Analysis of Using Regularization Technique in The Convolutional Neural Network Architecture to Detect Paddy Disease for Small Dataset

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Abstract. In some instances, convolutional neural network (CNN) methods such as large numbers of datasets can show very high accuracy. However, in cases such as the small number of datasets, the accuracy performance of CNN often decreases. This also intersects with the constraints of applying CNN to recognize types of diseases in rice with a small number of datasets. This research applied the combination of regularization techniques and CNN methods to recognize rice disease types with a total dataset reaching 120 leaf images. It is found that using CNN-regularization techniques shows better performance than standard CNN architecture. With an accuracy value reaching an average of 85.878\%, it is expected to open further research opportunities.

1. Introduction
Rice is the most important and strategic commodity in Indonesia, seeing its role as the staple food of the majority of Indonesia's population and its effect on the Indonesian economy. Moreover, from year to year, the level of rice consumption has increased along with an increase in the population [1]. However, in its development, many things can affect the stability of rice availability. The real challenge affecting rice availability is the symptom of a decrease in the level of productivity. One factor that causes a decrease in the level of productivity is the presence of disease attacks in the process of rice cultivation [2].

In general, symptoms of plant diseases often appear visually on plant leaves. The disease is an abnormal condition that injures plants causing plant organs to not function properly. Plant diseases have a critical effect on the quality and quantity of agricultural products. This is because the disease can destroy the normal state of plants and change or disrupt the vital functions of plants such as photosynthesis, transpiration, pollination, fertilization, germination. Accurate recognition and diagnosis of disease at an early stage are essential. As early as possible it is essential to know what types of pests and diseases that attack rice to know what decisions can be taken to prevent the disease continues [3].

Researches relating to the detection of diseases in rice plants were previously carried out. However, there are still many who focus on just one method, whether the method of machine learning (machine learning) or image processing (image processing). Yan Lu et al. [4] conducted studies to classify types of diseases in plants. The study used a dataset containing 500 images, including diseased and non-sick rice stems and leaves. The classification is carried out with ten common rice diseases. The research
shows that the research approach achieves higher accuracy than conventional machine learning methods. The experimental results represent the effectiveness and feasibility of the proposed model. D. Nidhis et al. [5] developed a method for detecting the types of diseases affected by rice leaves based on image processing methods. By evaluating the percentage of the affected area, the severity of the disease infection is calculated. Based on the severity of the disease, pesticides are used to offer bacteria, brown spots, and rice explosions, which are the main diseases affecting rice plants and their productivity. Taohidul Islam et al. [6] conducted a study to identify and classify diseases in rice plants. In his research, they were using image processing techniques based on the percentage of the RGB value of the affected part. They use the Naïve Bayes classifier, which is a simple classifier to classify diseases into various classes. Their approach succeeded in identifying and classifying three main types of rice plant disease using only one feature. Based on some of these studies, it is still rare that research combines a deep learning approach, especially the convolutional neural network (CNN) method with image processing.

Although deep learning can get good results in some cases, in cases such as a small number of datasets, it can appear whose name is overfitting, which results in decreased accuracy [7]. This study investigated a small dataset case to identify types of rice plant diseases based on rice leaf images. In this case, preprocessing techniques, namely regularization techniques such as flipped image augmentation and dropout, was applied to overcome the problem of the number of small datasets. The preprocessing technique is then applied to several CNN architectures. The results are then compared with architecture that was not applied to preprocessing techniques.

2. The Material and Method

2.1. Material
The data used in this study were sourced from the UCI dataset (leaf image of rice plants). The data consists of several datasets in the form of images related to the type of disease on rice leaves with R, G, and B pressures with different image sizes. The data form is classified based on the type of disease found in rice leaves. In this case, there are three types of disinfection classes on infectious rice leaves: brown spot, leaf blast, and bacterial blight, as shown in Figure 1. Each class consists of 120 sample datasets, of which 100 datasets are used as training data, and 20 datasets are used as validation data [8].

![Image of rice leaves infected disease.](image)

**Figure 1.** Image of rice leaves infected disease.

2.2. Method
Convolutional Neural Network (CNN) is one type of further development of neural networks. This is because the number of neurons in the hidden layer is higher than the simple model of neural networks.
The presence of a large number of neurons allows the method to apply the concept of deep learning to the given input. The method is usually used in data (input), which is an image. In general, the architecture of CNN is divided into two major parts, Feature Extraction Layer and Fully-Connected Layer (MLP).

2.2.1. Feature Extraction Layer
The process that occurs in this section is "encoding" from an image into features in the form of numbers representing the image (Feature Extraction). The feature extraction layer consists of two parts, namely the convolutional layer and the pooling layer. Convolutional Layer is a linear operation that uses a small matrix in this case, commonly called the kernel. The purpose of the convolutional layer is to extract features from an input image. Figure 2 shows an illustration of the convolution process. Convolutional Layer works with element-wise operations between the kernel and the input image in the form of tensors. The results from element-wise will then be added together to obtain results that refer to the position of the input image, commonly referred to as a feature-map. This process will continue to be repeated using a number of kernels, in order to obtain a variety of feature-maps. The existence of a variety of feature maps will show different characteristics of the input image. The size and number of kernels usually influence the process of running the convolutional layer (hyperparameter). Usually using 3 x 3 size, but sometimes using 5 x 5 or 7 x 7.

![Figure 2. Operation process of convolutional with 3x3 kernel size.](image)

While the Pooling Layer is a process of reducing the size of a feature-map matrix by using a pooling operation using a 2x2 filter. In this case, there are two types of pooling commonly used: average pooling and max-pooling. Average pooling is done by down sampling the average value of the feature-map matrix while max-pooling by taking the maximum value from the feature-map matrix. The next process is network training, which is the application of non-linear function processes that can transform input data into a higher matrix so that simple hyperplane cuts can be made which enable classification. In CNN, several activation functions are often used, namely sigmoid, tanh (), reLU, and softmax.
2.2.2. Fully-Connected Layer (MLP)

The feature map that is produced from the feature extraction is still in the form of a multidimensional array, so it must flatten or reshape the feature map into a vector so that it can be used as input from the fully-connected layer. The fully connected layer is a layer where all the neurons of activity from the previous layer are connected with neurons in the next layer and ordinary neural networks. Every activity from the previous layer needs to be converted into one-dimensional data before it can be connected to all neurons in the Fully-Connected layer. The Fully-Connected layer is usually used in the Perceptron Multi-layer method and aims to process data so that it can be classified. The difference between the Fully-Connected layer and the ordinary convolution layer is that the convolution layer’s neurons are connected only to certain regions of the input. At the same time, the Fully-Connected layer has neurons that are overall connected. However, the two layers still operate the dot product, so the function is not so different.

Figure 3 shows the flow of the proposed method, where the regularization technique was applied to overcome the problem of limited dataset availability. In this case, the regularization technique used is image augmentation and dropout. Image augmentation is the process of making a new image from a number of datasets used in the training process. Some of the processes carried out include image rotations, image shears, and image scaling so that the number of datasets was increased, which initially totaled 120 datasets to 360.

- Rotations: by applying affine transformation \( A = \begin{pmatrix} \cos \theta & -\sin \theta \\ \sin \theta & \cos \theta \end{pmatrix} \) where \( \theta \) between 10 to 175 degrees.
- Shears: by applying affine transformation \( A = \begin{pmatrix} 1 & s \\ 0 & 1 \end{pmatrix} \) where \( s \) range of \( [0.1, 0.35] \).
- Scaling: by applying affine transformation either in the x or y direction \( A = \begin{pmatrix} s_x & 0 \\ 0 & s_y \end{pmatrix} \)

At the same time, the dropout is the process of reducing the number of components such as weight or neurons in the CNN layer architecture. Components to be removed will be randomly selected and given a probability that is between 0 and 1.

Finally, the image obtained from the applying the regularization technique will be included in the classification training phases. This is done to maximize the score value of the class \( y \) by following optimization problems:
\[ I^* = \arg \max_s y(I) + |\lambda|I^2 \]

where \( I \) is input image, \( y \) is target class, and \( \lambda \) is a regulation parameter, where it’s value 0.01 and need to optimize further during training phase.

3. Results and Discussion

Figure 4 (a) shows an example result of applying regularization techniques to an image. The number of datasets was increased, which initially totaled 120 datasets to 360 datasets. Those datasets are used as input for new data in the process of training with other data to obtain a fit model in a convolutional neural network. Meanwhile, Figure 4 (b) show the results of applying CNN with regularization techniques to identify types of paddy diseases based on leaf images.

![Figure 4](image)

**Figure 4.** Applying regularization techniques to an image (a) and image recognition for paddy disease based on leaf image.

The training accuracy of applying the regularization technique on CNN is 85.878%. The results show that the use of the regularization method gives better value than the standard CNN standard model, which only reaches 40.667% in the case of small datasets, as shown in Table 1. The training accuracy is amount of correct classifications or total amount of classifications during training phase. Those accuracy is obtained by finding the average of the number of iterations carried out during the training data. The graph also reinforces these results in Figure 5, where the value of training accuracy and validation on CNN-regularization is always increasing compared to the standard CNN model.

**Table 1.** Comparison of classification accuracy result of each algorithm in the dataset.

| Run | CNN Standard (%) | CNN-Regularization Technique (%) |
|-----|------------------|---------------------------------|
| 1   | 65.4             | 13.33                           |
| 2   | 68.25            | 39.17                           |
| 3   | 68.09            | 35.83                           |
| 4   | 68.09            | 36.67                           |
| 5   | 70.3             | 41.67                           |
| 6   | 70.3             | 40.83                           |
| 7   | 70.3             | 47.5                            |
Meanwhile, confusion matrix analysis shows that CNN-regularization has better sensitivity and specificity than standard CNN methods, as shown in Figure 6. This is shown by the quite bright color in the diagonal matrix area (True Positive and True Negative). Although there is a slight error (False Positive and False Negative) in recognizing paddy disease based on rice images, as shown in the light blue matrix area. Confusion matrix analysis is used to summarize the results of the classification process.

**Figure 5.** Accuracy results for dataset training and validation of standard CNN (a) and CNN + regularization (b).

**Figure 6.** Confusion matrix to analyze the classification process of standard CNN (a) and CNN + regularization (b).
4. Conclusion
The use of the CNN model, which was preceded by a regularization technique in recognizing types of rice disease based on leaf images with a small number of datasets, can obtain better results than the standard CNN model. This can be shown by the average level of accuracy that achieves 85.878%. In addition, the matrix confusion analysis shows the classification process of the results of CNN-regularization is able to obtain high sensitivity and specificity, although there is still False Positive and False Negative in the case of small datasets.

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