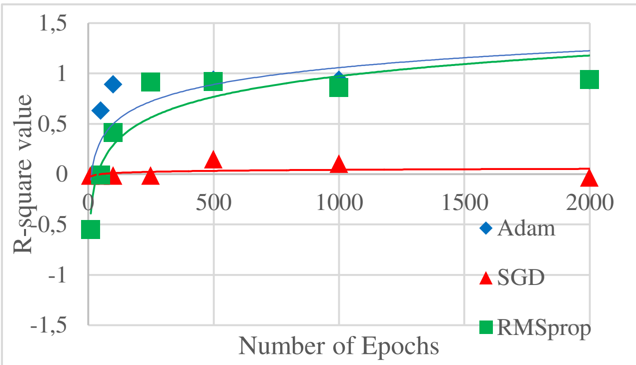

Figure-4. Number of epochs and R-square value.

Figure-5 shows the relationship between the number of epochs and the value of testing accuracy. Based on the figure, it can be seen that the pattern is almost similar to the results of the training accuracy and R-square value. The model with the Adam optimizer shows the highest testing accuracy results, using 1000 epochs this model can produce a testing accuracy value of 79.80%, far above the model with the RMSprop (56.03%) and SGD (20.19%).

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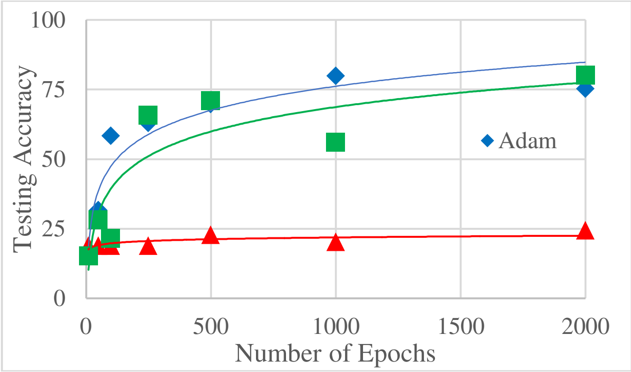

Figure-5. Number of epochs and testing accuracy.

The relationship between learning rate variations and train accuracy results is shown in Figure-6. Variations in learning rate values are taken from 0.1, 0.01 to 0.001. In general, the smaller the learning rate, the better the train accuracy level. The model using the Adam optimizer and the learning rate value of 0.001 is able to produce a train accuracy value of up to 86.15%, followed by the RMSprop optimizer model with a train accuracy value of 60.98%. While the model with the SGD optimizer with a learning rate of 0.001 only produces a train accuracy value of 22.24%.

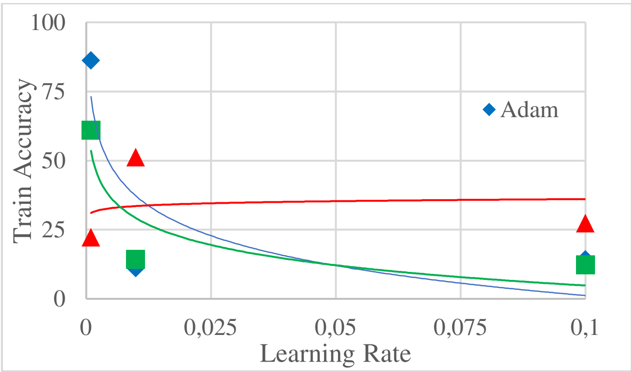

Figure-6. Number of epochs and testing accuracy.

CONCLUSIONS

Based on the results and discussion above, several conclusions can be drawn:

a) Deep learning methods, especially the Convolutional Neural Network algorithm, can be used as a means of classifying the compressive strength of geopolymer concrete

b) LeNet architecture using 1000 epochs with a learning rate of 0.001, and using the Adam optimizer function produces the best model with a train accuracy value of 86.15%, an R-square value of 0.93, and a testing accuracy value of 79.80%

c) The values of train accuracy, R-square, and testing accuracy are increasing along with the increasing number of epochs and the decreasing value of the learning rate. The Adam optimizer and RMS prop functions to provide good performance in modeling the compressive strength classification of geopolymer concrete, while the SGD optimizer has not shown good results in this regard.

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