KHATULISTIWA SMART : JOURNAL OF ARTIFICIAL INTELLIGENCE
e-ISSN : XXXX-XXXX
p-ISSN : XXXX-XXXX

Khatulistiwa Smart : Journal of Artificial Intelligence
Vol. 1 No. 1 (2024) : 8-16
Available online at : https://journal.literasikhatulistiwa.org/index.php/smart

Corn Plant Disease Detection Using CNN Model with Resnet50 Architecture

Indra Irawanto [1]
[1] Magister Teknik Informatika Universitas AMIKOM Yogyakarta
indrairawanto@students.amikom.ac.id[1]

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Received: 19 November 2024 *Accepted: 09 Desember* *Published: 31 Desember 2024*

Abstract Plant diseases are a significant problem in agricultural production. Plants affected by the disease can experience growth disorders, declining yields, and declining quality. This study aims to detect diseases in corn plants using a Convolutional Neural Network (CNN) model with ResNet50 architecture. Several scenarios with hyperparameter variations are tested to determine their effect on model accuracy. The first scenario using Adam's optimization algorithm, GlobalAveragePooling2D operation, dropout 0.5, and batch size 64 resulted in an accuracy of 85.97%. The second scenario uses the Flatten operation and results in 85.45% accuracy with a 0.5 dropout and 87.54% with a 0.2 dropout. The use of the SGD optimization algorithm in the third and fourth scenarios resulted in an accuracy of 61.30% and 60.09%, respectively. However, in the fifth scenario, with a dropout of 0.2, the accuracy increases to 73.25%. The results show that hyperparameter variations have a significant influence on model performance.

Keywords *Predictions; CNN; ResNet50; Corn Plant Diseases*

1. INTRODUCTION

Several advances in intelligent technology and the application of machine learning techniques in recent years have revolutionized various fields, including electronic media, medical, engineering, defense, and agriculture (Analuisa-Aroca et al., 2023). Among these fields, agriculture has experienced rapid development in recent years and is one of the sectors that has benefited most from advances in this intelligent technology (Karunathilake et al., 2023). Agriculture is the primary source of income for most of the world's population. Therefore, crop productivity is of great importance globally (Hairani & Widiyaningtyas, 2024). Utilizing innovative farming techniques can provide a significant boost to a country's economy. In addition, there are several plants that can have a significant impact on the country's economy (Balafoutis et al., 2020). This plant is mainly produced domestically and even exported abroad. One of these crops is corn, which has a vital role in the agricultural sector.

Plant diseases are a significant problem in agricultural production (Rizzo et al., 2021). Plants affected by disease can experience growth problems, reduced yields, and reduced quality (Demilie, 2024). This results in economic losses in the agricultural sector. In particular, agriculture is an essential economic activity for many countries, and agricultural products are a significant income source for domestic consumption and export (da Silva Ferreira et al., 2024). Plant diseases can have a negative impact on agricultural production potential (Mafukidze et al., 2022). Specifically, corn diseases are caused by various pathogens such as viruses, viroids, fungi, and bacteria. Frequently seen symptoms of infection include discoloration, rot, scab, blight, necrosis, wilting, and deformity. These symptoms are used to detect and identify leaf diseases in corn plants. Some fungal infections on leaves that commonly occur in corn cultivation are northern corn leaf blight (NLB), southern corn leaf blight (SLB), and gray leaf spot (GLS) (Masood et al., 2023).

Various studies have been carried out to test various object detection methods with the aim of finding more effective methods to use in object recognition for corn disease. Research conducted by (Hindarto, 2023) about improving model performance on maize foliar disease. "This research uses three different ResNet architectures, namely ResNet18, ResNet50, and ResNet10 with accuracy results of 96.68%, 95.73%, and 95.26%, using a dataset taken from Kaggle and consisting of four categories, namely "Blight" with 1146 images," Common_Rust" with 1306 images, "Gray_leaf_spot" with 572 images, and "Healthy" with 1162 images. Other research conducted by (Analuisa-Aroca et al., 2023) using a CNN model with ResNet-50 architecture with a data division of 70% used for training, 15% validation, 15% for testing and the best accuracy results were 94.74%. Other research was carried out by (ÖZDEN, 2023) who conducted experiments by analyzing various methods to improve the effectiveness of corn disease detection. In addition, the SMOTE technique was used to overcome data imbalances in the dataset. The models are trained using preprocessed images and separated into training, validation, and test sets. Experimental results show that the proposed model is 93% MobileNet, Xception (90%), VGG16 (89%), and InceptionV3 (88%).

Various studies have succeeded in presenting intelligent solutions that can help overcome farmers' problems related to plant diseases and increase farmer efficiency. The use of CNN in classifying types of plant diseases has been proven to be able to achieve a high level of accuracy, as in research (Analuisa-Aroca et al., 2023), (Hindarto, 2023) which uses various architectures and optimization techniques to improve classification performance. Future research will conduct experiments by combining these two techniques' potential. The proposed research can gain advantages in detecting and classifying plant leaf diseases more accurately and efficiently, as well as providing solutions that can help reduce crop failure and increase production yields.

2. RESEARCH METHODS

Research used to build and evaluate model performance. Necessary information such as the method chosen to obtain the data set, data preparation techniques, data analysis techniques, etc. as shown in Figure 1. Figure 2 explains the web diagram flow process for prediction.

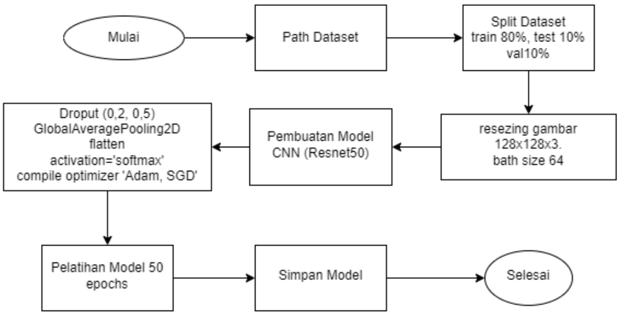

Figure 1. Process Flow Diagram Model

The diagram above illustrates the process flow for creating a CNN model using the ResNet50 architecture for image classification. The following is a summary of the flow process:

1. Starting the model creation process.
2. Determine the path or location of the dataset.
3. Divide the dataset into train (80%), test (10%), and validation (10%) parts.
4. Preprocessing changes the image size to 128x128 pixels with three color channels (RGB), and determines the batch size of 64.
5. Model creation using ResNet50 architecture, Implementing dropout with rates 0.2 and 0.5, Using Global Average Pooling2D layer, Flattening the pooling results into one dimension, Using the "softmax" activation function, Compiling the model with the "Adam" and "SGD" optimizers.
6. Model training for 50 epochs.
7. Save the trained model.
8. Process complete.

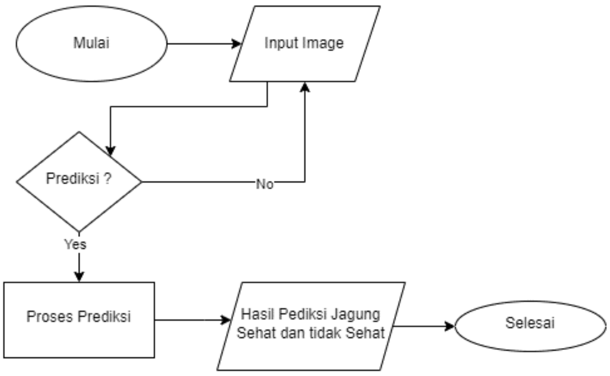

Figure 2. Process Flow Diagram Web

The diagram above illustrates the flow of the corn health prediction process via the web, starting from image input, carrying out the prediction process, to producing a prediction output in the form of healthy or unhealthy corn status.

This research uses a dataset originating from Kaggle data which consists of 4 classes consisting of 3,852 images. Three classes are corn plant diseases, corn leaf spot, leaf rust, corn leaf blight, and 1 class is healthy corn leaves. This dataset consists of 513 images of corn leaf spots, 1192 images of leaf rust, 985 images of corn leaf blight, and 1162 images of healthy corn leaves The following sample from the dataset is in Figure 3.

Figure 3. Sample Images from Dataset

At the corn leaf data collection stage with the aim of identifying and detecting corn leaf diseases, 3852 images were used. The created data set then undergoes preprocessing,, removing noise and producing more precise images. The resized data is divided into three parts, namely 70% train data, 15% test data, and 15% validation data. The distribution of training data is presented in Table 1. All images were resized to 128 x 128 pixels with three color channels so that the width and length were the same, and used a batch size of 64.

Table 1. Number of Dataset Shares

Data	Count	Trains	Test	Valid
Corn Leaves	3852	3081	385	386

Convolutional Neural Network (CNN) is a convolutional neural network used to process and analyze visual data, especially images. CNNs generally have convolution, pooling, and fully connected layers for image prediction or classification processes. The convolution process extracts features and learns informative feature representations from the input image. The features resulting from this convolution process are then collected and further processed by a pooling layer which reduces the size of the feature space using methods such as Max Pooling or Average Pooling (Suresh D. Shirbahadurkar, 2024). In this research, we use a CNN model with the ResNet50 architecture, which was carried out by (Pamungkas et al., 2023), which is known to have the ability to learn deeper feature representations through the use of residual blocks. Several scenario tests with varying hyperparameters to see their effect on model accuracy (Masood et al., 2023). The first scenario uses the Adam optimization algorithm, GlobalAveragePooling2D operation, dropout of 0.5, and batch size 64, resulting in an accuracy of 85.97%.

In the second scenario, we used the Flatten operation with the Adam optimization algorithm and found that with a dropout of 0.5, the accuracy achieved was 85.45%, while with a dropout of 0.2, the accuracy was 87.54%. Next, we tested the use of the SGD optimization algorithm. In the third scenario, with GlobalAveragePooling2D operation and a dropout of 0.5, the model achieved an accuracy of 61.30%. In the fourth scenario, when using the Flatten operation with the SGD optimization algorithm and dropout 0.5, the accuracy achieved is 60.09%.

Interestingly, when dropout was reduced to 0.2 in the fifth scenario, accuracy increased drastically to 73.25%. These results show that model accuracy varies depending on the type of optimization, pooling operation, and dropout rate used. These findings emphasize the importance of selecting appropriate hyperparameters in optimizing the performance of CNN models with the ResNet50 architecture. Using the ResNet50 architecture with several scenarios in CNN was proven to provide accurate results in detecting diseases on corn leaves (Analuisa-Aroca et al., 2023). ResNet50's efficient and lightweight architecture is well suited for intelligent farming applications in the field, where computing resources may be limited. Several factors, including data preprocessing and model training influence the success of this model. The results of this experiment show that the CNN method with the ResNet50 architecture is effective in detecting diseases on corn leaves. The highest level of accuracy, namely (93.67%) in the classification of corn leaf spot disease, provides an indication that this model is reliable for use in real applications in agriculture. To predict corn leaf disease, implementing predictions on the web can be done in several steps (Tetteh & Thushara, 2023). First, the corn leaf image data uploaded by the user will be processed through a trained CNN model. Then, the prediction results will be displayed on the web interface, showing the type of disease detected and its confidence level (Mafukidze et al., 2022). It allows users to easily identify diseases on corn leaves quickly and accurately, supporting better farming decisions.

3. RESULTS AND DISCUSSION

This research produced several significant findings regarding corn plant disease detection using a CNN model with the ResNet50 architecture.

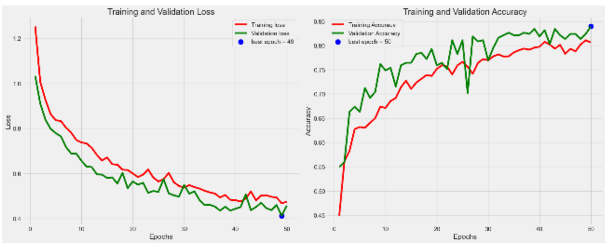

Figure 4. Scenario 1

In Figure 4, the first scenario, using the Adam optimization algorithm, 2D Global Average Pooling operation, dropout of 0.5, and batch size of 64, achieved an accuracy of 85.97%. It can be seen in the right graph, which shows the increase in accuracy both training data (red line) and validation data (green line) over 50 epochs. In addition, the left graph shows a decrease in loss values for both training data (red line) and validation data (green line) as the epochs increase, with stabilization starting to appear after around 30 epochs.

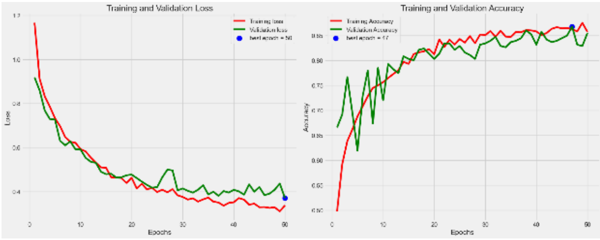

Figure 5. Scenario 2

In Figure 5 the second scenario, using the Flatten operation and Adam's optimization algorithm, this scenario produces an accuracy of 85.45% with a dropout of 0.5, and 87.54% with a dropout of 0.2. This can be seen in the graph on the right which shows an increase in accuracy in both the training data (red line) and validation data (green line) over 50 epochs. The graph on the left shows a decrease in loss values in both the training data (red line) and validation data (green line) as epochs increase, with stabilization starting to appear after about 40 epochs.

Figure 6. Scenario 3

In Figure 6, when using the SGD optimization algorithm, the third scenario with the GlobalAveragePooling2D operation and a dropout of 0.5 achieved 61.30% accuracy. Meanwhile, the fourth scenario with the Flatten operation and a dropout of 0.5 resulted in an accuracy of 60.09%. This can be seen in the graph on the right which shows an increase in accuracy in both training data (red line) and validation data (green line) for 50 epochs. The graph on the left shows a decrease in loss values in both the training data (red line) and validation data (green line) as the epochs increase, with stabilization starting to appear after about 40 epochs.

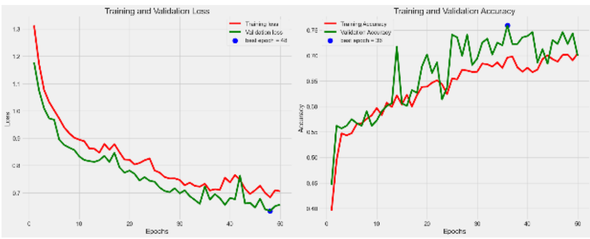

Figure 7. Scenario 4

In Figure 7, the fourth scenario with Flatten operation and a dropout of 0.5 resulted in an accuracy of 60.09%. This can be seen in the graph on the right which shows an increase in accuracy in both training data (red line) and validation data (green line) for 50 epochs. The graph on the left shows a decrease in loss values in both the training data (red line) and validation data (green line) as the epochs increase, with stabilization starting to appear after about 40 epochs.

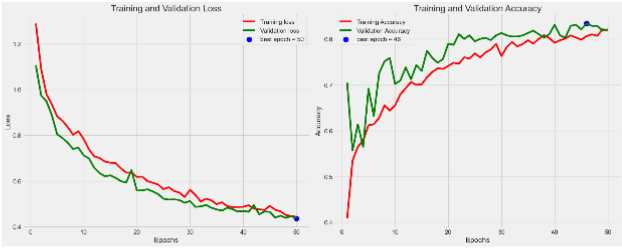

Figure 8. Scenario 5

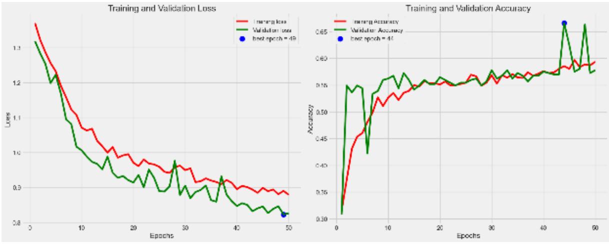

Figure 9. Scenario 6

In Figures 8 and 9, the fifth and sixth scenarios show the results when the dropout is reduced to 0.2. In figure 8, the accuracy increases to 72.25% with the Adam optimization algorithm and the GlobalAveragePooling2D operation. In figure 9, the accuracy reaches 73.25% with the SGD optimization algorithm and the Flatten operation. The graphs present the plot results of several training scenarios. These results show the variation of model accuracy based on the type of optimization, pooling operation, and dropout rate used, confirming the importance of proper hyperparameter selection in optimizing the performance of CNN models with ResNet50 architecture.

Figure 10. Implementation of Website Prediction Results

In Figure 10, the prediction results displayed on the web interface show the type of disease detected and its confidence level. This web interface displays the prediction "Corn leaf spot" with a confidence level of 93.64765179176313%.

4. CONCLUSIONS

Based on the results of the study, the use of CNN models with ResNet50 architecture proved effective in detecting diseases in corn plants. Hyperparameter variations such as optimization type, pooling operation, and dropout level have a significant influence on model accuracy. The scenario with Adam optimization algorithm and 0.2 dropout on Flatten operation showed the best accuracy of 87.54%, confirming the importance of experimentation and hyperparameter adjustment to achieve optimal results. Therefore, we recommend the use of data augmentation techniques and experiments with various hyperparameter configurations to develop better models. In addition, the implementation of this model in web applications can provide real benefits to farmers in detecting diseases quickly and accurately, supporting better agricultural decisions.

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