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Classification of Corn Leaf Disease Using Convolutional Neural Network

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Abstract. Corn is a crop that plays a major role in food supply worldwide. Known as a cereal crop with high economic value, corn is one of the most important raw materials in the agricultural industry in many parts of the world. Leaf blight is characterized by small spots that gradually enlarge and turn brown. It is a decay of foliage caused by the fungus or species Rhizoctonia solani. Leaf spot is caused by the fungus Hel-minthoporium maydis, while stem rot is caused by Fusarium granearum. From these problems, a machine learning-based solution is given to classify corn leaf diseases using the Convolutional Neural Network (CNN) algorithm. CNN are used to classify corn leaf diseases. The selection of CNN is based on its ability to extract local attributes from image data and combine them for a more detailed and abstract representation, which is better. Classification was performed using 2145 datasets for leaf blight and 1574 datasets for leaf spot. The accuracy results obtained from this study reached 99% with the last training accuracy value of 99.06% and the last validation accuracy result of 98.50%. For future research may use more modern architectures such as classification using EfficientNet B3 architecture with transfer learning or MobileNet to improve accuracy results.

Keywords: CNN, Corn, Image Classification, Image Processing, Machine Learning

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1. Introduction

Corn or zea mays, is a crop that plays a major role in food supply worldwide [1], [2]. Known as a cereal crop with high economic value, corn is one of the most important raw materials in the agricultural industry in many parts of the world [3], [4]. Since ancient times, corn has been an integral part of human life, whether as a source of food, animal feed, industrial raw materials, or as a symbol of culture and tradition. In addition, corn has a high adaptability to different environmental conditions, making it a very diverse crop that can grow in various types of land, ranging from lowlands to mountains. According to the World Agricultural Organization (FAO), Indonesia was the world's largest maize producer at the end of 2017. However, there are four main diseases: leaf rust, leaf spot, blight, and downy mildew that result in low maize production [5]. Downy mildew is usually caused by a fungus called Sclerospora maydis. Blight is characterized by small spots that gradually enlarge and turn brown. It is a decay of foliage caused by the fungus or species Rhizoctonia solani. Leaf spot is caused by the fungus Helminthoporium maydis, while stem rot is caused by Fusarium granearum [6].

Current technological developments will allow farmers to minimize errors in identifying diseases in corn plants by using an artificial intelligence approach [7], [8]. Artificial Intelligence in computer science, is the study of how computers can perform at a human level or better [9]. Machine learning is a branch of artificial intelligence that allows computers to learn and make data-based decisions without being explicitly programmed [10]. Machine learning involves training algorithms and models that use data to recognize patterns and make predictions. In its development, machine learning also has an expanded field, namely deep learning [11]. One of the most popular deep learning algorithms for processing images is Convolutional Neural Network (CNN) [12], [13], [14]. CNN is an evolution of multilayer perceptron (MLP) designed to process data containing two-dimensional image data. CNN is used to classify labeled data using supervised learning techniques. In the guided learning method, there is training data and test data.

Several studies have been conducted to identify and classify plant leaf diseases early. Suherman on corn leaf data using Naïve Bayes method resulted in 90% accuracy [15]. Onion disease identification research was conducted by Khamdani et al. This research explains the diagnosis of onion disease with the KNN method. KNN is used to diagnose onion plants by identifying k groups of objects in the research data. In this case the accuracy achieved was 85.835% [16]. Research conducted by Muslim et al. namely the classification of chili diseases using the convolutional neural network (CNN) method. For the type of chili plant disease, it can be seen that the convolutional neural network architecture can classify three types of chili plant disease types by labeling the input data. The results of validating the convolutional neural network architecture on test data show 60% accuracy [17]. Based on the above information, this research was conducted to classify diseases in corn leaf plants based on leaf spots using the Convolutional Neural Network method, with the hope of getting more accurate results that can be a differentiator from other studies.

2. Methods

2.1. Dataset

Here, we used a dataset in the form of a bar image containing a collection of images of corn leaves infected by two main types of diseases, namely blight which has a total of 2145 data, and gray spot which has a total of 1574 data. The data will be used for training and data validation, with jpg format as in Figure 1 and Figure 2.

Figure 1. Leaf Blight Disease

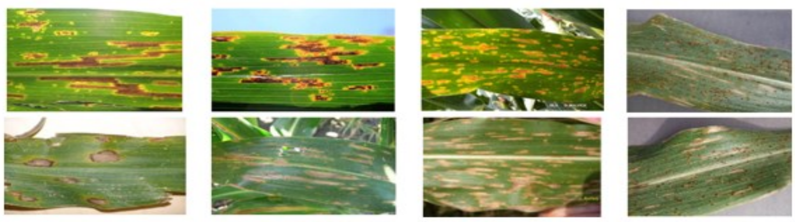


Figure 2. Leaf Spot Disease

This data is taken from the kaggle plat-form, which is a leading website for sharing datasets and solutions in the fields of data science, machine learning, and data analytics. This dataset consists of images of corn leaves taken from various field conditions and different shooting angles. There are 3 data needed for this research, namely: Training data. Training data is used as a training process for corn disease data, where a dataset of 800 disease images will be trained. Validation Data. Validation data is data used during the training process, namely data used to test accuracy during the training process. The data used is 200 data. Testing Data. Test data is data used to test the system with new data.

2.2. Data Augmentation

Data augmentation [18] is a technique that increases the diversity of images in a dataset by performing transformations such as random rotation, shifting, and zooming. First, create a training data generator (train_datagen) that performs various transformations such as rotating the image by 30 degrees, flipping the image horizontally, using a shear with a limit of 0.3 and filling missing pixels with the nearest value. In addition, the image is zoomed 10% and shifted 20% of the width and height. Next, the same generator for the validation data (val_datagen) was created with the same transformation. The purpose is to allow the model to be trained for a larger variety of images, so that it can be applied to new data.

2.3. Convolutional Neural Network

Convolutional Neural Network [19], [20] is a type of neural network used for image processing. CNN uses the concept of convolution, which is a data processing process that moves a filter or kernel through each part of the image. Each filter is used to capture a specific feature of the image, such as: lines, outlines, or colors. This process is repeated at each layer of the CNN, so that the detected features become more complex and abstract at higher layers [21]. CNN consist of three main components: a convolutional layer, a union layer, and a fully connected layer. Convolution is used to extract features from an image using filters or kernels. This process is done by performing mathematical operations on each pixel of the image using a shifted filter. The pooling process is used to reduce the size of the image and increase its robustness to changes in scale and orientation, following the convolution process. The last process, the fully connected layer, is used to classify the processed image by connecting each neuron in the previous layer to each neuron in the next layer. The selection of CNN is based on its ability to extract local attributes from image data and combine them for a more detailed and abstract representation, which is superior. This research uses the Python programming language and the Tensorflow framework for training and testing data. The CNN structure used in this research combines multiple convolutional layers and a pooling process to reduce the spatial dimension of the extracted features. In the convolutional layers, the number of filters is controlled using a combination of 3x3 or 5x5 and can vary between each layer. The ReLU activation function introduces nonlinearity into the training process. To classify corn leaf diseases into their corresponding classes, fully connected layers are created by connecting multiple convolutional layers and unifying the layers using a feature extraction process. The backpropagation algorithm and adaptive moment estimation optimization (Adam) are used in the CNN training process to minimize the cross-entropy loss function. The following CNN architecture layer can be seen in the Table 1.

Based on Table 1, the layer type had been explain as follow :

Input Layer: Although not explicitly shown, the input layer usually has dimensions (148, 148, 3) for color images. Convolutional Layer 1 (conv2d): Output shape: (148, 148, 16) Number of parameters: 448 This is the first convolutional layer that extracts the basic features from the input image.

Max Pooling Layer 1 (max_pooling2d): Output shape: (74, 74, 16) Reduces the spatial dimension while retaining important information.

Convolutional Layer 2 (conv2d_1): Output shape: (72, 72, 32) Number of parameters: 4640 The second convolutional layer for extracting more complex features.

Max Pooling Layer 2 (max_pooling2d_1): Output shape: (36, 36, 32) Again reduces the spatial dimension.

Convolutional Layer 3 (conv2d_2): Output shape: (34, 34, 64) Number of parameters: 18496 The third convolution layer for more abstract features.

Max Pooling Layer 3 (max_pooling2d_2): Output shape: (17, 17, 64) Last dimension reduction.

Flatten Layer: Output shape: (18496) Converts 3D data to 1D for input to the fully connected layer.
Dense Layer 1: Output shape: (200) Number of parameters: 3699400 Fully connected first layer.
Dropout Layer 1: Output shape: (200) Helps prevent overfitting.
Dense Layer 2: Output shape: (500) Number of parameters: 100500 Fully connected second layer.
Dropout Layer 2: Output shape: (500) The last dropout layer before the output.
This model uses a classic CNN architecture with three convolution-pooling blocks, followed by two fully connected layers with dropouts in between.

Table 1. Our Proposed CNN Architecture Layers

Layer (type)	**Output Shape**	**Param #**
Conv2D	(None, 148, 148, 16)	448
MaxPooling2D	(None, 74, 74, 16)	0
Conv2D_1	(None, 72, 72, 32)	4640
MaxPooling2D_1	(None, 36, 36, 32)	0
Conv2D_2	(None, 34, 34, 64)	0
MaxPooling2D_2	(None, 17, 17, 64)	0
Flatten	(None, 18496)	0
Dense	(None, 200)	3699400
Dropout	(None, 200)	0
Dense_1	(None, 500)	100500
Dropout_1	(None, 500)	0
Dense_2	(None, 2)	1002

2.4. Pre-processing

The researcher performed data processing at this stage. This involved adjusting the image size as needed and creating a data set for classification purposes. The TensorFlow pre-processing library was used to perform this data pre-processing [22]. Data preprocessing is the first step taken before processing the data and is used to perform the classification process. The data preparation stage includes determining the amount of data used, which is 3719 images of two classes, with the class divisions being blight and leaf spot. For data augmentation, image pre-processing steps were performed using the Hard Image Data Generator.

2.5. Confusion Matrix-based Evaluation

Confusion Matrix [12], [23] is a visual evaluation tool commonly used in machine learning. Confusion matrix represents the predicted class results and rows represent the actual class results, making it possible to calculate all possible cases of classification problems. The accuracy calculation is done to determine the success rate of the CNN model in corn leaf classification. Accuracy serves as a reference point for model comparison and new CNN system development. From the confusion matrix in Figure 4, the formula are visualised in (1) until (3).

$$\text{Accuracy} = \frac{(TP+TN)}{Tp+FP+TN+FN} 100\% \qquad (1)$$

Where, True Negatives (TN) is the sum of correctly recognized but misclassified (negative) corn leaf image data. False Positive (FP) is the amount of corn leaf image data that is misclassified (negative) but considered as correctly classified data (positive). True Positives (TP) is the number of corn leaf images that were correctly classified as false positives. False Negative (FN) is the opposite of true positives.

2.6. Research Method Flow

Based on the flowchart in Figure 3, the research work begins with collecting datasets in the form of images found on the Kaggle platform. After the dataset is found, pre-processing is carried out on the dataset, then after processing the data will be divided into 3 parts, namely material data, training data, and validation data. Training data and validation data will go through the CNN architecture training process, after the training data is obtained, it will be evaluated using the confusion matrix. Then the last step is the process of classifying test data.

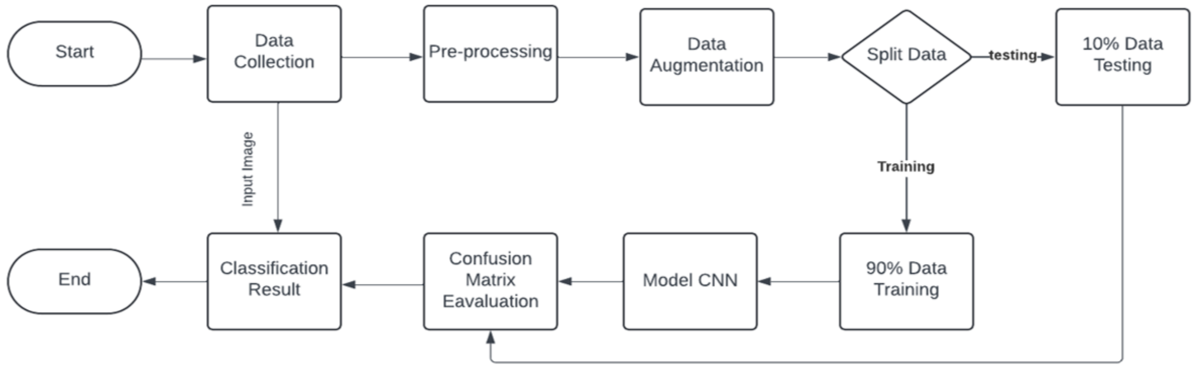


Figure 3. CNN Research Flow

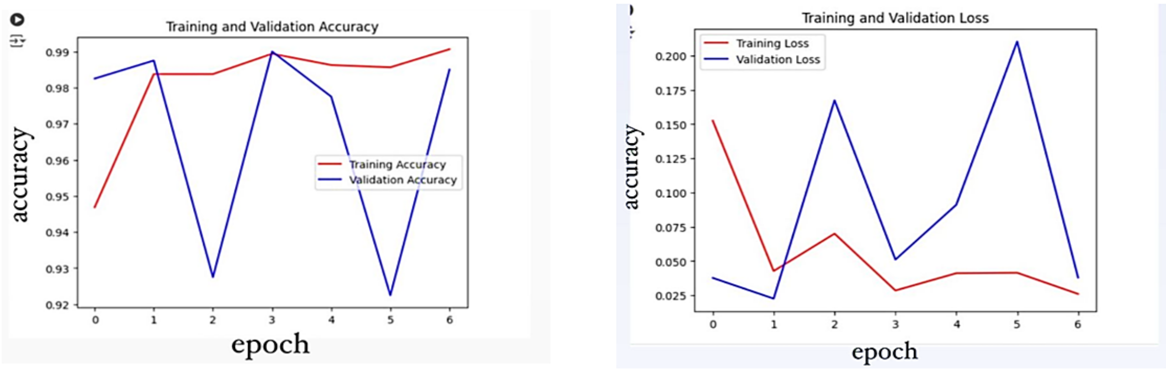
3. Results and Discussion

After conducting a series of experiments using the convolutional neural network (CNN) method to classify corn leaf diseases, the results were promising. The trained CNN model achieved a classification accuracy of 99.06% on the last training data and a classification accuracy of 98.50% on the last validation data. Visualization of the features extracted by the CNN showed that the model accurately represented important patterns such as lesions, blotches, and discoloration that characterize diseased leaves as in Table 2.

Table 2. The Training and Validation Result

Epoch	Loss	Accuracy	Validation Loss	Validation Accuracy
1	0.1525	0.94690	0.0377	0.9825
2	0.0428	0.9837	0.0226	0.9875
3	0.0700	0.9837	0.1674	0.9275
4	0.0285	0.9894	0.0511	0.9900
5	0.0412	0.9862	0.0911	0.9775
6	0.0415	0.9856	0.2103	0.9225

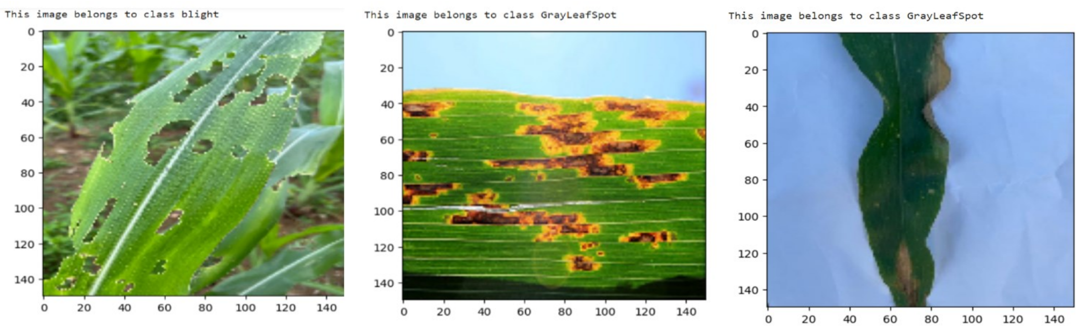
Based on results of table 2, In the first epoch, the model obtained a loss of 0.1525 and an accuracy of 94.69%, with a validation loss of 0.0377 and a validation accuracy of 98.25%. In the second epoch, the model showed improvement with a loss of 0.0428 and an accuracy of 98.37%, while the validation loss dropped to 0.0226 and the validation accuracy rose to 98.75%. In the third epoch, although the accuracy remained at 98.37%, the loss increased to 0.0700, and the validation loss rose significantly to 0.1674, so the validation accuracy dropped to 92.75%. In the fourth epoch, the model again showed improvement with a loss of 0.0285 and an accuracy of 98.94%, validation loss decreased to 0.0511 and validation accuracy increased to 99.00%. In the fifth epoch, the model recorded a loss of 0.0412 with an accuracy of 98.62%, while the validation loss increased to 0.0911 and the validation accuracy decreased to 97.75%. Finally, at the sixth epoch, the model obtained a loss of 0.0415 and an accuracy of 98.56%, but the validation loss increased sharply to 0.2103, so the validation accuracy dropped to 92.25%. It had been seen that the accuracy value reached 98.5% after running with 6 epochs which took 15 minutes. The more epochs the longer the training process. Based on the results from Table 2, the graph shown in Figure 4 is used.



(a) Training Accuracy (b) Training Loss

Figure 4. CNN based Training and Loss Graph

According to Figure 4, there are two types, namely the accuracy increased graph (a), and the accuracy decrease graph (b), which show good results when testing disease data using the CNN method, although the two graphs are not the same, the graph in Figure (b) shows that the loss drops in the same direction. The final step of this research is classification based on images of corn leaves taken using a smarthphone camera. The results of the new data testing process shown in Figure 5. The figure shows the results of the classification of diseases on corn leaves that mention the type of disease that is on the corn leaves correctly.



(a) Blight (b) Leaf Spot

Figure 5. Visualization Result of Classification

4. Conclusion

Based on research that has been conducted by researchers it can be concluded that the classification of diseases on corn leaves using the Convolutional Neural Network (CNN) method shows good results, namely getting an accuracy of 99% with 160 epochs that require 6 steps, resulting in a loss value of 0.0415, an accuracy value of 0.9856, a validation loss value of 0.2103, a validation accuracy value of 0.9225. for the last training accuracy results reached 99.06% and the last validation accuracy results reached 98.50%. For the last training accuracy results reached 99.06% and the last validation accuracy results reached 98.50%. Convolutional Neural Network (CNN) methods with data augmentation techniques can improve model performance in image recognition without utilizing transfer learning. Data augmentation involves manipulating image datasets with rotation, flipping, zooming, and lighting changes to generate new variations of the original data. These techniques help improve the robustness and generalization of the model by artificially expanding the dataset. In this study, the CNN machine learning method was applied only to the available training and testing datasets, with no ability to classify other leaf types outside of the pre-trained datasets. This means that the resulting CNN model can only recognize and classify leaves included in the training and testing datasets, but cannot be applied to identify leaves of other species not included in these datasets. This research still has shortcomings because it has not been tested on a larger and more complex dataset so it requires improvement to get better results, such as adding more new datasets with clearer image resolution. Future research may use more modern architectures such as classification using EfficientNet B3 architecture with transfer learning or MobileNet to improve accuracy results.

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