Detection of Rice Plants Diseases Using Convolutional Neural Network (CNN)

Achmad Ramadhanna'il Rasjava^{1,*}, Aditya Wisnugraha Sugiyarto², Yori Kurniasari², Syaifullah Yusuf Ramadhan³

¹ChemistryDepartment, ²Mathematics Department, ³Statistics Department, Faculty of Mathematics and Natural Science, Universitas Negeri Yogyakarta,

Jl. Colombo No.1, Karang Malang, Caturtunggal, Kec. Depok, Kabupaten Sleman, Daerah Istimewa Yogyakarta 55281, Indonesia.

Email*: ramadhanachmad44@gmail.com

Abstract. As a rice-producing plant, rice plant (*Oryza sativa* L.) is one of the most important crops in Indonesia. Rice production is increasing every year along with an increase in rice demand and population. The amount of rice production is affected by the condition of the rice plants. The worse the condition of rice plants, the rice production will also lower. Rice plant is very susceptible to diseases or pests that can reduce its productivity, including brown spot disease, leaf smut and bacterial leaf blight. As the development of science and technology, currently known as Artificial Intelligence. Artificial intelligence is a combination of several scientific disciplines such as mathematics, statistics, computer science, and even social science. Using artificial intelligence, the system now have the ability to interpret external data correctly to learn from the data and then use the learning to achieve certain goals through flexible adaptation. The artificial intelligence fields consists of several branches, such as machine learning and deep learning. Neural Network (NN) is one of the methods used in the deep learning.NN has many types, one of which is the Convolutional Neural Network (CNN). CNN is the best-knownmethod used for processingimages data compared to other types of NN. Therefore, in this study the identification of rice plants diseases was carriedout using CNN method. From this study,better results were obtained compared to other methods, obtaining 100% accuracy for training data and 86,67% for testing data. The model obtained by the CNN method can be used for detecting 3 different types of rice plants diseases, there are brown spots, leaf smuts, or bacterial leaf blight disease based on the physical images of rice plant leaves.

Keywords: Artificial intelligience, CNN, Deep learning, Image detection, Rice plants diseases.

INTRODUCTION

Oryza sativa L. is one of the most important staple plants in the world (Londo et al. 2006).O. sativa produces rice which is a staple food in most parts of the world, especially Indonesia (Sugiyarto et al. 2019; Kumarathilaka et al. 2018). The demand for rice is increasing every year along with the increasing population (Sakiko 2019).Nevertheless, the need for rice that continues to increase is not proportional with the increase of rice production (Adekoya and Ekeh 2019). This condition is likely caused by the rice plants condition and the growth environment that not optimal, so the rice production decreases (Li et al. 2015; Asseng et al. 2017). Lower rice production by rice plants is possible due to the influence of weather, overheating air temperature, soil and air humidity, and disease (Jabran et al. 2015; Hubert et al. 2015; Kumar et al. 2009).

Observation of health and diseases of rice plants is very important for its harvest quality and quantity, but it is very time consuming and has a lot of resources to spend (Khirade and Patil 2015), so the automatic detection of plant diseases is very necessary in the agricultural sector (Lu et al. 2017). The automatic plant diseases detection can save a lot of expenses, time, and energy. Rice plants is one of the most important staple plants need to be observed about its health and diseases. This is due to the diseases in rice plants are able to influence the amount and quality of rice produced (Hubert et al. 2015; Kumar et al. 2009). Diseases that can attack rice plants include bacterial leaf blight (BLB) caused by the bacterium Xanthomonas oryzaepv. Oryzae. This disease can reduce rice productivity up to 40% (Sumera et al. 2017; Sumera et al. 2016; Kini et al. 2017), brown spot caused by the bacteria Helminthosporiumoryzae. This disease can reduce rice productivity by up to 30% (Tariq et al. 2012; Singh et al. 2017; Jatoi et al. 2018), and leaf smut caused by the fungus Entylomaoryzae. This disease can reduce rice productivity by 50% (Mallick et al. 2018; Prajapati et al. 2017; Mukherje et al. 2018).

In this study, we propose a method using deep learning and image processing for automatically detecting rice plants diseases using the images of its leaf. From these images, we will be able to detect rice plant diseases such as brown spot, bacterial leaf blight and leaf smut. Using this method, we are hoping that our research will be useful for agricultural sector by automatically detect rice plant diseases using its leaf images, thus saving a lot of expenses, time, efforts, and energy compared to traditional method for detecting rice plant diseases.

RESEARCH METHODS

In this study, the general method used was presented on (Figure 1).



Figure 1. General research method diagram.

Data

In this study, 63 images of rice leaves was used. The data was obtained through https://archive.ics.uci.edu as 90 photographic images of rice leaves broken down to 30 diagnosed with leaf smut, 30 diagnosed with brown spot and 30 diagnosed with bacterial leaf blight.From the data, the cleaning process of data that cannot be processed is carried out so that 63 images are ready to be processed with the details of 21 photo images of leaves affected by leaf smut, 21 photo images of leaves affected by brown spots, and 21 photo images of leaves affected by bacterial leaf blight. An example of photographic data for each disease is shown in (Figure 2).



Figure 2. Image of leaves diagnosed with leaf smut (a) brown spot (b) and bacterial leaf bright (c).

Classification Process (CNN)

The next step is to carry out the learning process to get the best model in the classification of the leaf photo image. In this study the CNN method is used for classification. However, before entering into the CNN method, preprocessing is done to the leaf photo data that has been obtained, namely dividing the data into 76% for training data and 24% for testing data. Training data is used to find the best classification model based on image input data and original classification results. Then, to test whether the model is good, we use data testing. The CNN process is presented in (Figure 3).



Figure 3. The Process of CNN.

Convolution Layer

The fundamental purpose of convolution is to extract features from the input picture. Convolution uses a small square matrix, which preserves the spatial relationships among pixels, to learn image features. The convolution operations are shown in the (Figure 4). The matrix that slides the filter on the original image and performs the convolution operation is called the feature map (Zhang 2018).



Figure 4. Convolution process with (slide = 1). (Li et al. 2008).

For every feature map, all neurons share the same weight parameter that is known as filter or kernel (yellow part in Figure 4). The filter is a feature detector for the original input picture. Different filters will produce different feature maps for the same picture. By simply adjusting the filter values, we can perform effects such as edge detection, sharpening, blurring, etc. that mean different filters detect different features, such as edges, curves, etc. from the picture.

Subsampling Layer

The subsampling layer is also called the pooling layer. Sometimes the image is too large and we need to reduce the number of training parameters. It is required to periodically introduce a pooling layer between subsequent convolution layers. The only purpose of pooling is to reduce the size of the image space. Pooling can take many forms: Max Pooling, Average Pooling, and so on. The most common form is Max Pooling that is shown in (Figure 5).



Figure 5. Max pooling process. (Prasoon et al. 2013)

Pooling operations are applied to each feature map separately. After convoluting and pooling, the image still retains most of the information as well as the size of the image has been reduced. The main role of the pooling layer is subsampling, which further reduces the number of parameters by removing unimportant samples in the Feature Map (Zhang 2018).

• Fully Connected Layer

Fully connected means that every neuron in the upper level is interconnected with every neuron in the next level. Convolution and pooling layer is a feature extractor, the fully connected layer is a classifier. The fully connected layer receives the output of the upper layer (which represents the feature map of the higherlevel features) and determines which category these features best fit.

For example, if the program determines the content of a picture as a dog, the feature map with higher values represent some of the more advanced features such as claws or four legs. Similarly, if the program determines the content of a picture as a bird, the feature map with higher values represent some of the more advanced features such as wings or beaks.

The fully connected layer is the Multi-Layer Perceptron that uses the softmax excitation function as the output layer. The softmax function converts a vector of any real value into a vector of elements 0-1 and 1. In general, a fullyconnected layer observes which category the advanced features most closelymatches and what weight they have. When calculating the weight and the dot product between previous layers, we can get the correct probability for the different categories (Zhang 2018).

RESULTS AND DISCUSSION

Before entering the classification process, the data augmentation stage is performed first, in which in this study the image of raw leaf photos was resized to 10% of the original size to facilitate the learning process. Because based on (Shorten and Khoshgoftaar 2019) using data augmentation the learning process will be better and have better accuracy. After that the classification process is done using the CNN method. In searching for the CNN architecture, trial and error techniques are used to obtain the best accuracy. In this study, an experiment was carried out by replacing many of the convolution layers of the CNN model. The results of experiments with trial and error can be seen in (Table 1).

Table 1. CNN Model trial results.

Number of	Accuracy	
Layer	Training	Testing
1	93.75%	53.33%
2	100%	73.33%
3	100%	66.67%
4	100%	86.67%
5	100%	80%

From the results of these experiments, that with 4 convolutional layers obtained accuracy for training data 100% and testing 86.67%. The architecture of the CNN method obtained is presented in (Figure 6).



Figure 6. The most optimal CNN model architecture obtained.

The CNN model architecture consists of 4 convolution layers, 3 max pooling layers, fully connected layers and softmax layers. This means that in the model the convolution process is carried out 4 times and the re-shaping process is 3 times before entering the fully connected artificial neural network. The process of finding the model uses a maximum iteration parameter of 200. In the CNN model, each convolution layer contains 16 filters with a size of 3x3 and the max pooling layer has a pool size of 2x2 and a stride of 2. The accuracy of the CNN model can be seen in (Figure 7).



Figure 7. Accuracy results from the most optimal CNN models (straight lines show training data) and (dashed lines show testing data)

CONCLUSION

Based on the results of the discussion, the best CNN model for classifying rice plant diseases based on leaf photo images is with 4 convolution layers and 3 re-shaping processes. The accuracy obtained with the model is 100% for training data and 86.67% for testing data. This result is the best compared to the accuracy for other CNN models so that the model can be used to classify rice plant diseases based on leaf photo images.

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