RiceDesease

by Budi Irmawati

Rice disease classification based on leaf damage using deep learning

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***Abstract*— Rice is the staple food of the Indonesian people. Food security is an absolute thing to do today to reduce rice imports. Various efforts were made to improve seed quality, resistance to pests, nutrition, and so on. It helps to Analysis identify diseases that may arise in rice plants. Efforts were made using the image of leaves affected by the disease and then analyzed using a deep learning algorithm. The architecture used is google net and customnet. The selection is based on a good level of accuracy and the computational time required to obtain the model. the convex hull algorithm helps to find the focus of disease objects on rice leaves. Data augmentation increases the variation in the amount of data and reduces unbalanced datasets. The results obtained are by using this algorithm, accuracy is obtained 80.94%, and the average computation time is three minutes and twenty seconds. Error calculation of classification are MSE 0.4227, RMSE 0.6501, and MAE 0.2555.**

Keywords*—*rice leaf, deep learning, convolutional neural network, convex hull, data augmentation

I. Introduction

Rice as a food commodity is one of the main components of increasing the community's basic needs. However, the pressure to increase rice production is constrained by problems of agricultural land conversion, damage to irrigation networks, climate change, and pest and disease attacks. The total population in Indonesia was approximately 271.1 million in 2020, and it has resulted in the importance of food security. The population growth rate of East Java from 2010 to 2017 was 0.64%, while a report from rice food security said that East Java has advantages in agriculture and plays a role in the national food sector. Rice consumption in East Java reached 213,783 tons in 2018 [1].

Rice quality and production quantity research are influenced by biotic and abiotic factors such as rainfall, soil fertility, temperature, pests, bacteria, and viruses. For disease management, farmers detect disease through a direct approach using visuals that do not cost money, thus leading to less healthy farming, consuming a lot of time and resources [2].

Rapid disease identification is critical to plan management areas and land leases and reduce the company's loss factor. Rice disease can result in a loss of 20-40% of the company's production in crop yields and is closely linked to the global economy. Depthwise separable neural network model with Bayesian optimization (ADSNN-BO) using MobileNet structure and an augmented mechanism is proposed to get disease detection quickly and accurately with the help of Artificial Intelligence [3].

The application of a convolutional neural network (CNN) for automatic identification of Landscape photos is taken using a specific time duration in a particular area. It's to know the growth of woody vegetation that grows back in an exact time. The step is to examine changes in woody vegetation cover between pairs of landscape images and whether the classification results based on the intuitive approach can be used to measure the regrowth area. CNN in this research was trained using wood and non-wood vegetation tiles measuring 50x50 pixels [4].

There is research to identify communication between the drone and its controller. It is done based on the radio frequency emitted, which means that the drone's position is flying. The frequency points were measured and entered into the CNN. The research results prove that using CNN to detect the presence of drones has accuracy and an F1 score above 99.7%. The drone has identification with an F1 score of 88.4% [5].

Tree mapping uses color images taken by Unmanned Aerial Vehicle (UAV) RGB photos of the forest into several objects that automatically form tree-like clusters. The research begins by calculating the slope of the three-dimensional model obtained through the UAV drone. Object-based CNN classification was applied to each crown image based on the resulting images using color and three-dimensional information and a slope model. The system has successfully classified seven tree class groups, including several types of tree species, with an accuracy of more than 90% [6].

From some of the literature above, the importance of this research is to help farmers recognize rice diseases. Initial research was conducted using a deep learning convolutional neural network (CNN) to identify damage to the rice leaf image. The CNN method is completed using 34 layers with the addition of a proposal region with a convex hull. The hope is that there will be savings in computational time in the training process compared to the existing architecture.

II. Background

A. Rice Food Security

Most people consume rice, which has become one of Indonesia's most dominant food commodities. The government has implemented policies including increasing productivity through various new technologies ranging from providing seeds, processing land to post-harvest, and increasing the planted area and harvested area by increasing the rice planting index [7].

B. Types of Diseases in Rice Plants

There are three types of rice plant diseases based on leaf damage, namely BrownSpot, Hispa, and LeafBlast, and one normal condition can be explained as follows:

- BrownSpot. Brown leaf spot disease on rice (Oryza sativa l) is caused by the fungus Helminthosporium oryzae. It is insulated, cylindrical, and slightly curved, as shown in Fig. 1 [8].
- Hispa is parallel lines or white spots along the central axis of the leaf. Irregular white bumps, also known as leaf wilt, are shown in Fig. 2 [9].
- LeafBlast. Symptoms of Leaf Blast Disease. There are brown rickshaws in the shape of a rhombus and elongated in the direction of the leaf veins. The edges of the becak are brown with a grayish-white center, as shown in Fig. 3 [10].
- Healthy (average condition). It is a rice leaf under normal conditions. A healthy plant is if every plant organ can carry out physiological functions according to its genetic potential.

Fig. 4 shows Healthy plants with nutrient needs that are met can create immunity naturally. Biologically, healthy plants have a substantial role in inhibiting infection and disease development [11].

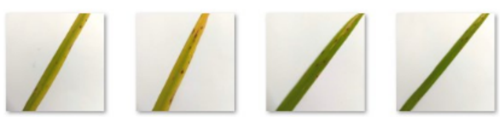

Fig 1. Brown Spot

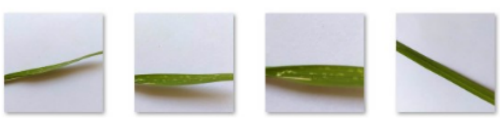

Fig 2. Hispa

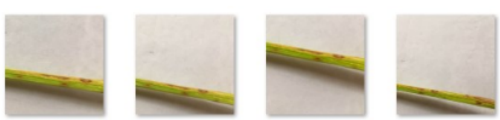

Fig. 3. LeafBlast

Fig. 4. Healthy leaf

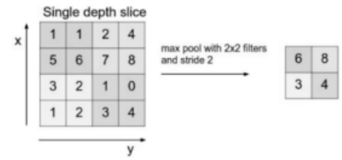

Fig. 5. Max Pooling layer [19].

C. Deep Learning

Artificial Neural Network (ANN) contains more layers fully connected between neurons in the input layer, hidden layer, and output [12]. Wensheng Wang (2017) researched a convex hull to find the region of an object. The research was conducted using an active contour algorithm with an increased threshold. [13].

D. Convolutional neural network

The inside of the CNN is divided into two main blocks: the feature map, which combines segmentation and feature extraction, and a classification layer [14]. It contains:

- Convolution means applying a function to the output of another part repeatedly.

$$output = \frac{W-N+2P}{S} + 1 \quad (1)$$

where S = Stride, P = Zero padding, W = Image input Length/Height, and N = Filter Length/Height [16, Eq. (1)].

- Batch Normalization is a layer to speed up the training process by normalizing the output distribution of each node in a layer and allowing the network to be more stable [16].
- Rectified Linear Units are a thresholding or activation function in artificial neural networks [18, Eq. (2)].

$$f(x) = \begin{cases} x, & jika\ x \geq 0 \\ 0, & lainnya \end{cases} \quad (2)$$

- The pooling layer has a stride value, meaning it will shift every n step. as shown in Fig. 5 [18].
- Flatten layer helps bridge the transformation of multidimensional vectors into single vectors that can be used as input from a fully connected layer for the classification process [20]

E. Data Augmentation.

The data changes for the translation process, differences in viewing angles, sizes or lighting, and combinations. Are transformations carried out are Shear, Reflection, Scaling, and Rotationas showed by formula 3 [22, Eq. (3)].

$$A = \begin{bmatrix} \cos(\theta) & \sin(\theta) & 0 \\ -\sin(\theta) & \cos(\theta) & 0 \\ 0 & 0 & 1 \end{bmatrix} \quad (3)$$

With A=Kernel filter, θ=rotation angle of a matrix. Where the rotation result will follow the following formula:

$$x' = x\cos(\theta) - y\sin(\theta) \text{ and } y' = x\sin(\theta) - y\cos(\theta) \quad (4)$$

The coordinates above are calculated to determine the rotation transformation's initial position [23, Eq. (4)]

F. Convex Hull.

This method finds a set of 'outermost' points that form a convex hull so that these points can be connected and form a polygon. Convex hull will produce the minimum number of lines to cover all the set of points

$$C \equiv \left\{\sum_{j=1}^{N} \lambda_j p_j : \lambda_j \geq 0 \; for\ all\ j\ and \sum_{j=1}^{N} \lambda_j = 1\right\} \quad (5)$$

With N=point $p_1, \ldots, p_N$, j=indexing [24, Eq. (5)].

G. Confusion matrix.

The Confusion Matrix plots the number of wrong quantities entered the class during the prediction process.

$$Accuracy = \frac{TP+TN}{TP+TN+FP+FN} \quad (6)$$

Where TN (True Negative) = tests result are harmful and entirely free from disease, TP (True Positive) is positive data that is predicted to be correct.

III. Research Methods

The flowchart of this research method is shown in Fig. 6. The system begins by inputting an image by dividing the train data, validation, and test data.

A. Dataset

The requirements are taken from the internet, from the Kaggle website. There are four classes: brown spot, hispa, leaf blast, and healthy, where each contains 400 files with a size of 224x224x3, with a depth of 24 bits.

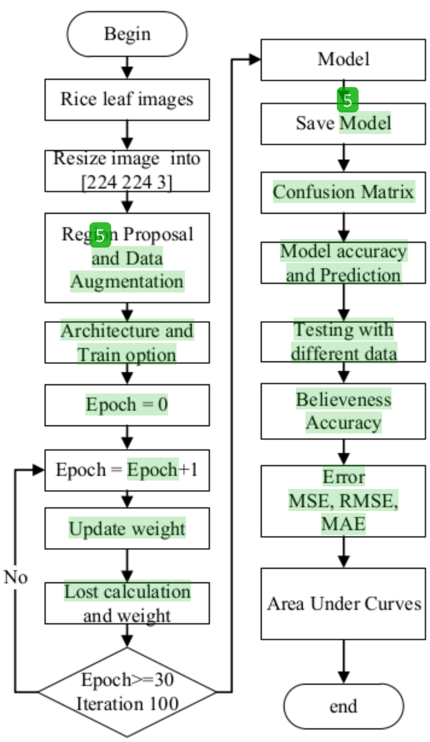

Fig 6. Research Methods

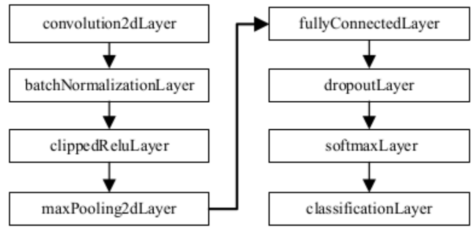

Fig 7. The proposed architectures

Fig 8. Results of preprocessing rice leaf image using convex hull

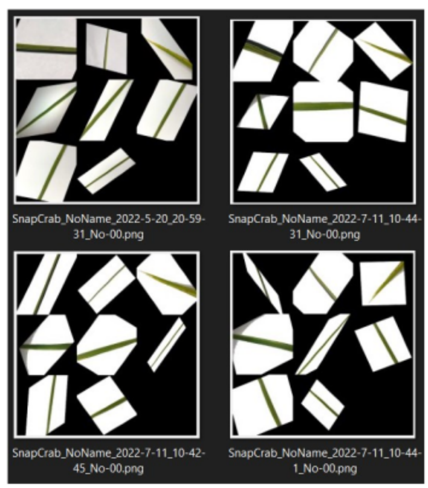

Fig. 9. Augmentation Process

IV. Result and Analyze

A. Preprocessing

This stage prepares the data to be ready to be used as input from the deep learning system. The conditions are met by setting the image size to 224x224x3 and cleaning the background shown in Fig 8.

It is necessary to focus on the object of disease in rice leaves to obtain a better model. A convex hull searches for

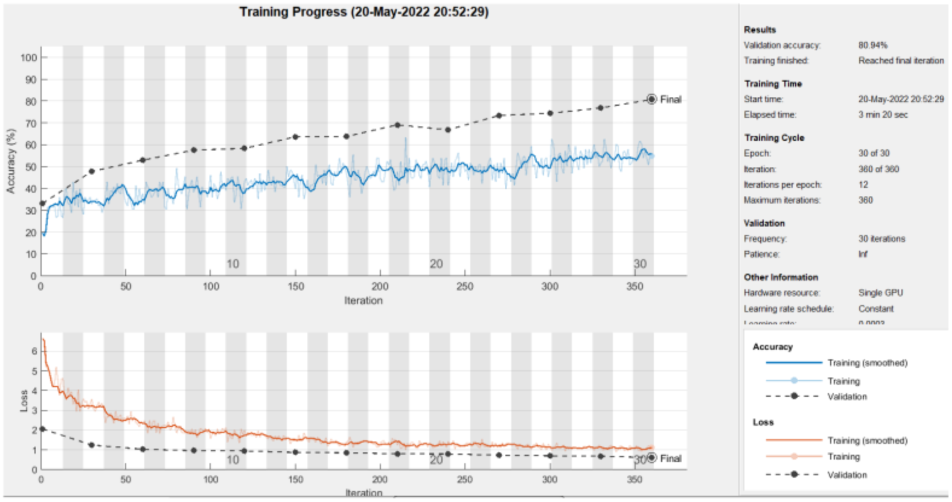

Fig. 10. Training Process

the object's edge points, then after getting the edge, it is continued by equating the background to white.

B. Experimental setup

Initially, the training process was carried out to obtain a model. The data is divided into 80% training data and 20% testing data. In addition, data validation is used at least 20-80% of the training data. After the model is formed, a new testing data test is carried out to test the system. In the experimental setup, changes were made to implementing the CNN architecture and learning parameters using training optimization

C. Data augmentation

The image of the rice leaf is straight, so it is necessary to enlarge and vary the position of the image so that it can be seen from various sides shown in Fig. 9.

D. Parameter training

The learning rate $3x10^{-4}$, minibatch size = 10; Max Epochs=30, Shuffle in every epoch, Validation Data, and augmentation using imdsValidation with Adaptive Moment Estimation (ADAM) as shown in Fig 10

E. Visualization of a segmented image

The Maps feature layer's output results show the image mapping process by multiplying the input image with filters or kernels. Fig 11 shows the Visualization of the leaf in the feature maps layer. Feature visualization for a neural network unit is done by looking for inputs that maximize unit activation. One of the modules that can be used on hidden Layers is Google Deep Dream, which repeatedly adds layer visual features to the original image. The results show that the training process can be carried out with optimal accuracy values, with less training time in the training process shown in Fig 10. Four classes are mapped in the confusion matrix: brown spot, hispa, leaf blast, and healthy. For the Brown spot class of 315 images, 14 images wrongly entered the Healthy class, and 12 joined the LeafBlast class.

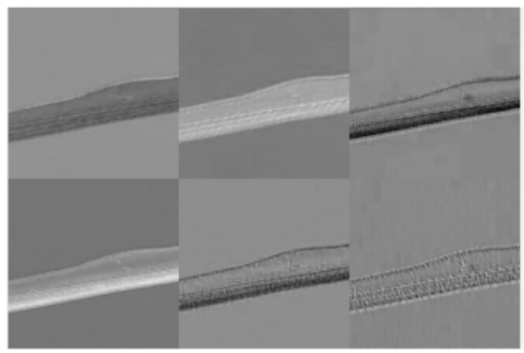

Fig 11. Visualization of feature maps

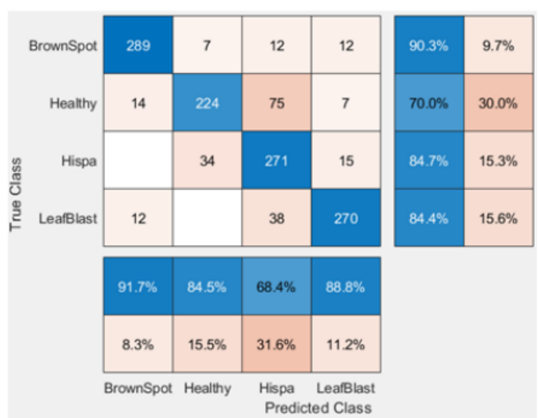

Fig 12. Confusion Matrix

Fig. 13. Prediction result of Rice leaf disease (in %)

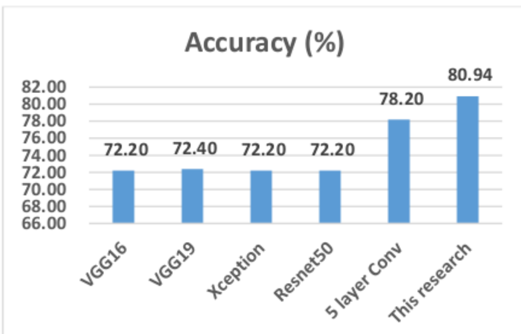

Fig. 14. Comparison of Accuracy

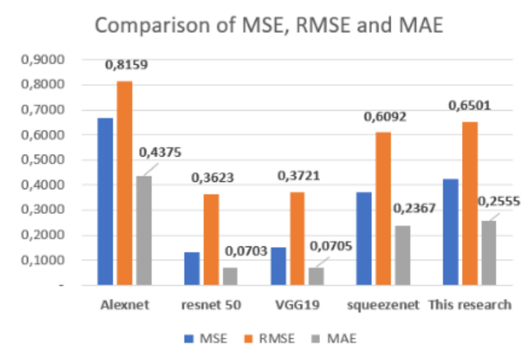

Fig. 15. Comparison of Error Classification

F. Prediction

This stage is to get predictions of test data of the model that has been built. The level of confidence in the test data outside the area of the training process and it Shows in Fig 13. It shows the results of confidence in the model that has been trained. The higher the confidence value, the better the system can predict the test data correctly.

In the first picture, the confidence level is 45%, meaning that this data tends not to fit the model. In the third and fourth pictures, the confidence level is above 95%, which means that the test data is predicted correctly according to the type.

G. Comparison of accuracy

Tejaswini, who researched rice leaf images, compared the accuracy using the VGG16, VGG19, xception, resnet50, and 5-layer Conv architectures shown in Fig. 14 [24].

The comparison shows that the model's accuracy resulting from the purpose is 70-80% using the rice leaf dataset. In contrast, the foreground object is not square, which means that the convolution process for object identification does not work optimally to get results. It is compared when using the overall object of an image frame and a square object

H. Comparison of Error

A comparison graph of MSE (Mean Square Error), RMSE (Root Mean Square Error), and MAE (Mean Absolute Error) errors is shown in Fig. 15. The results show that for this research, it is not the smallest when compared to resnet and VGG. However, remember that the training process to form a resnet and VGG model takes more than half an hour.

V. Conclusion

The rice disease classification observed through damage to rice leaves has been carried out and uses deep learning technology. Previous research's weaknesses in accuracy can be overcome by using custom layers and data augmentation. The results obtained are that the system can classify rice leaf image data into four classes of rice plant conditions: Brown spot, Healthy, Hispa, and Leafblast. The classification results show an average accuracy of 80.94%, with the computation time to get an average model of 3 minutes and 20 seconds. However, when testing with the learning outcomes model, the time required is about 0.2 seconds. Error calculation of classification are MSE 0.4227, RMSE 0.6501, and MAE 0.2555.

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