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Identification of Disease in Potato Leaves Using Convolutional Neural Network (CNN) Algorithm

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***Abstract*— Potato crops have many benefits for human life, one of the most useful benefits of potatoes for humans is the carbohydrate content in them and carbohydrates are the main food for humans. The development of potato crop agriculture is very important for the sustainability of human life. There are several obstacles in developing potato farming, including a disease that attacks potato leaves which if left untreated will result in poor production or even crop failure in the future. One of the obstacles in the development of potato plants is the disease on potato leaves, namely early blight caused by the fungus Alternia solani, then late bligt disease caused by Microbe phytopthora infestans de bary. This disease has its respective symptoms so that farmers can take precautions if they see symptoms on potato leaves, but in this preventive step can only be done by experts who have knowledge in the field of diseases in potato plants while the average farmer does not have sufficient knowledge. So, the identification process becomes less accurate and takes a long time. Technology in the field of informatics in the form of digital image processing can be used to solve problems in disease identification in potato leaves, so this research will propose the right method for detecting disease in potato leaves. The identification process in this study uses three types of data in the form of healthy leaves, early blight, and late blight. The method used to identify is deep learning using the Convolutional Neural Network (CNN) architecture. The result of this research is that the 70:30 data division produces better accuracy than the 80:20 data division. The accuracy obtained is 97% on training data and 92% on validation data using 20 batch sizes at 10 epochs.**

Keywords—Potato diseases, late blight, early blight, identification, CNN

I. Introduction

Potato plants have many benefits for human life. The main human need is carbohydrates and potatoes are one of the foods that contain carbohydrates. But in the development of potato crops there are obstacles that must be faced by farmers, this obstacle is in the form of potato leaf disease. If not treated promptly, the potato leaf disease will result in a decrease in potato farm income, and this means a decrease in food production [1]. So it is necessary to detect disease in plants at the right time in order to effectively control and prevent plant diseases. [2]. The most common diseases in potato plants are diseases that attack the leaves of potato plants, namely early blight and late blight. Cold and humid places are one of the factors for leaf disease in potato plants [3].

A potato leaf disease called early blight has early symptoms characterized by circular spots on the middle of the leaves and it could also be on the edges of the leaves as shown in Fig. 1 (a). Then these spots will widen and the color of the leaves turns brown, the fungus Alternia solani is the cause of this leaf disease. Furthermore, Microbe Phytopthora infestans de Bary is the main cause of potato leaf disease called late blight, plant leaves affected by this disease can cause plant damage. The Fig. 1 (b) shows a leaf with late blight, marked by the appearance of black lesions on the leaves and will continue to propagate [4].

(a) (b)

Fig. 1. Potato disease (a) early blight (b) late blight

This identification can help agricultural managers to provide effective and efficient handling of plants that are not healthy or abnormal. With the development of technology today there have been many digital image studies in agriculture both to identify diseases or identify good agricultural production. One of these digital image studies is to identify leaf rot in potato plants.

This study aims to create a system that can help farmers or agricultural managers in identifying diseases in potato leaves by using data on potato leaf images. The identification of leaves in potato plants is divided into three parts, namely potato plants with healthy leaves, late blight, and early blight. So in this study will identify this using the Convolutional Neural Network (CNN) architecture which is one of the Deep Learning methods. The data used in the form of disease data on leaves of potato plants obtained from the website Kaggle with the name PlantVillage [5].

II. Related Literature

Previous studies that have conducted trials in detecting diseases in plants include the following:

Suttapakti in his research titled "Potato Leaf Disease Classification Based on Distinct Color and Texture Feature Extraction" in identifying leaf diseases in potato plants focuses on feature extraction, because according to him in doing classification will get good results depending on accurate extraction features [6]. He was comparing the color extraction feature between Color Moments (CM) and Boundary Color (BC) and Maximum-minimum Color Difference (MCD) on 300 potato leaf images and results that MCD has better accuracy than others with a level of 82.5%.

Islam. M in his research "Detection of Potato Diseases Using Image Segmentation and Multiclass Support Vector Machine" uses the Support Vector Machine (SVM) method to detect disease in potato leaves with the amount of leaf image data used 200 data of diseased leaves and 100 normal or healthy leaves. The process in this study is to segment the image to display only leaf disease without displaying the background and normal leaves in the sense of leaf green, then the leaf image will be extracted using the Gray Level Co-occurrence Matrix (GLCM). The results of this study have an accuracy of 95% [7].

Research conducted by Mim "Leaves Diseases Detection of Tomato Using Image Processing" conducted a classification with 6 classes in the form of healthy, late blight, yellow curved, tomato mosaic, bacterial spots, septorial leaf spots. The algorithm used for classification is Convolutional Neural Network (CNN). In this study the best accuracy results obtained by running 30 epochs with 92.61% accuracy training results and validation accuracy produces 96.55% [8].

Prakash in his research entitled "Detection of Leaf Diseases and Classification using Digital Image Processing" segmented to remove background in leaf images using K-Means clustering, and also extracted leaf textures using the Gray Level Co-Occurrence Matrix (GLCM) feature so that showing only leaves that are not green or that are not normal. In the final stage, classification using the Support Vector Machine (SVM) algorithm and produces an accuracy of 90% of the image data used as many as 60 images [9].

From the description of the research that has been done in identifying plant diseases using leaf image datasets, it can be seen that there are those using the Support Vector Machine (SVM) algorithm with additional features extracting leaf texture features and producing good accuracy [7]. In the research conducted by Mim is to detect diseases of tomatoes with Convolutional Neural Network (CNN) and provide excellent accuracy in 6 classes [8]. So, in this study will identify diseases in potato plants using the CNN architecture from Deep Learning Method.

III. Proposed Method

In this paper, there are several stages of research completion as shown in Fig 1 in the form of a research framework. In this research framework, there are four stages in the form of dataset collection, image data pre-processing, training data, data evaluation.

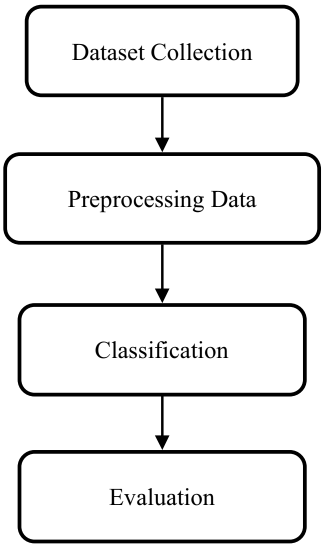


Fig. 2. Research Framework

Explanation of each discussion about Fig 1 will be discussed further:

A. Dataset Collection

The dataset used in this study is a picture of the leaves of a potato plant divided into three classes: the healthy leaves shown in Figure 2, early blight has shown in Figure 3, and the late blight shown in Figure 3. This dataset was obtained from the Kaggle website under the name "PlantVillage Dataset" uploaded by Tairu Oluwafemi Emmanuel and the latest changes were made in October 2018 [5]. The amount of data used is 500 data late blight, 500 initial early blight data, and 150 healthy leaf data. Details of the data agreed upon in Table 1.

TABLE 1 DETAIL DATASET

Sampels	**Number**	**Repository**
Late Blight	500	Kaggle (PlantVillage)
Early Blight	500	
Leaf Helathy	150	
Total	1125	

All images used in this study will be resized to 150x150 to speed up processing. Fig 3 are examples of pictures from each data class used Fig 3 (a) leaf healthy, Fig 3 (b) early blight and Fig 3 (c) late blight.

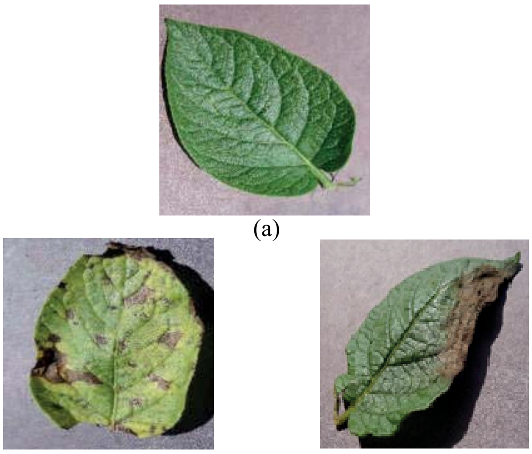


Fig. 3 Image data (a) leaf healthy (b) early blight (c) late blight

B. Preprocessing Data

At this stage the amount of data used is 1150 images from 3 classes as in Figure 5, the class divisions are late blight, early blight and leaf healthy. In Table 2, the details of the distribution of each data from each class used are divided into training data and testing data with data division of 80:20 and 70:30. The results of each of these data sharing will be compared to the results of its accuracy to determine which is better in dividing the proportion of data. The leaf image used first will be resized to 150x150 to speed up classification processing.

TABLE 2 DETAIL OF DATASET

Dataset	**80:20**		**70:30**	
	Train	**Val**	**Train**	**Val**
Late Blight	400	100	350	150
Early Blight	400	100	350	150
Leaf Healthy	122	30	105	45
Total	922	230	805	345

The distribution of data used is division 80:20 and 70:30, for data deviding 90:10 is not used in this study because considering the 150 leaf helathy data, if the data validation data used helati leaves only 10% it will not sufficient for the validation process with the number of batch sizes used in this study is 20 batch sizes.

C. Convolution

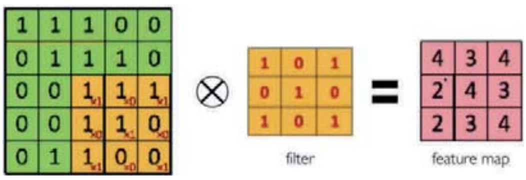


Fig. 4 Convolution process

Convolutional uses filters to recognize the attributes present in the leaf image. In this convolution process, matrix multiplication will be carried out on the filter and leaf image area. As shown in Fig. 4 it can be seen that this convolution process multiplies the pixels in the image by the filter pixels. This research will use 4 layers of convolution.

D. Pooling

After the convolution carried out, then it will do pooling. Pooling that often used is MaxPooling. Pooling here means the process carried out to get images with smaller pixels but still by maintaining the information in the image. The pooling process can be seen in Fig 5, where in the image area with a particular pixel area will be done pooling by selecting one of the highest pixels. This process is constructive because it will reduce the size of each image and will be able to speed up the classification process.

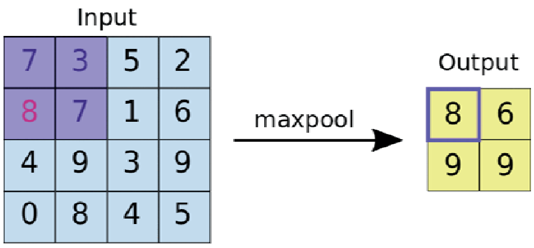


Fig. 5 MaxPooling

E. Classification

The next step is to classify images using the Convolutional Neural Network (CNN) architecture from Deep Learning Method. Convolutional Neural Network (CNN) architecture from Deep Learning Method is included in the supervised learning method where identification of an image by training existing image data and targeting image variables.

The convolutional layer in the Convolutional Neural Network (CNN) architecture helps neural networks in the CNN method recognize potato leaves based on the attributes they have. The neural network can recognize images of potato leaves based on the pixels in the picture

This research will use an image with a size of 150x150x3, which means here is a 150x150 size image and this image has three channels, namely red, green, and blue (RGB). This leaf image will be convoluted first with a filter. Then pooling will be done to reduce the image resolution while maintaining image quality, pooling used is MaxPooling on the input image.

The next process is a fully connected layer, wherein this process is doing flatten. The purpose of flattening here is to change the feature map resulting from pooling into vector form. For more details, shown in Fig 6 architecture of the Convolutional Neural Network (CNN).

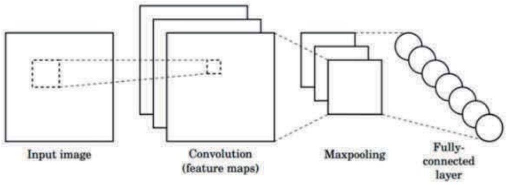


Fig. 6 Convolutional Neural Network Architecture

This research has the proposed model for Convolutional Neural Network (CNN) architecture in identifying diseases in potato leaves is shown in Table 3 using 4 convolution layers and 4 maxPooling.

TABLE 3 CONVOLUTIONAL NEURAL NETWORK MODEL

Layer	Output Shape	Param
conv2d (Conv2D)	(None, 148, 148, 32)	896
max_pooling2d (MaxPooling2D)	(None, 74, 74, 32)	0
conv2d_1 (Conv2D)	(None, 72, 72, 64)	18496
max_pooling2d_1 (MaxPooling2D)	(None, 36, 36, 64)	0
conv2d_2 (Conv2D)	(None, 34, 34, 128)	73856
max_pooling2d_2 (MaxPooling2D)	(None, 17, 17, 128)	0
conv2d_3 (Conv2D)	(None, 15, 15, 256)	295168
max_pooling2d_3 (MaxPooling2D)	(None, 7, 7, 256)	0
flatten (Flatten)	(None, 12544)	0
dense (Dense)	(None, 512)	6423040
dense_1 (Dense)	(None, 3)	1539
Total params: 6,812,995 Trainable params: 6,812,995 Non-trainable params: 0		

IV. RESULT AND EVALUATION

Epoch is a training process on neural networks until it returns to the initial stage in one round when all datasets go through this process. In training data with a neural network model, if you only use one epoch, this will be too large and will stress the training process in the dataset, because the data used is quite a lot, it is necessary to divide the data rate per batch (batch size). In this research, there were 20 batch sizes and to determine the number of epochs, the researchers adjusted the number of batch sizes to the number of samples used.

The next step is to conduct training on the potato leaf image which has been divided by the fit model. Table 4 is the result of the fit model in the 70:30 data division, then Table 5 shows the results of the fit model in the 80:20 data division. It can be seen from epoch 1 to epoch 10 that the accuracy value on the train data and the accuracy value on the validation data has increased.

TABLE 4 RESULT FROM FIT MODEL 70:30

Epoch	Data Training		Data Testing	
	Acc	Loss	Val Acc	Val Loss
1	0.4611	0.6103	0.4364	0.5946
2	0.5758	0.5156	0.7364	0.3630
3	0.6930	0.3964	0.8773	0.2759
8	0.9478	0.0898	0.8636	0.2510
9	0.9605	0.0666	0.9000	0.1728
10	0.9758	0.0560	0.9227	0.1207

Table 4 that the results of the classification on the train data are divided into 70:30. The results of the first epoch display the accuracy value on the train data is 46% with a loss value obtained that is 61% and so on until the 10th epoch displays an accuracy value of 97% with a loss value obtained at 0.05%. Where as in the validation data, the accuracy value on the first epoch is 43% with a loss value obtained by 59% and so on until the 10th epoch displays an accuracy value of 92% with the loss value obtained is 12%.

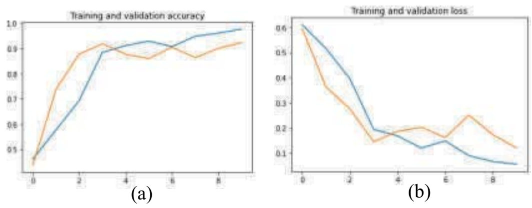


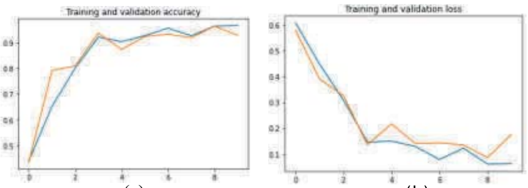
Fig. 7 Training and validation from 70:30 data dividing (a) accuracy (b) loss

The graph shown in Figure 7 (a) is the accuracy graph and the graph shown in Figure 7 (b) is the loss graph for the 70:30 data division. The blue line shows training data, and the orange line shows validation data. This graph shows that the fit model made is good because the increased accuracy and decreased loss on each epoch are stable.

TABLE 5 RESULT FROM FIT MODEL 80:30

Epoch	Data Training		Data Testing	
	Acc	Loss	Val Acc	Val Loss
1	0.4412	0.6077	0.4364	0.5796
2	0.6522	0.4482	0.7909	0.3902
3	0.8005	0.3083	0.8091	0.3253
8	0.9258	0.1222	0.9182	0.1352
9	0.9629	0.0610	0.9636	0.0861
10	0.9655	0.0623	0.9273	0.1755

Then in Table 5 shows the results of the classification on the data are devided into 80:20. The results of the first epoch display the accuracy value on the train data is 44% with a loss value obtained that is 60% and so on until the 10th epoch displays an accuracy value of 96% with a loss value obtained at 0.06%. Where as in the testing data, the accuracy value on the first epoch is 43% with a loss value obtained by 57% and so on until the 10th epoch displays an accuracy value of 92% with the loss value obtained is 17%.



(a) (b)

Fig. 8 Training and validation from 80:20 data dividing (a) accuracy (b) loss

The graph is shown in Fig 8 (a) is graph of accuracy and graph is shown in Fig 8 (b) is graph of loss for the 80:20 data division. This graph also shows that the fit model made with 80:20 data dividing is good because the increased accuracy and decreased loss for each epoch are as stable.

From this research it can be concluded that based on the implementation of the model, the distribution of the dataset has little effect on the results of accuracy, from the results carried out on potato leaf data has a slightly better result by dividing the 70:30 dataset compared to dividing the dataset at 80:20. The image used is changed to 150x150 size then classification is done with 10 epochs with a batch size of 20 with a total data of 1150 images. The accuracy value for the training data is 97% and for the validation accuracy is 92% for the 70:30 data dividing, while the accuracy value for the training data is 96% and for the validation accuracy is 92% for the 80:20 data dividing.

V. Conclusion

From this research it can be concluded that based on the implementation of the model carried out, the distribution of the dataset has an effect on the results of accuracy, from the results carried out on potato leaf data has good results by dividing the dataset 70% and 30% and the image used is changed in size 150x150. On the 10th epoch with a batch size of 20 with a total training data of 805 images and testing data of 345 images, the accuracy value on the train data is 97% and for validation accuracy is 92%.

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