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CLASSIFICATION OF JAVANESE NGLEGENA SCRIPT USING COMPLEX-VALUED NEURAL NETWORK

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Abstract

Javanese script is one of the traditional scripts in Indonesia used by the Javanese people. The Javanese script used in spelling consists of 20 main characters (nglegena) from the Ha to Nga script. Javanese scripts have very high values, and the uniqueness of the script is one thing that must be preserved. However, the widespread use of Javanese script has declined as technology has developed. In this context, one of the problems that arises is the difficulty in automatically recognizing and classifying the Javanese Nglegena script. Therefore, using computational methods to classify the Nglegena Javanese script automatically is very important. This research compares two methods for classifying the Javanese Nglegena script: Complex-Valued Neural Networks (CVNN) and Convolutional Neural Networks (CNN). This research aims to compare the accuracy of CVNN and CNN. In this study, the Complex-Valued Neural Network method had a higher average accuracy, namely 96.332%, and a loss of 0.1834. Meanwhile, the CNN method has an average accuracy of 93.72% and a loss of 0.4254. Artificial intelligence-based Javanese Nglegena script classification technology can help people recognize the Javanese Nglegena script, especially in education and culture.

Keywords: *Nglegena Javanese Script, Classification, CVNN, CNN*

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1. INTRODUCTION

Indonesia is an archipelagic country that has various ethnicities, races, religions, languages and cultures. This is what causes the Indonesian nation to have a rich culture and unique characteristics in each region. One reflection of culture in Indonesia is the many languages that were born in Indonesia[1]. A culture basically has various types. One of the cultural dimensions that is very influential is regional languages. In regional languages there are characters as a form of writing or representation of the language. One language that has special characters as a form of writing for the language is Javanese with Javanese writing or better known as Javanese script.[2].

Javanese script or Hanacaraka/Carakan is one of the traditional scripts in Indonesia [3]. Javanese script is used by Javanese people, especially in royal palaces such as Yogyakarta and Surakarta, to develop the tradition of writing in Javanese. [4]. Hanacaraka is generally used to write texts such as stories (serat), historical notes (babad), ancient songs (kakawin), or predictions (primbon). The Javanese script used in Javanese spelling basically consists of 20 main characters (nglegena), namely from the Ha to Nga script. The main character has the meaning of the wuda (naked) character because it has not been followed by sandhangan[5]. The Javanese script is still related to the Balinese script, which is both a development of the Kawi script. Javanese script was previously used in everyday life, but was reduced after being banned by the Japanese government and the introduction of Latin letters in Java. This caused the beginning of the extinction of the Javanese script[6].

Javanese script has a long history and is an important cultural heritage. However, widespread use of Javanese script has declined with the development of modern communications technology. This causes a decrease in the number of individuals who are able to read, write and recognize Javanese script. Therefore, it is important to develop technology that can assist in the maintenance and restoration of Javanese script. In this context, one of the problems that arises is the difficulty in recognizing and classifying Javanese characters automatically. Manual recognition of Javanese script requires in-depth knowledge and special skills, which not everyone has[7]. Therefore, the use of computational methods to automatically classify Javanese characters is very important. Artificial intelligence is developing very rapidly, artificial intelligence has the ability, one of which is to classify images into certain groups[8].

Artificial intelligence-based Javanese script classification technology can help people get to know Javanese script, especially in the fields of education and culture. The use of Complex-Valued Neural Network technology can be an interesting idea to help understand and process data that has complex properties in the form of characters. This method can be used in various applications, such as recognizing the characters of each letter of the Javanese Nglegena script or in order to preserve and promote Javanese culture.[9].

There is similar research that has been carried out previously for the classification of Javanese script using the Backpropagation Neural Network method. The accuracy obtained in this study was 76.1% with 156 correct and 49 errors in classification from a total of 205 data[10]. Other research using Convolutional Neural Networks for Javanese script classification obtained accuracy results of 85%. The dataset used is 20 classes of Javanese script data, each of which is contained in each folder containing 108 images[11].

Based on the problems described above, the author is interested in conducting research that can be used by someone who wants to learn the Javanese Nglegena script independently. Apart from that, the author also wants to introduce the Complex-Valued Neural Network method which is still rarely used for image classification. Therefore, the author conducted research with the title "Classification of Javanese Script Using Complex-Valued Neural Network". This research can classify and recognize 20 Javanese Nglegena script, from Ha to Nga, using the Complex-Valued Neural Network method.

2. RESEARCH METHOD

The methods used in this research are Complex-Valued Neural Network (CVNN) and Convolutional Neural Network (CNN). This research uses the same layer architecture and parameters to compare the best accuracy between the CVNN and CNN methods. The only difference in the CVNN method is that in its architecture there is an additional complex.

2.1 Complex-Valued Neural Network

Complex-Valued Neural Network is a system that processes complex-valued input using complex-valued weights, thresholds and activation functions and produces complex-valued output. One of the characteristics of CVNN is its ability to process complex value information precisely. CVNN can improve the model's ability to understand and process data that has real and imaginary components, which is usually difficult for conventional neural networks to handle.[12]. The Complex-Valued Neural Network system consists of many complex-valued perceptrons that are connected to each other. The learning process in Complex-Valued Neural Network is carried out using complex-valued backpropagation[13].

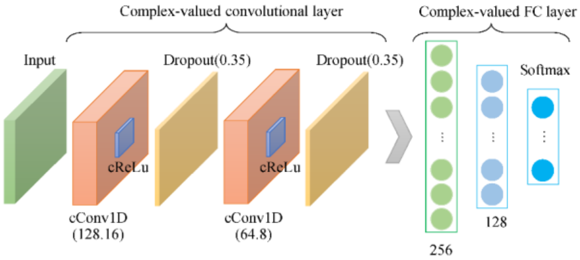


Figure 1. Complex-Valued Neural Network

2.2 Convolutional Neural Network

CNN is simply an artificial neural network that uses a convolution multiplication matrix in its architecture[14]. The convolution function in CNN is used for feature extraction, and from this process it will produce certain features which will be processed by the multilayer perceptron to produce an output from the input[15]. There are three main processes in the convolution layer, namely convolution, sub sampling / pooling, and ReLu activation[16]. CNNs are ideal for Javanese script classification because of their processing image data. CNN applies convolutional layers to Javanese script imagery to simulate human vision and understand the features of self-confidence[17].

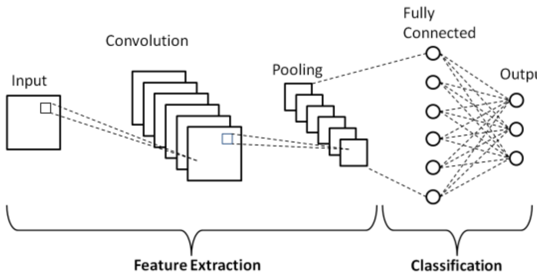
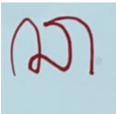
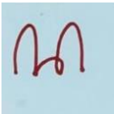
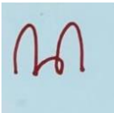
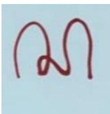
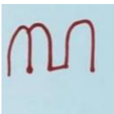
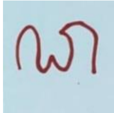
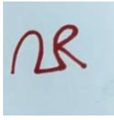
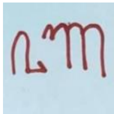
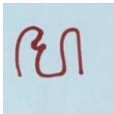
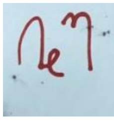
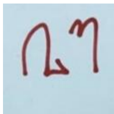


Figure 2. Convolutional Neural Network

3. RESULT AND DISCUSSION

The dataset used is the Nglegena Javanese script dataset which consists of 20 classes, namely "ha", "na", "ca", "ra", "ka", "da", "ta", "sa", "wa ", “la”, “pa”, “dha”, “ja”, “ya”, “nya”, “ma”, “ga”, “ba”, “tha”, “nga”. In this research, there are 2 data sources used, namely primary data and secondary data. Primary data was obtained by handwriting from all groups, such as elementary school, middle school, high school, college students, and people both young and old. The primary data used were 400 images of Javanese script letters with 20 classes consisting of 20 handwriting samples from different people. Secondary data is used to support primary data.

Table 1. Nglegena Javanese Script Dataset

No	Figure	Javanese Script Class	Quantity
1.		script “Ha”	20
2.		script “Na”	20
3.		script “Ca”	20
4.		script “Ra”	20
5.		script “Ka”	20
6.		script “Da”	20
7.		script “Ta”	20
8.		script “Sa”	20
9.		script “Wa”	20
10.		script “La”	20
11.		script “Pa”	20
12.		script “Dha”	20
13.		script “Ja”	20
14.		script “Ya”	20
15.		script “Nya”	20
16.		script “Ma”	20
17.		script “Ga”	20
18.		script “Ba”	20
19.		script “Tha”	20
20.		script “Nga”	20

Secondary data is taken from the data provider site, Kaggle (url: kaggle.com) with the name of the data used, Javanese Script, this data consists of a set of Javanese script images with png image format which are divided into 20 classes, namely Ha, Na, Ca, Ra, Ka, Da, Ta, Sa, Wa, La, Pa, Dha, Ja, Ya, Nya, Ma, Ga, Ba, Tha and Nga. The secondary data has a total of 12,000 images of Javanese characters.

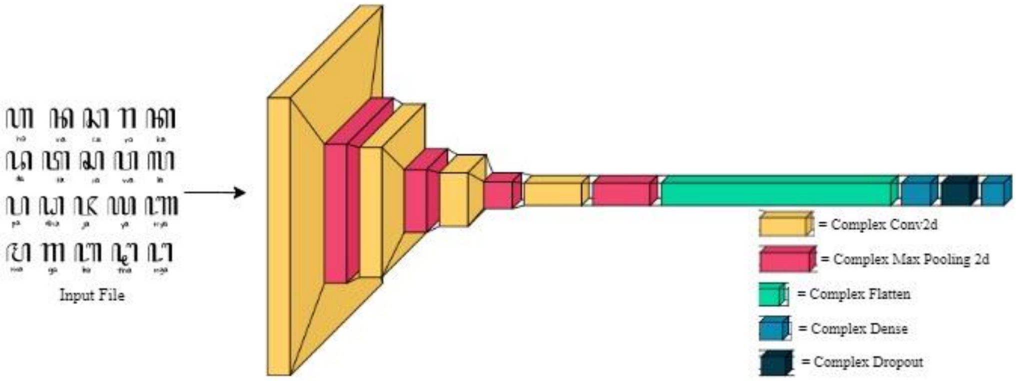


Figure 3. CVNN Model Architecture

The CVNN model starts by creating a sequential model object and defining a kernel variable with a value of 3. This model consists of several types of layers. First, there is a ComplexConv2D layer that is used to perform convolution operations on the input image. This model has four ComplexConv2D layers with the number of filters increasing from 64, 128, 256, to 512. Each ComplexConv2D layer uses a kernel with a size of 3x3 and a ReLU activation function. After each ComplexConv2D layer, there is a ComplexMaxPool2D layer that is used to perform the max pooling operation.

After the complex-valued convolution and complex max pooling layers, the model has a ComplexFlatten layer which is used to convert the output of the previous layer into a one-dimensional vector. Next, there are two ComplexDense layers or complex-valued fully connected layers. The first ComplexDense layer has 256 neuron units with a ReLU activation function. The ComplexDropout layer is placed after the first ComplexDense layer to avoid overfitting. This ComplexDropout layer randomly deactivates a portion of the neuron units (20%) during the training process. The second ComplexDense layer is the last fully connected layer with 20 neuron units, corresponding to the number of classes to be predicted. A softmax activation function is used in this layer to generate the desired class probabilities. The model is compiled using the categorical_crossentropy loss function, stochastic gradient descent (SGD) optimizer, and accuracy matrix.

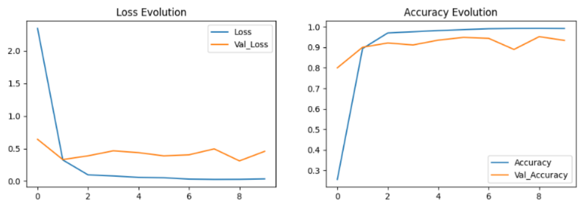


Figure 4. CVNN Model Evaluation Graph

CVNN model performance using epoch 10, batch size 1, and grayscale color mode. The experiment was carried out 5 times using the same parameters to prove that the accuracy produced by CVNN was higher than CNN. The following are the accuracy results as in the table below:

Table 2. CVNN Model Performance

No	Train		Val		Test	
	Acc (%)	Loss	Acc (%)	Loss	Acc (%)	Loss
1.	99.85%	0.005	93.37%	0.457	95.23%	0.210
2.	99.91%	0.003	94.56%	0.358	96.72%	0.174
3.	99.90%	0.003	93.97%	0.403	96.48%	0.156
4.	99.91%	0.002	95.91%	0.394	96.25%	0.203
5.	99.79%	0.008	93.53%	0.470	96.98%	0.147

The CNN model starts by creating a sequential model object and defining a kernel variable with a value of 3. This model consists of several types of layers. First, there is a Conv2D layer that is used to perform convolution operations on the input image. This model has four Conv2D layers with the number of filters increasing from 64, 128, 256, to 512. Each Conv2D layer uses a kernel with a size of 3x3 and a ReLU activation function. After each Conv2D layer, there is a MaxPool2D layer that is used to perform the max pooling operation.

After the convolution and max pooling layers, the model has a Flatten layer which is used to convert the output of the previous layer into a one-dimensional vector. Next, there are two Dense layers or fully connected layers. The first Dense layer has 256 neuron units with ReLU activation function. The Dropout layer is placed after the first Dense layer to avoid overfitting. The Dropout layer randomly deactivates a portion of the neuron units (20%) during the training process. The second Dense layer is the last fully connected layer with 20 neuron units, corresponding to the number of classes to be predicted. A softmax activation function is used in this layer to generate the desired class probabilities. The model is compiled using the categorical_crossentropy loss function, stochastic gradient descent (SGD) optimizer, and accuracy matrix.

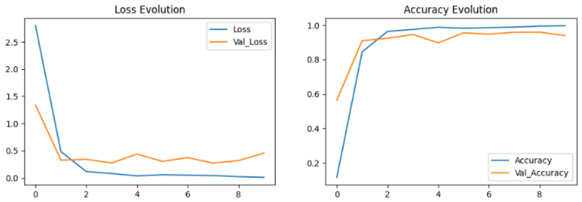


Figure 5. CNN Model Evaluation Graph

Performance of the CNN model using epoch 10, batch size 1, and grayscale color mode. The experiment was carried out 5 times using the same parameters to see that the accuracy obtained by CNN was lower than CVNN. The following are the accuracy results as in the table below:

Table 3. CNN Model Performance

No	Train		Val		Test	
	Acc (%)	Loss	Acc (%)	Loss	Acc (%)	Loss
1.	99.07%	0.074	93.97%	0.386	92.19%	1.127
2.	99.54%	0.014	94.37%	0.180	95.08%	0.158
3.	99.90%	0.006	94.29%	0.307	94.38%	0.237
4.	99.80%	0.004	94.64%	0.362	92.42%	0.378
5.	99.88%	0.002	95.56%	0.265	94.53%	0.227

After experimenting 5 times on CVNN and CNN, then calculate the average accuracy produced on the test data. The CVNN method has an average accuracy of 96.332% and a loss of 0.1834. Meanwhile, the CNN method has an average accuracy of 93.72% and a loss of 0.4254. The following is a comparison chart of the accuracy results on the test data.

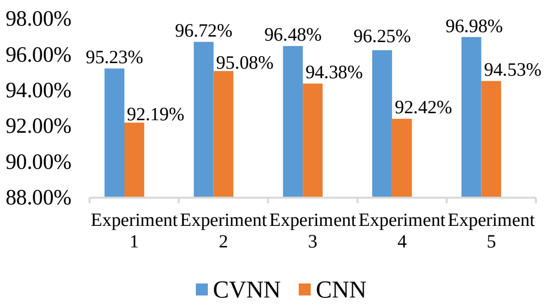


Figure 6. Comparison of Accuracy Results on Test Data

CVNN has higher accuracy performance because CVNN is a type of artificial neural network that uses complex numbers as inputs, outputs, and parameters in it. Complexity in CVNN has a richer representation. Complex numbers provide two dimensions, the real and imaginary parts, which can store more information than using only real numbers like in CNN.

In addition, CVNN is more invariant to data transformations, such as rotation, shifting, and magnification. Since complex numbers can intrinsically describe rotations and shifts, CVNN models are better able to cope with variations in the data. Thus, the performance of the model generated by CVNN is better than CNN.

4. CONCLUSION

This research successfully implemented the Complex-Valued Neural Network (CVNN) and Convolutional Neural Network (CNN) methods in the Python programming language to classify the Nglegena Javanese script. In this study, the Complex-Valued Neural Network method has an average accuracy of 96.332% and a loss of 0.1834. Meanwhile, the Convolutional Neural Network method has an average accuracy of 93.72% and a loss of 0.4254.

Suggestions that can be proposed for further development in the field of classifying Javanese Nglegena script using the Complex-Valued Neural Network (CVNN) model are to increase the dataset with wider variations, using sandhangan and pairs characters. Explore more advanced model architectures and optimization techniques. Apart from that, it is recommended to develop web-based or mobile interactive applications that facilitate users in learning and recognizing Javanese script completely.

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