CLASSIFICATION OF POTATO LEAF DISEASES USING CONVOLUTIONAL NEURAL NETWORK

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CLASSIFICATION OF POTATO LEAF DISEASES USING CONVOLUTIONAL NEURAL NETWORK

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Abstract—*Potatoes are an agricultural product that has the fourth highest content of wheat flour after corn, wheat, and rice. Although potatoes play a critical role in agriculture, this crop is susceptible to various diseases and pests. There are several potato leaf diseases that are not yet known to farmers. Dry spot potato leaf disease (late blight) and late blight. If not treated, this disease on potato leaves will spread to the stem and reduce crop yields, causing crop failure. By using technology in the form of digital image processing, this problem can be overcome. This research proposes an appropriate method for detecting disease in potato leaves. Classification will be carried out in three classes, namel, Early Blight, Healthy and Late Blight using the Deep Learning method of Convolutional Neural Network (CNN). The data used comes from an online dataset via the kaggle.com page with the file name Potato Disease Leaf Dataset (PLD) totaling 3251 training datasets which are then divided into training, testing, and validation. The processes carried out are image pre-processing, image augmentation, then image processing using a Convolutional Neural Network (CNN). In the classification process using the CNN method with RMSprop optimizer, the accuracy was 97.53% with a loss value of 0.1096.*

Keywords*: Classification, CNN, Potato Leaf, RMSprop.*

Intisari—Kentang merupakan produk pertanian yang mempunyai kandungan tepung terigu tertinggi keempat setelah jagung, gandum dan beras. Meskipun kentang memiliki peranan yang sangat penting dalam pertanian, tanaman ini rentan terhadap berbagai penyakit dan hama. Ada beberapa penyakit daun kentang yang belum diketahui petani. Penyakit daun kentang bercak kering (penyakit busuk daun) dan penyakit busuk daun. Jika tidak diobati, penyakit pada daun kentang ini akan menyebar hingga ke batang dan menurunkan hasil panen dapat menyebabkan gagal panen. Dengan menggunakan teknologi berupa pengolahan citra digital hal tersebut dapat diatasi, penelitian ini mengusulkan metode yang tepat untuk mendeteksi penyakit pada daun kentang. Klasifikasi akan dilakukan dengan tiga kelas yaitu *Early Blight*, *Healthy*, dan *Late Blight* dengan menggunakan metode *Deep Learning Convolutional Neural Network* (CNN). Data yang digunakan bersumber dari dataset *online* melalui laman kaggle.com dengan nama file *Potato Disease Leaf Dataset* (PLD) sebanyak 3251 dataset pelatihan yang kemudian dibagi menjadi pelatihan, pengujian dan validasi. Proses yang dilakukan adalah pra-pemrosesan gambar, augmentasi gambar, kemudian pemrosesan gambar menggunakan *Convolutional Neural Network* (CNN). Pada proses klasifikasi menggunakan metode CNN dengan RMSprop *optimizer* diperoleh akurasi sebesar 97,53% dengan nilai loss sebesar 0,1096.

Kata Kunci: Klasifikasi, CNN, Daun Kentang, RMSprop.

INTRODUCTION

One of the food plants that grow most widely in the Indonesian highlands and contains fiber and vitamin C, which is good for body health, is potatoes (Amatullah, Ein, and Santoni 2021). Potatoes are an agricultural product that has the fourth highest content of wheat flour after corn, wheat, and rice (Lesmana, Fadhillah, and Rozikin 2022). Potatoes are also a significant export commodity in many countries, contributing to the global agricultural economy (Erlangga 2023).

Although potatoes are critical to global food security, this crop is also susceptible to various diseases and pests. One of the main problems faced in potato cultivation is potato leaf disease. The variety of diseases that can occur in potatoes certainly makes it difficult for farmers to identify diseases that attack potato plants (Teresia Ompusunggu 2022). Potato leaf disease dry spot also called early blight. Cold and damp places are one of the factors for developing leaf blight (Fitriana and Hakim 2019) Late blight disease will appear during the plant's growth period between the 5th and 6th weeks. The initial symptom of this late blight disease is the presence of wet spots on the edges of the leaves which can also be in the middle. Then these spots will widen and the color of the leaves will change to brown or gray. Meanwhile, the symptoms of dry spot disease (early blight) are characterized by dry spots in the form of brown circles on the underside of the leaves (Fuadi and Suharso 2022).

Diseases on potato leaves if left unchecked will spread to the stalks reduce crop yields and cause crop failure (Rozaqi, Sunyoto, and Arief 2021). This disease can be recognized visually because it has unique color and texture characteristics. But visual recognition has a drawback, namely that it is difficult to recognize the similarities between one type of disease and another (Lubis et al. 2023). In dealing with the problem of potato leaf disease, this has been done a lot (Ahmad and Iskandar 2020) not only in the agricultural sector but also in the technological sector, he has also taken part in identifying diseases in potato plants (Rashid et al. 2021) using image processing or what is usually called digital image processing (Hidayat, Saputri, and Aziz 2022).

Several studies that discuss the classification of potato leaf diseases include research on the Identification of Potato Leaf Diseases Based on Texture and Color Features Using the K-Nearest Neighbor Method in research (Amatullah et al. 2021) carried out the process of resizing, feature extraction, dataset division (training, testing) and calculating accuracy and predictions using K-Nearest neighbor resulting in an accuracy of 80%.

Potato Leaf Disease Classification Using Deep Learning Approach (Sholihati et al. 2020) using 5,100 data from Google which was divided into 5 classes which were processed using the VGG16 and VGG 19 models to get an accuracy of 91.0% and 90%.

Implementation of Potato Leaf Disease Object Detection Using the Convolutional Neutral Network Method (Nauval and Lestari 2022) In this research, classification was carried out with three classes, namely healthy leaves, early blight and late blight using a Convolutional Neural Network (CNN) architecture. The results of this research are considered good because the 10th epoch with a batch size of 20 produced training accuracy of 95% and validation accuracy of 94%.

Based on several studies, it shows that CNN has a better level of accuracy on image data. The Convolutional Neural Network method is very popular in deep learning circles because CNN extracts features from input in the form of images and then changes the dimensions of the image to be smaller without changing the characteristics of the image(Omori and Shima 2020) Therefore, this research implemented the CNN method as a classification of potato leaf diseases. It is hoped that the CNN method will be useful for identifying potato leaf diseases so that it can reduce the number of diseases on potato leaves.

MATERIALS AND METHODS

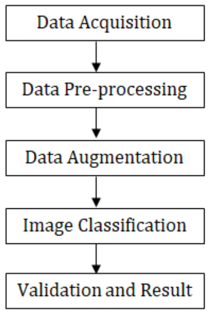

Figure 1. Research Methods

1. Data Acquisition

The first step is to take and collect the images to be studied which are sourced from an online dataset via the www.kaggle.com page with the file name Potato Disease Leaf Dataset (PLD) which was uploaded by Rizwan Saaed in jpg format. with dimensions of 256 x 256 pixels. The images taken from this source were 3251 images with the data details as follows:

Tabel 1. Dataset Acquisition

Data Type	Class	Total Images
Data Training	Early Blight	1303
	Healthy	816
	Late Blight	1132
Total		3251

The image below is a dataset of potato plant leaves which are divided into 3 classes, namely Early Blight, Healthy, and Late Blight. This dataset is then placed in the Google Drive folder.

(a) (b) (c)

Figure 2. (a) Early Blight, (b) Healthy, (c) Late Blight

2. Pre-Processing Data

In the pre-process, the image resizing stage is carried out. The resizing stage is changing the horizontal (horizontal) resolution and perpendicular (vertical) resolution. The purpose of resizing is so that the data that will later be used can be displayed in the same form or without varying sizes because resizing can result in less memory being used. In this research, the image was resized from its actual size of 256x256 to 200x200.

3. Augmentation Data

Data augmentation needs to be applied in this study because 3251 datasets are still inadequate to get optimal performance. The augmentation parameters used in this study are carried out automatically by applying simple geometric transformations, such as translations, rotation, change in scale, shearing, vertical and horizontal flips.

4. Image Classification Using CNN

One type of neural network commonly used on image data is CNN. Because of the depth of the network level, CNN is included in the Deep Neural Network type and is often used in image data. There are two methods used by CNN, namely classification using feedforward and learning stages using backpropagation.

Around 1988 Yann LeCun introduced CNN. Deep learning has improved and become successful since CNN was introduced and became one of the methods of Deep Learning. Long before that, in the 1950s, Hubel and Wisel conducted research on the visual cortex, which is part of the cat's brain. They found that there is a small part of cells that are sensitive to certain areas of the eye in the visual cortex. There are 2 types of visual cortex discovered by Hubel and Wisel, namely simple cells and complex cells. From the results of his observations, Kunihiko (Darmanto 2019) designed the Neocognitron which is a Hierarchical Multilayered Neural Network model in the 1980s. This model is then used for several cases such as character classification from handwriting (Handwriting Character Recognition).

There are similarities in the structure that CNN has with artificial neural networks. In image classification, CNN receives input or input images to be processed and classified into certain categories. The difference between CNN and ANN is in the additional architecture of CNN which is optimized for the features in the input image. There are several main components in CNN, including (Peryanto, Yudhana, and Umar 2020):

1. Convolution Layer
2. Pooling Layer
3. Fully Connected Layer
4. Dropout

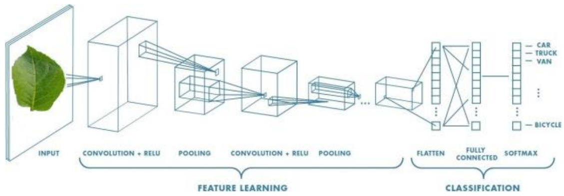

Figure 3. Convolutional Neural Network Architecture

Building Model

Using the CNN algorithm, the sequential model is formed. Keras helps to construct this model section by section, with a Convolution two-dimensional layer for handling images & image input size (256,256) whatever the size image inputted. There was a flat layer among the two-dimensional layer of convolution as well as the dense layer acting as a bridge between them. For this model, ReLU or rectified linear units are used in the form of an enabling function. In the framework, SoftMax was introduced as an activation for forecasting depending on the maximum likelihoods. The equation for the SoftMax function is given below:

$$P(x) = \frac{e^{x^T w^i}}{\sum_{k=1}^{k} \; e^{x^T w^i}}$$

Here, W signifies X and W's internal product.

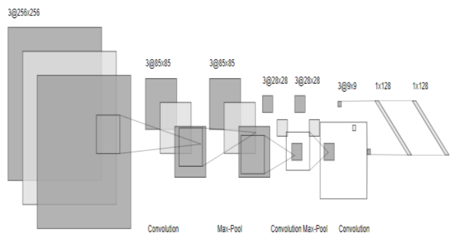

Figure 4. Model of CNN

Compiling the Model

The use of "Adam" and “RMSprop” as an optimizer. This is an effective optimization tool throughout the training period to change the learning rate. For our loss function to make things easier to realize, categorical cross-entropy is used to train the system and include an accuracy metric to represent the accuracy score on the validation set (Asif, Rahman, and Hena 2020).

RESULTS AND DISCUSSION

To find the best accuracy in the CNN model, several parameter calculations are required. Comparing several optimizers and epochs will be carried out in this research which is a step in the

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CNN model learning process, where the number of epochs to be determined can influence the size of the learning process and will stop at the time and value determined by iteration. According to previous research, the number of epochs is influenced by several factors, namely the amount of data, learning rate and optimizer. But the more you add, the more often the network weights will be updated. So it can be assumed that the measure of time will be linear with the number of data sets. A difference in numbers that is too small will usually result in accuracy results that are not much different. So the epochs that will be used in this research are 10 and 20 epochs with two optimizers, namely Adam and RMSporp.

This classification process was carried out with 3251 data which was divided into training, testing and validation data, then used 32 batch sizes. The next step is to carry out training on potato leaf images which have been divided into fit models.

1. Comparison of Epoch with Adam Optimizer

Determining the number of epochs usually depends on the research by looking at the number of data samples. The following are the results of comparing epochs with training results using Adam optimizer.

Tabel 2. Comparison of Epoch with Adam Optimizer

Epoch	Accuracy	Loss
10	0.9506	0.1403
20	0.9432	0.1707

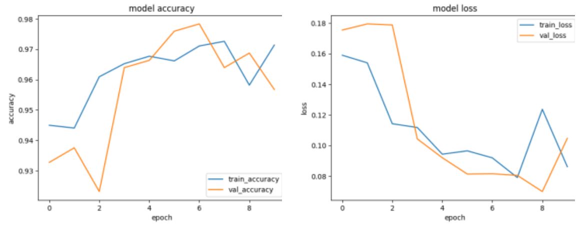
Based on Table 2, the results of the epoch iteration can be seen by using the Adam optoimizer which produces different accuracies, namely the accuracy at epoch 10 get 95.06% with a loss value of 0.1403, then epoch 20 get 94.32% accuracy with a loss value of 0.1707 so it can be seen that from the two epochs the accuracy is obtained. best at 10 epochs.

From the results of the confusion matrix shown in table 3, it can be explained that based on table 2, which shows the results of predicting the model on testing data, new data shows better results in this case.

Table 3. Confusion Matrix with Adam Optimizer

		Prediction Class		
		Early Bright	Healthy	Late Blight
Actual Class	Early Bright	11	1	0
	Healthy	0	9	0
	Late Blight	0	0	11

Based on table 3, it shows that the prediction results from the model on testing data show better results. In this case, the model predicts that 11 images are predicted to be in the Early Blight class and 9 images are included in the Healthy class. then 11 images were predicted in the Late Blight class and 1 image was not predicted correctly.



(a) (b)

Figure 5. (a) Accuracy graph (b) Loss graph

Figure 5 shows the performance graph of loss and accuracy results from the Adam optimizer with an epoch value of 10. If you look at the graph, the training and validation accuracy continues to increase but is less stable, whereas with the loss graph, the training loss value and validation loss value experience an unstable decrease.

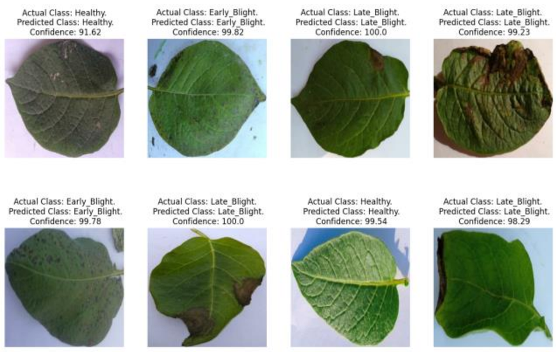


Figure 6. Image classification and prediction results with Adam Optimizer

The model generated from the classification results is used for image prediction. These images are Early Blight, Healthy and Late Blight classes. Based on Figure 6, the classification results show that there are many images that were predicted correctly and there are accuracy values for the predicted images.

2. Comparison of Epoch and RMSprop Optimizer

The following is an iteration with epoch 10 and 20 using RMSprop optimizer.

Table 4. Comparison Epoch and RMSprop Optimizer

Epoch	Accuracy	Loss
10	0.9753	0.1096
20	0.9679	0.0916

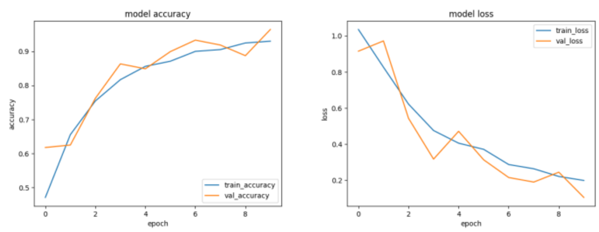
Based on Table 4, the results of the epoch iteration can be seen by using the Adam optoimizer which produces different accuracies, namely the accuracy at epoch 10 is 97.053% with a loss value of 0.1096, then epoch 20 is 96.79% accurate with a loss value of 0.0916, so it can be seen that from the two epochs got the best accuracy at 10 epochs.

From the results of the confusion matrix shown in Table 5, it can be explained that based on Table 4, the results of predicting the model on new data testing data show better results in this case.

Table 5. Confusion Matrix with RMSprop Optimizer

		Prediction Class		
		Early Bright	Healthy	Late Blight
Actual Class	Early Bright	10	0	1
	Healthy	1	5	0
	Late Blight	0	1	15

Based on Table 5, it shows that the prediction results from the model on testing data show better results. In this case, the model predicts that 10 images are predicted to be in the Early Bright class and 5 images are included in the Healthy class. then 15 images were predicted in the Late Blight class and 3 images were not predicted correctly.



(a) (b)

Figure 7. (a) Accuracy Graph (b) Loss Graph

Figure 7 shows the performance graph of loss and accuracy results from the RMSprop optimizer with an epoch value of 10. The training and validation accuracy values continue to increase, while in the loss graph, the training loss values and validation loss values experience a steady decline.

Figure 8. Image classification and prediction results with Adam Optimizer

The model generated from the classification results is used for image prediction. The images are from the Early Blight, Healthy, and Late Blight classes. Based on Figure 8, the classification results show that there are many images that were predicted correctly and there are accuracy values for the predicted images.

3. Accuracy Comparison Results

The following is a comparison used to determine the best model from all optimizers that have been trained. The following are the results of each CNN model with the best accuracy based on the optimizer and epoch.

Tabel 6. Accuracy Comparison Result

No	Optimizer	Epoch	Accuracy	Loss
1	Adam	10	0.9506	0.1403
2	RMSprop	10	0.9753	0.1096

Based on Table 6, it can be seen that using the Adam optimizer with 10 epochs produces an accuracy of 95.06% with a loss value of 0.1403, then the RMSprop optimizer using 10 epochs produces an accuracy of 97.53% with a loss value of 0.1096. So it can be concluded that using the RMSprop optimizer with 10 epochs produces the highest accuracy.

CONCLUSION

Based on the discussion explained in the previous chapter, it can be concluded that the classification of potato leaves using the CNN architecture, the CNN model can identify types of potato leaf images, Early Blight, Healthy, and Late Blight. By using the RMSprop optimizer and the softmax activation function implemented in the CNN architecture, potato leaf image classification with 10 epoch iterations obtained the highest accuracy value of 97.53% and the lowest loss value of 0.1096.

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