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# Deep convolutional neural network alexnet and squeezenet for maize leaf diseases image classification

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## Abstract

Maize productivity growth is expected to increase by the year. However, there are obstacles to achieving it. One of the causes is diseases attack. Generally, maize plant diseases are easily detected through the leaves. This article discusses maize leaf disease classification using computer vision with a convolutional neural network (CNN). It aims to compare the deep convolutional neural network (CNN) AlexNet and Squeezenet. The network also used optimization, stochastic gradient descent with momentum (SGDM). The dataset for this experiment was taken from PlantVillage with 3852 images with 4 classes i.e healthy, blight, spot, and rust. The data is divided into 3 parts: training, validation, and testing. Training and validation are 80%, the rest for testing. The results of training with cross-validation produce the best accuracy of 100% for AlexNet and Squeezenet. Furthermore, the best weights and biases are stored in the model for testing data classification. The recognition results using AlexNet showed 97.69% accuracy. While the results of Squeezenet 44.49% accuracy. From this experiment environment, it can be concluded that AlexNet is better than Squeezenet for maize leaf diseases classification.

## 1. Introduction

Along with the development of the food processing industry, the demand for maize also increases. Maize is the second staple food after rice. Maize also has an important meaning in industrial development because it is a raw material for the food and animal feed industry. Based on the report of the Directorate General of Food Crops (Ditjen TP) of the Agriculture Ministry of Indonesia, maize production in the last 5 years has increased by an average of 12.49 percent per year. In 2018 maize production was estimated to reach 30 million tons of maize seeds [1][2].

Maize production must be maintained for the prosperity of rural communities that uses maize as a staple food. However, to increase maize production, there are important obstacles, the emergence of disease symptoms in maize plants. Symptoms of this disease can be seen from the changes in the leaves. The diseases on maize leaves include blight, spot, and rust. The disease disorder is caused by macroorganisms and microorganisms that can interfere with the growth of maize [3]. For this reason, early detection is necessary.

Alternative for maize leaves diseases detection is using computer vision. Outline, there are 2 methods for doing the task of computer vision viz. machine learning and deep learning. After decades machine learning has become the most used method. Classification methods such as Support Vector Machine, k-Nearest Neighbor, Decision Tree, Naïve Bayes have been commonly used for conventional classification [4][5][6]. However, the difficulty of the Machine learning method is to determine the right type of feature extraction. The selected features include color, shape, and texture with all its derivative features  Selection of the right features will determine the success of the recognition [7][8].

Currently, deep learning is an alternative to do this task. Deep Learning can perform feature extraction automatically in the early layers of the network. Convolution layer, pooling and Rectified Linear Unit (ReLU) including parts to perform feature extraction. Researches on image classification, especially diseases on maize leaf using deep learning have been done. Previous studies use Convolutional Neural Network (CNN) AlexNet for maize leaves disease image classification, which resulted in good accuracy of 93.5%, sensitivity of 95.08%, and specificity of 93% with limited data of 200 images [9]. There is also the same classification task using AlexNet with various datasets and results [10][11][12][13][14][15].

Besides AlexNet, there is Squeezenet which is one of the architectures on CNN. Squeezenet has published that the capabilities are comparable with Alexnet. However, Squeezenet has a smaller model size of 0.5MB than Alexnet [16]. Squeezenet for maize diseases classification has been carried out [10]. However, a fair comparison cannot be made because the dataset and the test environment are different. For this reason, the novelty in this article is to compare alexnet and squeezenet for image classification of diseases on maize leaves. The experiment using the same dataset, environment, and test scenarios between alexnet and squeezenet.

## 2. Research Method

### 2.1 AlexNet

AlexNet was introduced by Alex Krizhevsky, Ilya Sutskever, and Geoffery E. Hinton from the University of Toronto Canada. AlexNet model has two parts, feature extraction, and classification. Five convolution layers for feature extraction and fully connected layer + a softmax layer for classification. AlexNet consisting of 11 layers. The 11 layers of AlexNet were [17]:

1. Layer C1: Convolution Layer (96, 11×11)
2. Layer S2: Max Pooling Layer (3×3)
3. Layer C3: Convolution Layer (256, 5×5)
4. Layer S4: Max Pooling Layer (3×3)
5. Layer C5: Convolution Layer (384, 3×3)
6. Layer C6: Convolution Layer (384, 3×3)
7. Layer C7: Convolution Layer (256, 3×3)
8. Layer S8: Max Pooling Layer (3×3)
9. Layer F9: Fully-Connected Layer (4096)
10. Layer F10: Fully-Connected Layer (4096)
11. Layer F11: Fully-Connected Layer (1000).

The block diagram of AlexNet for maize leaf diseases classification shows in Figure 1.

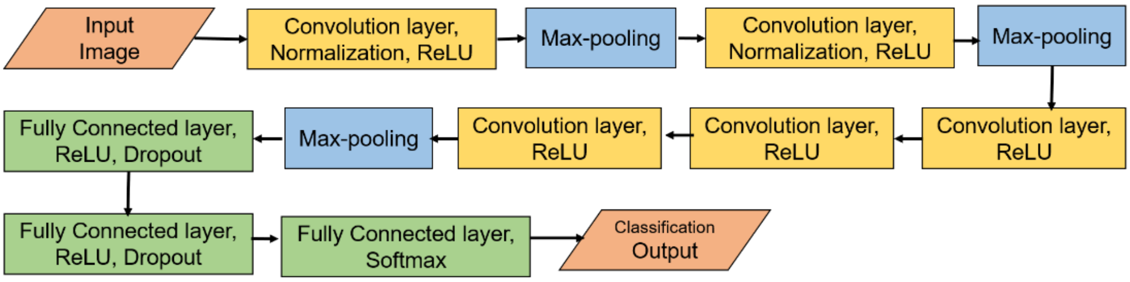


*Figure 1. Block Diagram for Maize Leaf Diseases Images Classification using AlexNet*

### 2.2 Squeezenet

SqueezeNet is a CNN architecture that achieves AlexNet accuracy (winner of ImageNet classification task 2012) with 50 times fewer parameters and 2 times faster training time. SqueezeNet consists of 2 convolution layers, 3 max-pooling, 9 fires in which there is a squeeze layer and expand layer, 1 average pooling, and softmax. Figure 2 shows a block diagram for maize leaf diseases classification [16].

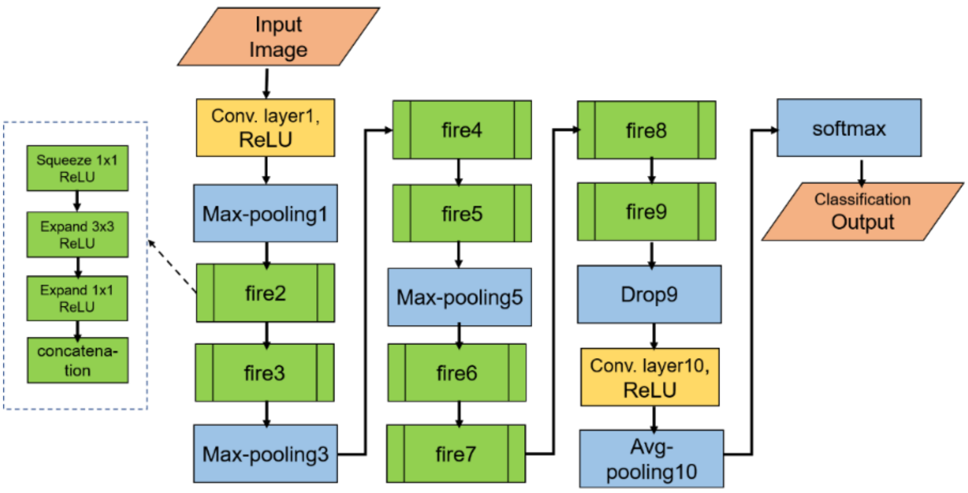


*Figure 2. Block Diagram for Maize Leaf Diseases Image Classification Using SqueezeNet*

Squeezenet has a building brick called a fire module and four pooling layers. The fire module consists of 2 layers: squeeze and expand layer. Squeeze and expand layers keep the same feature map size. Squeeze layer reduces the depth and expand layer vice versa [16].

### 2.3 Stochastic Gradient Descent with Momentum (SGDM)

Optimization with Gradient Descent is carried out to obtain optimal weight and bias parameter values, reduce prediction loss (error) and increase accuracy. We update the weights and biases during the backward pass process using SGDM. SGDM is one of the Gradient Descent optimization algorithms. SGDM is a method for accelerating Gradient Descent by utilizing the gradient information in the previous step. The accumulation of gradients is useful for controlling the effect of oscillations, then the optimization path is expected to be more stable. The following is the SGDM Equation 1, Equation 2, Equation 3, and Equation 4 [18][19].

$$m_0 = 0 \tag{1}$$

$$g_t = \nabla_{\theta_{t-1}} L\,(\theta_{t-1}) \tag{2}$$

$$m_t = g_t + \boldsymbol{\beta} m_{t-1} \tag{3}$$

$$\theta_t = \theta_{t-1} - \alpha m_t \tag{4}$$

With $m_0$ is first momentum; $g_t$ is gradient; $m_t$ is momentum update; $m_{t-1}$ is previously momentum; $\nabla_{\theta_{t-1}} L\,(\theta_{t-1})$ is gradient Loss function. Figure 3 shows the CNN process with SGDM optimization. The process begins with data input, then CNN forward-pass is performed to produce a predictive output value. The results of the prediction are compared with the target output value to produce a loss/error. Furthermore, the CNN backward-pass process is carried out by updating the weights and biases using SGDM optimization.

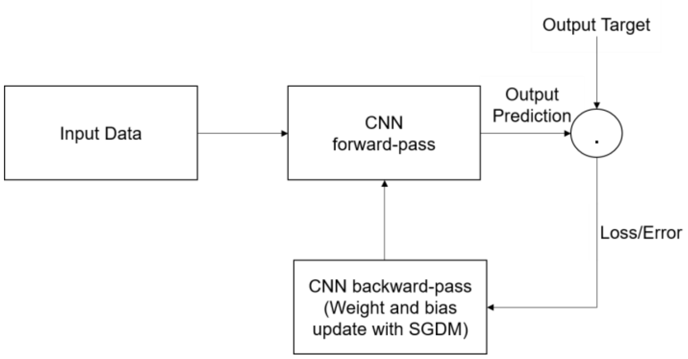


*Figure 3. CNN with SGDM Optimization*

### 2.4 Dataset

The experiment used 3,852 data consisting of 4 classes of maize leaf diseases: 985 blight, 513 spot, 1192 rust, and 1162 healthy. The dataset was obtained from https://www.kaggle.com/abdallahalidev/plantvillage-dataset. The example of image dataset shown in Figure 4 [20]. The 12 images at the top consist of 6 blight and 6 spot, while the 12 images at the bottom consist of 6 rust and 6 healthy leaves.

*Figure 4. Images of Maize Leaf Diseases [20].*

### 2.5 Research Methodology

Research methodology is the steps of research carried out to solve problems. The research consists of several steps i.e:

1. Input training data
2. Classification of the training data using CNN with 10-fold cross-validation. The training data is divided into 10 equal parts, 9 parts for training data, and 1 part for validation. Training for 10 scenarios using 10 different part of data for validation [21][22].
3. Compare the results of each fold. The best performance then saves as the best model. The best models retain all the weights and biases of the best folds.
4. Input testing data on the system. Classification of the testing data with the best model of CNN.
5. Output classification results for testing data.

The research steps shown in Figure 5. The research steps for CNN AlexNet and Squeezenet are the same. Image data for training and validation are 80%, the rest for testing [23][24].

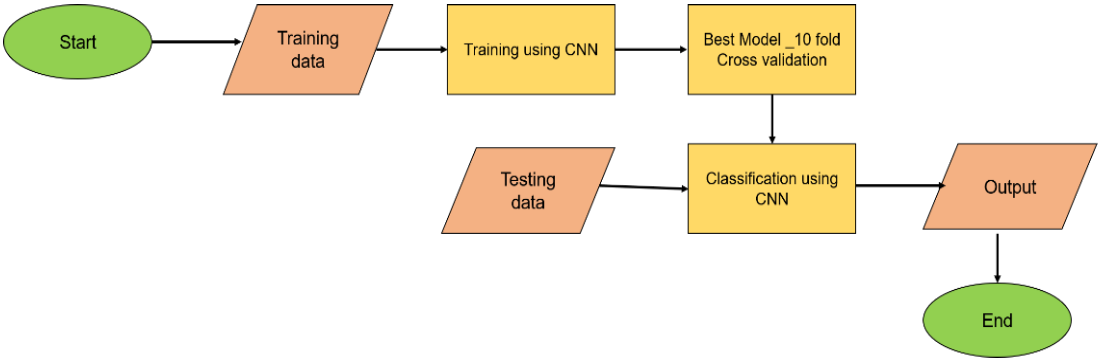


*Figure 5. Flowchart of Maize Leaf Diseases Image Classification*

### 2.6 System Requirement

This section describes the specifications of the devices used to test the system, including the operating system using the software *windows* 10. Spesification of CPU Intel ® Xeon ® 2.3 GHz. No CPU Cores 2, RAM 12 GB. Disk Space 25 GB. GPU NVIDIA K80/T4, GPU Memory 12 GB, GPU Memory Clock 0.82 GHz/1.59 GHz. The system used Pytorch, Phyton library. It also required torchsummary library to print the model's summary in Keras style [25][26].

## 3. Results and Discussion

### 3.1 Training data

This section presents the test scenarios and the results. Test scenarios are applied to get the best model. The data consists of 4 types: manual public data, manual augmentation data, random public data, and random augmentation data. The difference between manual and random data relates to the order of the training data. In the manual data, the placement of training data is done manually (managed by humans). While random data, the system chooses randomly which is used for training. For public data is original data from Plantvillage. It used 3080 images for training+validation data. While data augmentation uses additional $90^0$ rotated image data. The number of augmentation data is 3852. So, the total of training+validation data (augmentation data scenario) is 6160. The scenario is carried out with 2 epochs (50 and 60) [27] and a learning rate of 0.01 [28]. The scenario for training data as follows [9][29][30][31][32][33]:

1. Manual public data
2. Manual augmentation data
3. Random public data
4. Random augmentation data

The results of the performance measure and computation time from training+validation using AlexNet are shown in Table 1. While the results of Squeezenet are shown in Table 2.

*Table 1. Result of Training+Validation using AlexNet*

| Epoch | Data | Accuracy (%) | Precision (%) | Recall (%) | Computation time |
|---|---|---|---|---|---|
| 50 | Manual public data | 99.1 | 98.9 | 99.65 | 39 min. 19 sec. |
| | Manual augmentation data | 91.8 | 81.625 | 86.85 | 26 min. 51 sec. |
| | Random public data | 88.5 | 89.32 | 89.11 | 28 min. 17 sec. |
| | Random augmentation data | 96.29 | 93.32 | 94.15 | 24 min. 30 sec. |

| | | | | | |
|---|---|---|---|---|---|
| 60 | Manual public data | 100 | 100 | 100 | 49 min. 57 sec. |
| | Manual augmentation data | 100 | 100 | 100 | 45 min 24 sec. |
| | Random public data | 91.51 | 90.41 | 89.03 | 31 min 19 sec. |
| | Random augmentation data | 100 | 100 | 100 | 30 min 26 sec. |

The results of the 8 scenarios in Table 1 show that the best performance measure is found in epoch 60 with random augmentation data. The performance measure consists of 100% accuracy, precision, and recall respectively with a computation time of 30 min. 26 sec.

*Table 2. Result of Training+Validation using SqueezeNet*

| Epoch | Data | Accuracy (%) | Precision (%) | Recall (%) | Computation time |
|---|---|---|---|---|---|
| 50 | Manual public data | 99.99 | 99.99 | 99.99 | 532 min. 38 sec. |
| | Manual augmentation data | 99.54 | 99.02 | 99.575 | 476 min. 42 sec. |
| | Random public data | 95.22 | 94.8 | 93.4 | 288 min. 26 sec |
| | Random augmentation data | 98.9 | 98.47 | 97.12 | 326 min. 11 sec. |
| 60 | Manual public data | 100 | 100 | 100 | 528 min. 41 sec. |
| | Manual augmentation data | 99.8 | 99.18 | 99.25 | 559 min. 32 sec. |
| | Random public data | 97.3 | 96.2 | 96.43 | 352 min. 57 sec. |
| | Random augmentation data | 98.3 | 98.22 | 97.37 | 389 min. 46 sec. |

For the results of the training data with 8 scenarios in Table 2, the best scenario is found in epoch 60 with manual public data. Accuracy, precision, and recall are 100% respectively with a computation time of 528 min 41 sec. To underline, the classification using squeezenet takes a relatively long time because it uses minibatch 32 which is half the size of the minibatch used on Alexnet. The limitations of the computer system are to perform computations with large minibatch sizes.

**3.2 The Recognition Results**

The training and validation step is carried out to obtain the best model which is used for the recognition. The recognition was done with the random images. From 20% of the testing data, ten images for each class (Spot, Rush, Blight, and Healthy) were taken for recognition. Table 3 and Table 4 show the recognition results using AlexNet and Squeezenet.

*Table 3. Result of Recognition using AlexNet*

| No | Class | Acc. (%) | Result | Class | Acc. (%) | Result | Class | Acc. (%) | Result | Class | Acc. (%) | Result |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 1 | Spot | 99.3 | Spot | Rush | 100 | Rush | Blight | 99.99 | Blight | Healthy | 100 | Healthy |
| 2 | Spot | 100 | Spot | Rush | 100 | Rush | Blight | 99.99 | Blight | Healthy | 99.95 | Healthy |
| 3 | Spot | 91.37 | Spot | Rush | 100 | Rush | Blight | 99.98 | Blight | Healthy | 99.97 | Healthy |
| 4 | Spot | 99.93 | Spot | Rush | 100 | Rush | Blight | 97.87 | Healthy | Healthy | 99.99 | Healthy |
| 5 | Spot | 99.33 | Spot | Rush | 100 | Rush | Blight | 99.97 | Blight | Healthy | 100 | Healthy |
| 6 | Spot | 99.98 | Spot | Rush | 100 | Rush | Blight | 99.37 | Blight | Healthy | 100 | Healthy |
| 7 | Spot | 99.82 | Spot | Rush | 100 | Rush | Blight | 100 | Blight | Healthy | 99.97 | Healthy |
| 8 | Spot | 99.99 | Spot | Rush | 100 | Rush | Blight | 99.57 | Blight | Healthy | 100 | Healthy |
| 9 | Spot | 99.99 | Spot | Rush | 99.48 | Rush | Blight | 99.99 | Blight | Healthy | 63.21 | Healthy |
| 10 | Spot | 99.97 | Spot | Rush | 100 | Rush | Blight | 58.79 | Healthy | Healthy | 100 | Healthy |

The recognition result for maize leaf image diseases using AlexNet are relatively good. From the 40 testing data, there were 2 incorrect recognitions, the 4$^{th}$ and 10$^{th}$ blight images. The recognition with a low value is shown by the 9$^{th}$ healthy image with an accuracy of 63.21%.

*Table 4. Result of Recognition using SqueezeNet*

| No | Class | Acc. (%) | Result | Class | Acc. (%) | Result | Class | Acc. (%) | Result | Class | Acc. (%) | Result |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 1 | Spot | 53.35 | Spot | Blight | 54.93 | Blight | Rush | 55.40 | Rush | Healthy | 28.48 | Healthy |
| 2 | Spot | 44.69 | Spot | Blight | 47.63 | Blight | Rush | 55.87 | Rush | Healthy | 28.49 | Healthy |

| | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 3 | Spot | 48.56 | Spot | Blight | 38.99 | Blight | Rush | 44.94 | Rush | Healthy | 26.71 | Healthy |
| 4 | Spot | 52.08 | Spot | Blight | 43.35 | Blight | Rush | 48.33 | Rush | Healthy | 26.08 | Healthy |
| 5 | Spot | 55.73 | Spot | Blight | 45.71 | Blight | Rush | 49.59 | Rush | Healthy | 26.05 | Healthy |
| 6 | Spot | 48.62 | Spot | Blight | 54.41 | Blight | Rush | 49.39 | Rush | Healthy | 27.02 | Healthy |
| 7 | Spot | 52.82 | Spot | Blight | 51.15 | Blight | Rush | 44.05 | Rush | Healthy | 40.01 | Healthy |
| 8 | Spot | 56.95 | Spot | Blight | 43.05 | Blight | Rush | 52.06 | Rush | Healthy | 26.54 | Healthy |
| 9 | Spot | 42.87 | Spot | Blight | 48.68 | Blight | Rush | 40.88 | Rush | Healthy | 41.92 | Healthy |
| 10 | Spot | 60.01 | Spot | Blight | 55.86 | Blight | Rush | 42.12 | Rush | Healthy | 26.34 | Healthy |

The results of the recognition using Squezeenet resulted in poor recognition. All images are recognized with a relatively low percentage of accuracy. However, it can recognize all classes correctly.

The recognition results show that AlexNet is better used for image classification of maize disease with a predetermined test scenario. Squeezenet does not produce the expected accuracy. There are several possible causes:

1. Errors when choosing the best model from a comparison of 4 training data scenarios. Furthermore, it is necessary to ensure that the best performance results from the 4 data training scenarios (the best model for each scenario) need to be tested on the recognition data.
2. Augmentation of random training data using AlexNet produces the best model compared to three other training scenarios. However, in SqueezeNet, the best model was not found for augmentation data. It needs to be modified with other augmented data such as translation, flip, and scale.
3. Determine the value of the variable on the network. There are learning rate, epoch, minibatch-size variables that need to be tested for training and testing data. The combination of appropriate values for these 3 variables to obtain better performance. In addition, it is necessary to choose the right optimization method, for example, Root means Square Propagation (RMSProp) [18] and Adaptive Moment Estimation (Adam) [34].
4. The use of hardware specifications that do not support the computations performed. Hardware that has limited conditions, cannot be maximized to process large data and large minibatch values.

## 4. Conclusion

In this article, we have discussed the classification of maize leaf images using AlexNet and Squeezenet. The system was tested using data from Plantvillages which has 4 classes: healthy, rust, spot, and blight. The total data consists of 3852 images. The experiment uses the optimization of Stochastic Gradient Descent with momentum (SGDM) with epochs of 50 and 60, minibatch size of 64 and 32.

The results of training data and validation with 4 scenarios (manual public data, manual data augmentation, random public data, and random augmentation data). The results of the training data show a 100% performance measure for accuracy, precision, and recall. Meanwhile, for the recognition stage, the average percentage of accuracy is 97.69% for AlexNet, while the recognition with SqueezeNet is relatively poor.

For more comprehensive testing, various gradient descent optimization methods such as RMSProp and Adam can be carried out. While the variation of variables needs to be done, for example, the number of epochs, minibatch size, validation frequency, and learning rate.

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