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Convolutional Neural Network Activation Function Performance on Image Recognition of The Batak Script

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Abstract: Deep Learning is a sub-set of Machine learning, Deep Learning is widely used to solve problems in various fields. One of the popular deep learning architectures is The Convolutional Neural Network (CNN), CNN has a layer that transforms feature extraction automatically so it is widely used in image recognition. However, CNN's performance using the tanh function is still relatively low, therefore it is necessary to select the right activation function to improve accuracy performance. This study analyzes the use of the activation function in image recognition of the Batak script. The result of this study is that the CNN model using the ReLU and eLU functions produces the highest accuracy compared to the CNN model using the tanh function. The CNN model using eLU produces the best accuracy performance in the training process, which is 99.71% with an error value of 0.0108. Meanwhile, in the testing process, the highest accuracy value is generated by the CNN Model using the ReLU function with an accuracy of 94.11%, an error value of 0.3282, a precision value of 0.9411, a recall of 0.9411, and an f1-score of 0.9416.

Keywords: Deep Learning, Convolutional Neural Network, Activation Function, tanH, ReLU.

INTRODUCTION

Deep learning or also known as deep neural network is one of the sub-classes of Machine Learning in the scope of artificial intelligence that has a network capable of unsupervised learning from unstructured or unlabeled data. Currently, deep learning is widely used to solve various problems in the fields of pattern recognition, classification, clustering, dimensionality reduction, computer vision, natural language processing (NLP), regression and other fields.

Deep learning has many types of architectures, one of which is Convolutional Neural Network (CNN). CNN has a convolution layer, pooling layer, and dense layer. CNN is able to perform feature extraction automatically using the convolution process in the convolution layer. CNN is designed to process data in the form of multi dimensional arrays, for example image data (Modi, 2018).

According to Bergstra (2011), CNNs have from ten to possibly fifty hyper-parameters that can be tuned. Hyper-parameters refer to parameters that cannot be updated during machine learning training and are used in building model structures, such as hidden layers and activation functions, or in determining the efficiency and accuracy of model training, such as the learning rate (LR) of Stochastic Gradient Descent (SGD), Batch Size, and Optimizer (Yu, 2020).

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According to Faza (2018), the selection of the activation function is very influential on the format of the input data in Artificial Neural Networks. Artificial Neural Networks use activation functions to perform complex calculations in the hidden layer and then transfer the results to the output layer. The activation function introduces a non-linear property in neural networks. Onwujekwe and Yoon (2020), stated that the activation function can speed up the training process and improve accuracy. In research conducted by Susilawati and Muhathir (2019), the use of activation functions can increase the MSE value as the epoch increases in the RBM neural network.

Some of the activation functions used in deep learning are sigmoid, hyperbolic tangent, and Rectifier Linear unit (Nair & Hinton, 2010), exponential Linear unit (Clevert et al., 2015). CNNs have a non-linear activation function that allows the network to learn. This function controls how neurons fire depending on the input received from the previous layer. However, standard activation functions, such as the sigmoid function or the hyperbolic tangent function, have the drawback that they cause the gradient at large values to become almost zero so that the value of updates performed by Stochastic Gradient Descent becomes very small (Ide & Kurita, 2017). This problem is called the vanishing gradient problem (Hochreiter, 1998). Vanishing gradient causes the model to be unable to learn from the data, thus affecting the performance of deep learning in classification or prediction. The RELU activation function (Hahnloser et al., 2000) is able to avoid the vanishing gradient problem, because for positive outputs, the gradient becomes constant and does not disappear.

Based on the above problems, we will analyze the performance of recognizing the Batak script using deep learning by selecting the appropriate activation function. The expected results of this research are in the form of performance analysis results such as speed and accuracy.

LITERATURE REVIEW

Batak script or *Surat Batak* is the script used by the Batak tribe in the province of North Sumatra. Kozok (2009) says that the Batak script comes from the Brahmi (Indian) writing family and is classified as abugida. An abugida is a pair of characters and their diacritics, the characters symbolize a consonant, the diacritics symbolize the vowels. The writing system used by the Indian alphabet and its derivative alphabets belongs to the abugida group. This also applies to the writing of the Batak script which has a consonant part called ina ni surat and a diacritic part called *anak ni surat*.

CNN is one of the deep learning architectures and has the same working principle as Multi Layer Perceptron (MLP), both of which use the backpropagation algorithm in the data classification process. The difference between CNN and MLP is that the architecture of CNN is preceded by the process of recognizing patterns directly from the pixels of an image so as to minimize preprocessing. Each neuron in CNN is represented in the form of 2 dimensions, while in MLP it is only 1 dimension. The weights in CNN are in the form of 4 dimensions derived from a collection of convolution kernels.

CNN has 2 main layers, namely: Feature Extraction Layer and Fully Connected Layer. In the first layer, the input will be converted (encoding) into features in the form of numbers that represent the input. This layer consists of 2 parts, namely the Convolutional layer and the Pooling layer. In the second layer, the classification process consists of the Flatten layer, Fully-connected layer, and Softmax.

METHOD

The general architecture used in this research can be seen in the following image.

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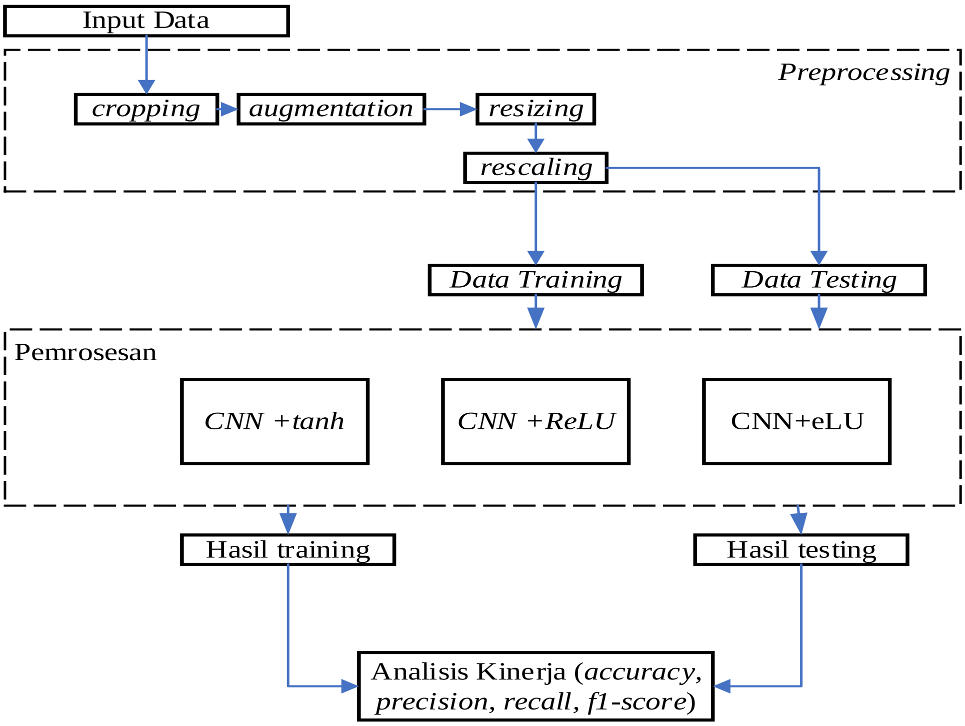

Figure 1. General Architecture

The initial stage in this research is to collect data related to the data to be studied, then do initial data processing (preprocessing), then the data is divided into two, namely data for training and data for testing. In the next stage, classification is carried out using CNN using the selection of activation functions. The final results of the classification will be evaluated and analyzed to determine the performance level of the results of the research that has been done.

Data Preprocessing

The preprocessing stage is the initial stage to prepare the data that has been collected and then several steps are taken so that the data can be used for the training and testing process in the research. Some of the processes carried out at the Preprocessing stage, namely cropping, augmentation, resizing, rescaling, and rescaling.

Cropping

After the data has been collected, it is processed using the Cropping Technique. The selection of the image form of the Batak script is done by observing directly, the script image in the manuscript is selected with the criteria that it can still be read clearly and does not coincide with each other. The script "a", "ma", "i", and "na" are cropped from one part of the script.

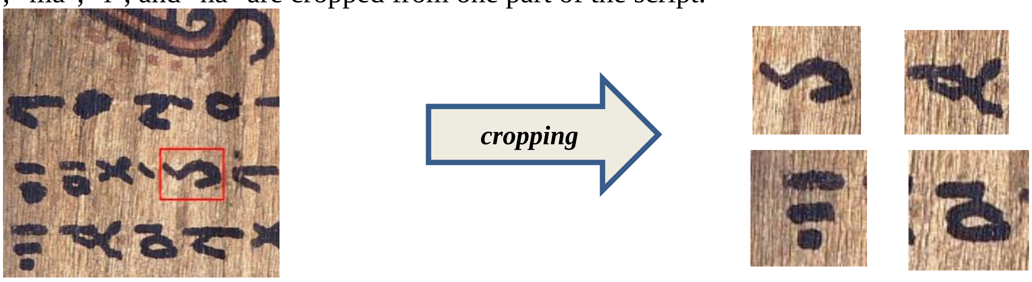

Figure 2 Cropping Process

Each script image in the digitized ancient manuscript is cropped with a square dimension to avoid changing the shape of the image from the original when resized. The labeling process is carried out on all cropped script images. The labeling is adjusted to the type of script used, namely 'a', 'ba', 'da', 'ga', 'ha', 'i', 'ja', 'la', 'ma', 'na', 'nya', 'nga', 'pa', 'ra', 'sa', 'ta', 'u', 'wa', and 'ya'. Example of labeling for script a, i.e. a_001, a_002, a_003 and so on.

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Augmentation

The augmentation process is done to increase the number and variety of shapes of script images that have gone through the cropping process. In this research, the augmentation method used is adjusted to the characteristics of the shape of the Batak script. This is done to prevent changes in the extreme variation of the shape of the script image from the original shape of the characteristics of the script.

Resizing

The resizing process changes the image size to be uniform. The script image resulting from the augmentation process that has a variety of sizes must be resized into a uniform size so that it meets the input dataset standards for the training and testing process. An example of the resizing process can be seen in Figure 3.

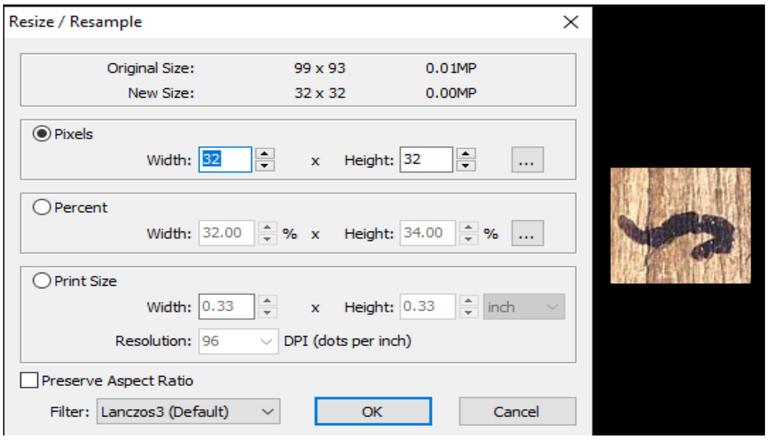

Figure 3. Resizing Process

In Figure 3 the image that was originally 99x93 pixels in size was changed to 32x32 pixels in size. The results of the resizing process can be seen in Figure 4 below.

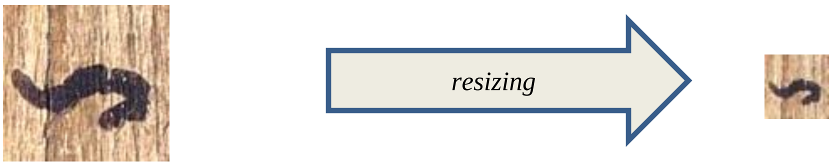

Figure 4. The results of the resizing process

Data Processing Phase

At this stage, there are several steps that are carried out, namely determining the model or network architecture, dividing the dataset, carrying out the training and testing process. The training process is carried out using 3 scenarios, namely CNN training with tanH activation function, ReLU activation function, and eLU activation function.

RESULT

Data Pre-processing Results

The cropping process produces a script image of 19 different classes. Next, the augmentation process is carried out, this aims to increase the number and variety of images. From the results of the augmentation process, the amount of data obtained is 800 image data per class. The image data is then resized to 32x32 pixels. Some examples of images resulting from pre-processing are presented in Table 1.

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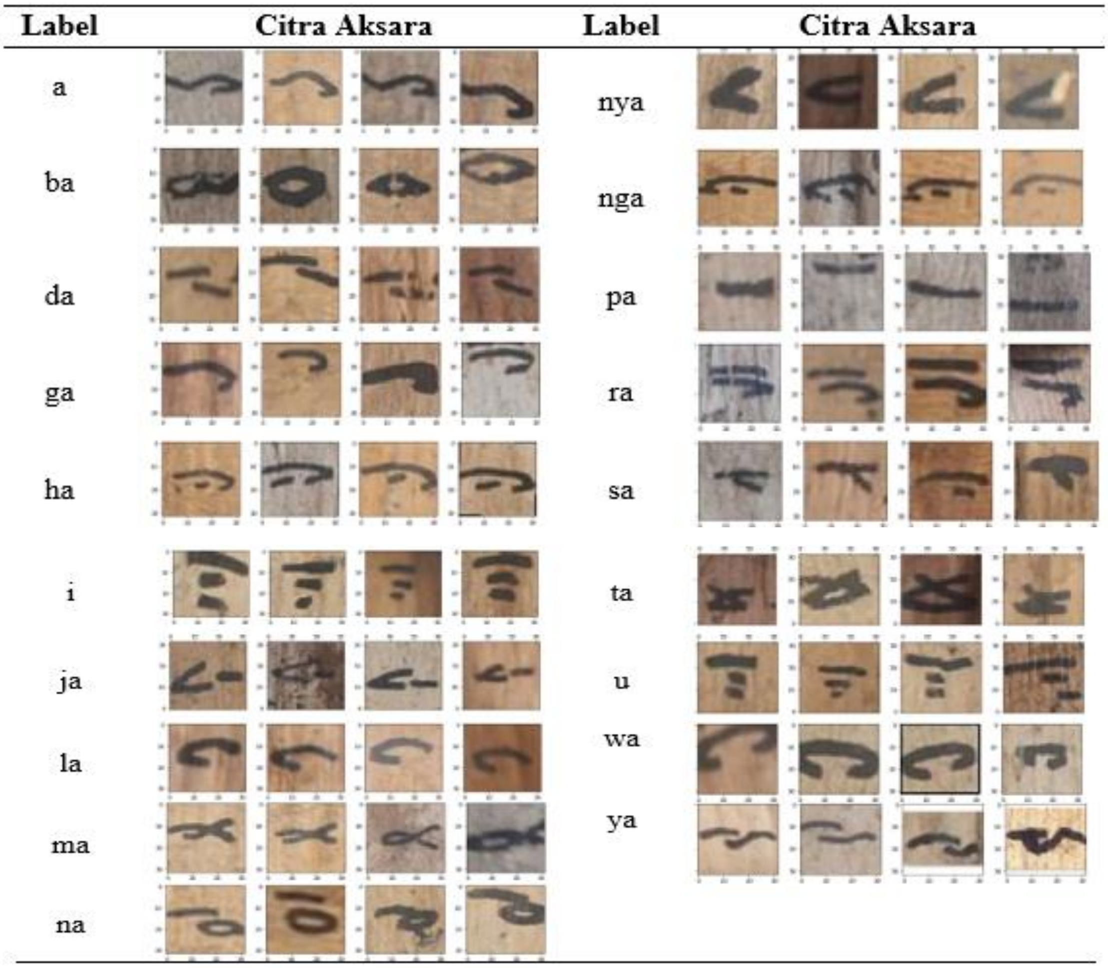
Table 1. pre-processing results



Network Architecture

The CNN network architecture or model used in this study can be seen in Table 2

Table 2. CNN architecture model

Layer (type)	Output Shape	Param #
conv2d_40 (Conv2D)	(None, 32, 32, 6)	456
average_pooling2d_40(AveragePooling2D)	(None, 16, 16, 6)	0
conv2d_41 (Conv2D)	(None, 16, 16, 16)	2416
average_pooling2d_41 (AveragePooling2D)	(None, 8, 8, 16)	0
flatten_20 (Flatten)	(None, 1024)	0
dense_60 (Dense)	(None, 120)	123000
dense_61 (Dense)	(None, 84)	10164
dense_62 (Dense)	(None, 19)	1615

Total params: 137,651
Trainable params: 137,651
Non-trainable params: 0

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From Table 2, the CNN architecture used consists of 7 layers. The first four layers are used to perform feature extraction from the input, which consists of 2 convolution layers with 456 and 2416 neurons, and 2 pooling layers using average pooling. The next three layers are fully connected layers consisting of 3 dense layers with 123000, 10164, and 1615 neurons respectively.

CNN training results using tanh activation function

The training process is carried out with the CNN method using the tanh activation function with data as much as 12,160 script image data. The results of error (loss) and training accuracy can be seen in Table 3.

Table 3. CNN training results using tanh activation function

epoch	*loss*	*Acc*	*val_loss*	*val_acc*
1	3,0343	0,0653	2,6858	0,2138
2	2,5107	0,2535	2,1202	0,4148
3	1,9977	0,4272	1,8119	0,5007
4	1,6994	0,5132	1,5389	0,5526
5	1,4531	0,5819	1,3201	0,6283
6	1,2549	0,6363	1,2415	0,6345
7	1,1124	0,6778	1,0017	0,7243
8	0,9918	0,7129	0,9149	0,7451
9	0,9063	0,7421	0,8194	0,7707
10	0,7771	0,7783	0,6874	0,8145
11	0,6995	0,8031	0,6757	0,8178
12	0,6114	0,8288	0,5655	0,8461
13	0,5358	0,8506	0,5145	0,8536
14	0,4892	0,8567	0,4604	0,8786
15	0,4439	0,8743	0,4511	0,8697
16	0,3988	0,8863	0,3937	0,8908
17	0,3592	0,8989	0,2938	0,9276
18	0,3158	0,9138	0,2842	0,9276
19	0,2784	0,9247	0,2506	0,9349
20	0,2429	0,9332	0,1915	0,9546
21	0,2094	0,9448	0,1903	0,949
22	0,1934	0,9465	0,1428	0,9717
23	0,1617	0,9609	0,1856	0,9484
24	0,1501	0,9625	0,1478	0,9635
25	0,125	0,9679	0,1082	0,976
26	0,1114	0,9697	0,1269	0,9664
27	0,0939	0,9774	0,0867	0,9786
28	0,0741	0,9847	0,0568	0,9898
29	0,0689	0,984	0,0749	0,9832
30	0,0871	0,9771	0,0818	0,9773

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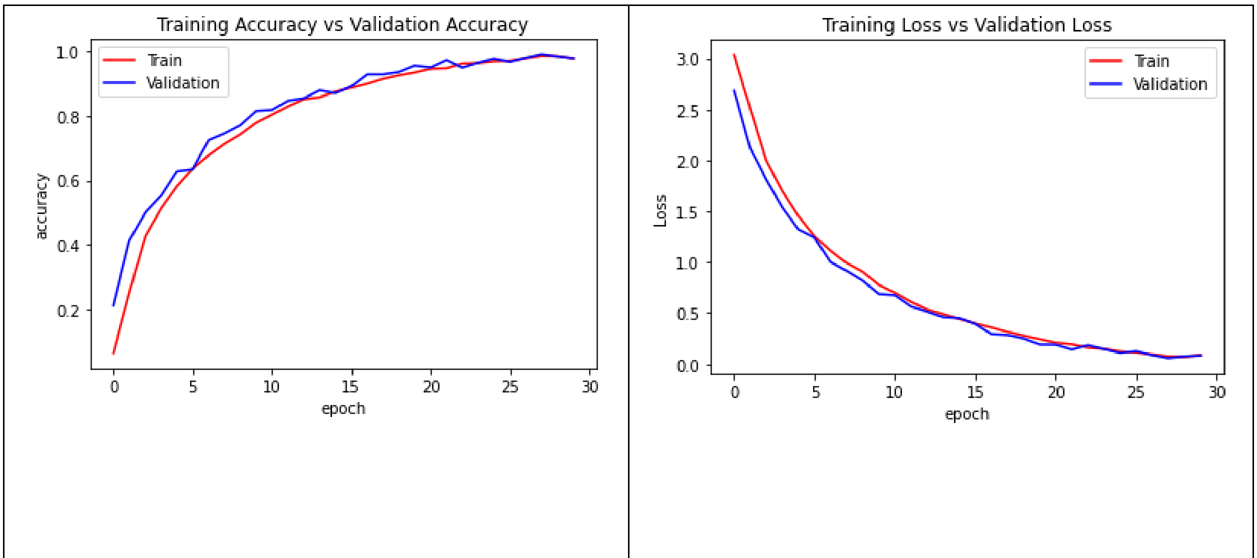
Based on Table 3, the error value (Loss) is inversely proportional to the number of epochs, the more the epoch value increases, the smaller the resulting error value. At the 10th epoch the resulting error is 0.7771, but at the 20th epoch the resulting error decreases to 0.2429 and gets smaller until it reaches the 30th epoch. In addition to the error value, it can be seen that the training accuracy results are directly proportional to the increase in the number of epochs. The best accuracy value is obtained at the 28th epoch of 0.9847 with an error of 0.0741, while the maximum epoch accuracy value is 0.9771. The training process lasted for 236.55 seconds. Changes in error and accuracy in the training process can be seen in Fig. 5.



(a) Grafik Akurasi *CNN* | (b) Grafik *Loss CNN*

Figure 5. Graph of CNN training results using tanh activation function

From figure 5. It can be seen that the model produces a very good level of traning accuracy performance. The model does not experience overfitting or underfitting, this can be seen from the movement of the two charts which are quite stable and smooth.

To find out the performance of the model, testing was carried out using 3040 testing data. From the test results, an accuracy of 87.11% was obtained with an error of 0.4714..

DISCUSSIONS

In this section, we will compare the performance of the results obtained in the previous subchapters. For comparison of accuracy and error performance results and CNN training time can be seen in Table 4.

Table 4. Comparison of CNN model performance results

Model	Akurasi	*Error*	Waktu *training*
CNN menggunakan fungsi aktivasi *Tanh*	97,71%	0,0871	249,59 detik
CNN menggunakan fungsi aktivasi *Relu*	99,19%	0,0243	251,13 detik
CNN menggunakan fungsi aktivasi *elu*	99,71%	0,0108	256,52 detik

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In Table 4. the difference in accuracy performance between the CNN model using Relu and the CNN model using eLU is not significant. However, both outperform the accuracy performance of CNN models that use tanh. CNN models that use eLU activation function obtain the highest accuracy results compared to CNN models that use Relu and tanh activation functions. Likewise, the CNN model that uses the eLU activation function has the lowest error compared to the other 2 models. Based on this, it can be said that the CNN model that uses the eLU activation function has better performance than other models with an accuracy of 99.71% and an error of 0.0108.
To see a comparison of the speed of training accuracy performance produced by these models can be seen using the graph of the training results of the three models in Figure 6.

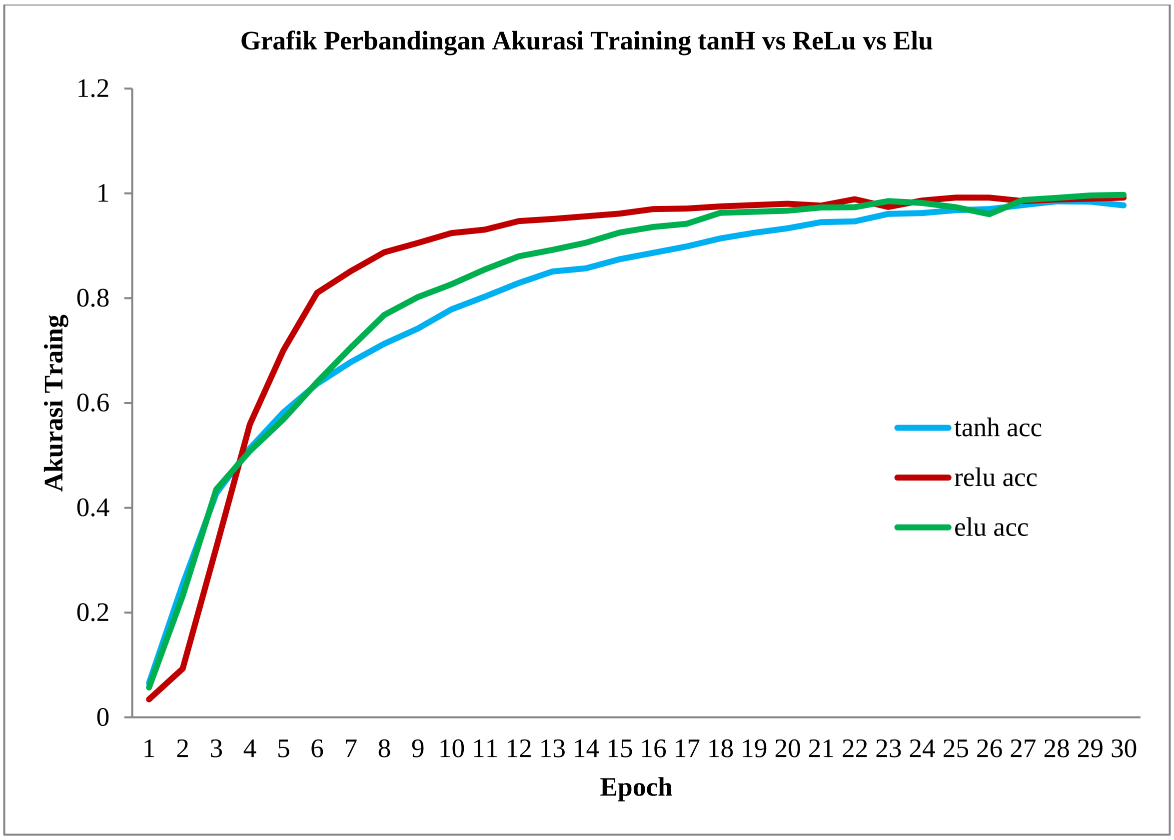

Figure 6. Comparison Chart of Training Accuracy tanh vs Relu vs Elu

From Figure 6, the accuracy performance of CNN models using ReLU after the 4th epoch is above the accuracy performance of other CNN models. The CNN model with ReLU has reached convergence starting from the 13th epoch while the other models only reached it at the 18th epoch and 25th epoch. Based on this, the CNN model using ReLU converges faster than the other 2 models.

For a comparison of the decrease in error value, it can be seen in Figure 7 The decrease in error value (loss) of the CNN model with ReLU occurs quite sharply from the beginning of the epoch to the 6th epoch and then continues to fall steadily until it reaches the maximum epoch. The CNN model with Relu has a lower error value decrease than the CNN model with tanh.

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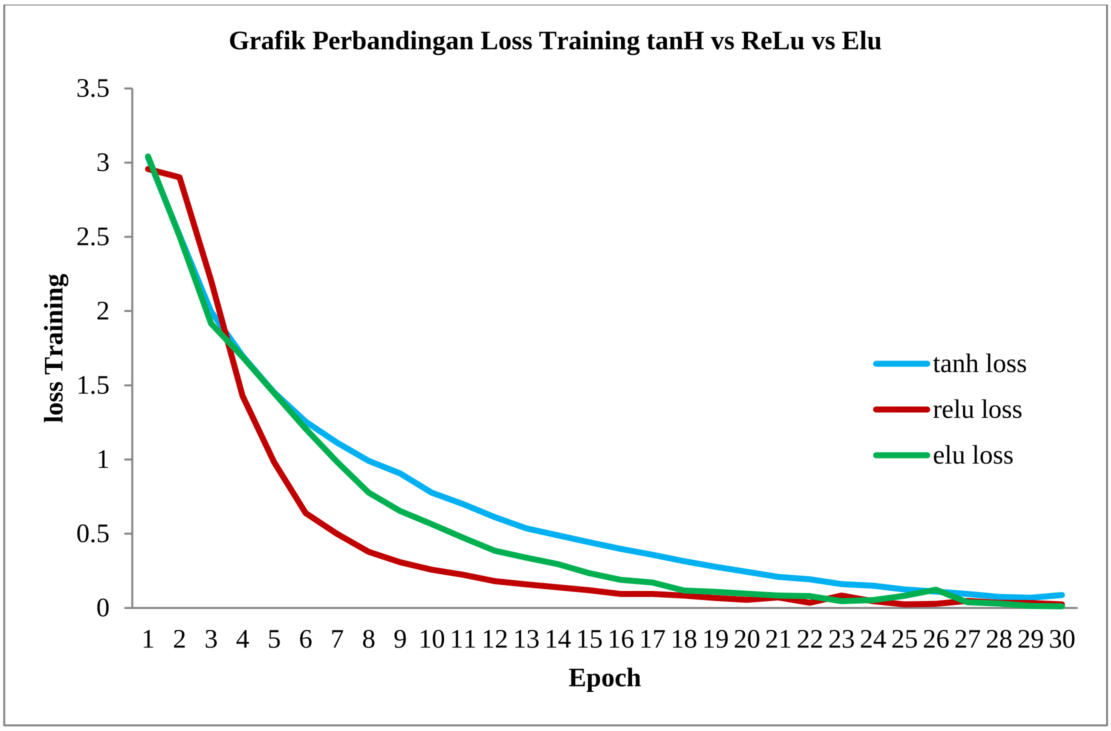

Figure 7. Comparison Chart of Loss Training tanh vs Relu vs Elu

In addition to performance benchmarks based on accuracy, model performance is also measured based on Precision, Recall and f1-score values. To see the model's ability to recognize characters in each class, measurements are made based on each class tested. The comparison of the precision value for each class can be seen in Figure 8.

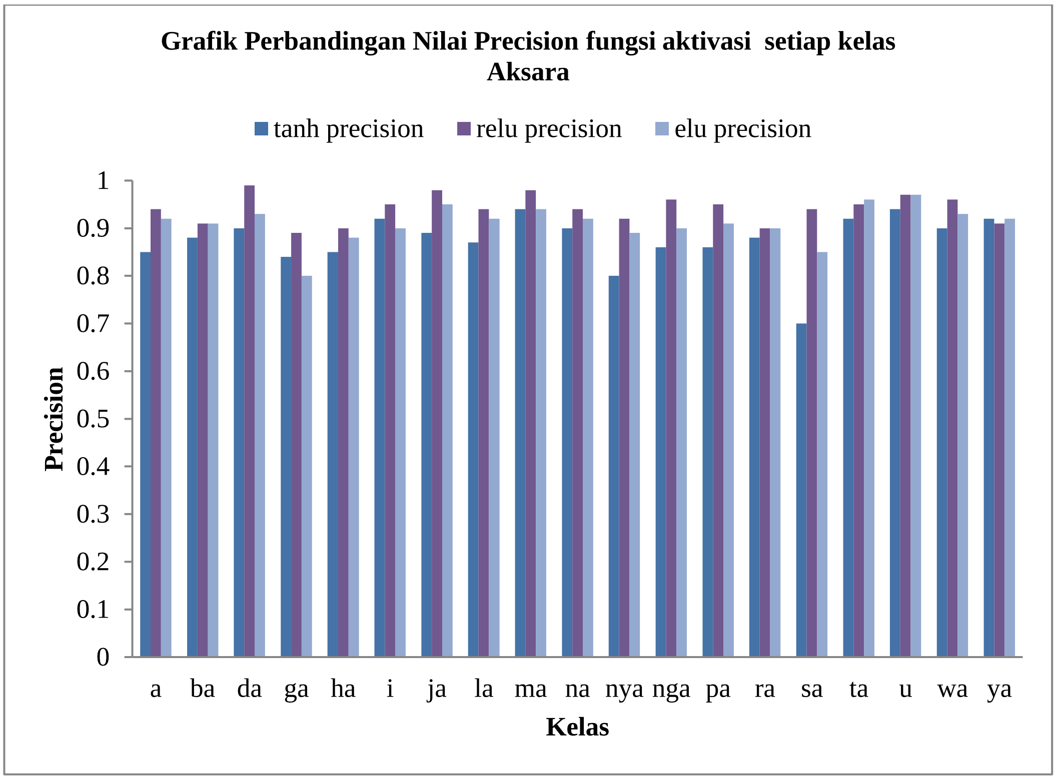

Figure 8. Comparison Chart of Precision tanh vs Relu vs Elu

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Based on Figure 8, the lowest average precision values are obtained by CNN models with tanh activation function, and the highest average values are produced by CNN models with Relu activation function. From the graph, it is also known that the sa, nya, and ga classes have the lowest precision values compared to other classes. This means that the proportion of these classes that are predicted correctly is lower than the other classes.

A comparison of the recall value of the activation function for each Aksara class can be seen in Figure 9.

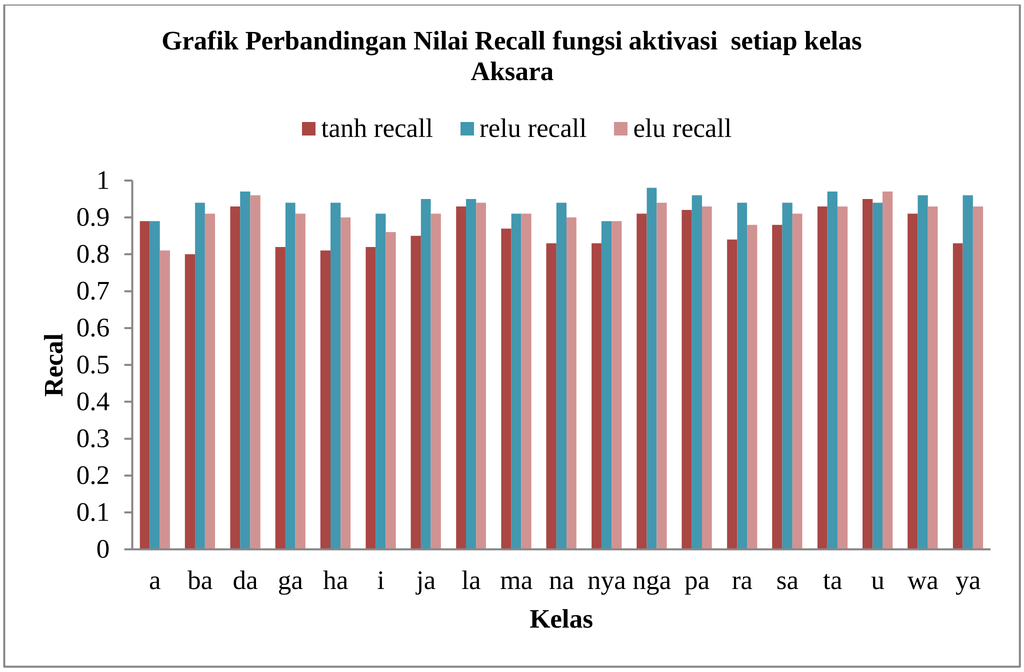

Figure 9. Comparison Chart of Recall tanh vs Relu vs Elu

In Figure 9 the three models show an overall good average recall value. The recall value of the CNN model with the Relu activation function exceeds the recall value of the other two models, this means that the ability of the CNN model with the Relu activation function to recognize script characters correctly is very good compared to other models. For comparison of f1-score values can be seen in Figure 10.

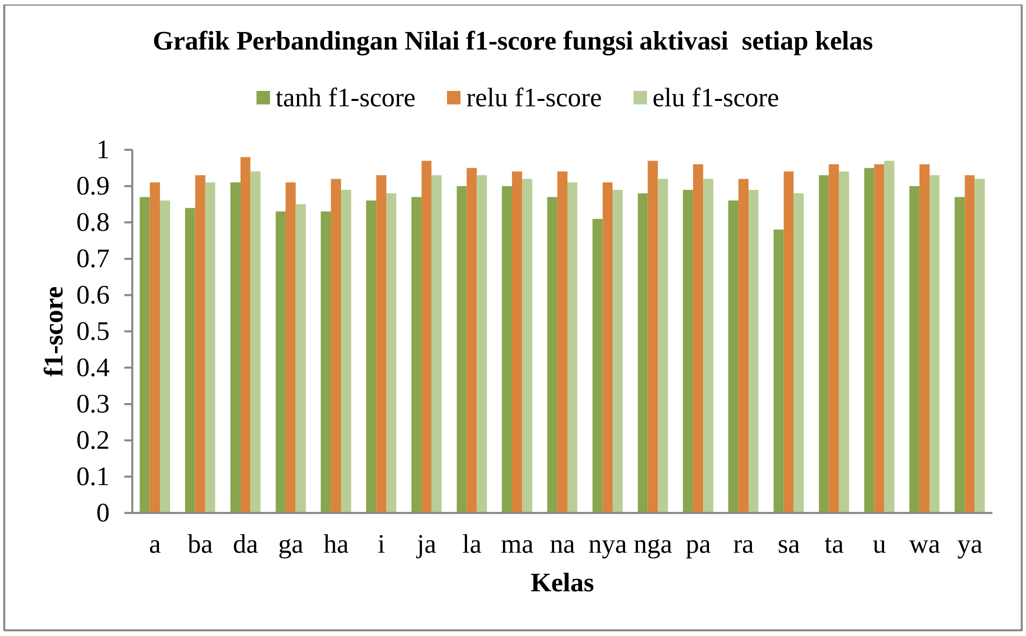

Figure 10. Comparison Chart of f1-score tanh vs Relu vs Elu

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From Figure 10, it can be seen that the comparison of the f1-score values of CNN models using the Relu activation function dominates almost all classes, followed by CNN models using the elu and tanh activation functions. For comparison of test accuracy performance can be seen in Table 5.

Table 5. Comparison of CNN model testing results

Model	***Testing***	***error***	***Precision***	***Recall***	***F1-Score***
CNN + *tanH*	87.11%	0,4714	0,8747	0,8711	0,8711
CNN + *ReLU*	94,11%	0,3282	0,9411	0,9411	0,9416
CNN + *eLU*	90,99%	0,4743	0,9105	0,9116	0,9095

Based on Table 5, the performance of testing accuracy on CNN models using ReLU activation exceeds the performance of the other two models by a difference of 3.12% (eLU) and 7% (tanH) as well as a decrease in the lowest error value of 0.3282 compared to the other two models. This shows that the ReLU activation function is able to improve the performance of CNN accuracy in the recognition of hobo script images.

CONCLUSION

From the results of the research and discussion that has been carried out, the following conclusions can be drawn: The results of the study show that the selection of the right activation function is very influential on increasing accuracy in the Deep Learning training and testing process. The Deep Learning method using the ReLU and ELU activation functions is able to improve accuracy performance and decrease the error value compared to the Deep Learning method using the tanh activation function, which is able to improve the accuracy and decrease the error value compared to the Deep Learning method using the tanh activation function.

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