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Detection Of Brown Spot And Leaf Blight In Rice With The You Only Look Once (YOLO) Algorithm

Riki Ruli A. Siregar[1]; Teuku Rifki Dhulul Fata [2)]; Indrianto[3]*

1. Department of Computer Science, IPB University, Jawa Barat 16680, Indonesia
2. Informatika, Institut Teknologi PLN, DKI Jakarta 11750, Indonesia
3. Pasca Sarjana Teknologi Informasi Universitas Gunadarma, Jawa Barat 16451, Indonesia

[*)]Email: teuku1731317@itpln.ac.id

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ABSTRACT

Rice is a plant that produces rice as the staple food for almost all Indonesians. Rice plays a vital role in the food chain in Indonesia. However, many types of diseases on rice leaves attack and inhibit the growth of rice in Indonesian rice fields. Among them are brown spots and leaf blight. So far, the classification of diseases on rice leaves is only based on the experience of farmers. This results in uncertainty and diagnostic inaccuracy in classifying various diseases on rice plants. In this case, a method is needed to solve the problem. The method used in this research is digital imagery by processing images of diseases on the leaves of rice plants using the YOLO (You Only Look Once) algorithm. YOLO uses a single Convolutional Neural Network (CNN) for object classification and localization using Bounding Box. This research aims to provide options to users in determining the diagnosis of leaf spots and blight diseases on the leaves of rice plants. The average Precision (mAP) evaluation result is 69%, indicating that this method is suitable for detecting diseases on rice leaves.

Keywords: *Rice; disease; YOLO; diagnosis*

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1. INTRODUCTION

Rice (Oryza sativa L.) is a food crop that produces rice as the staple food of almost all Indonesians. Rice consumption in 2010, 2015, and 2020 is projected to be 32.13 million tons, 34.12 million tons, and 35.97 million tons, respectively. The total population in the three periods is estimated at 235 million, 249 million, and 263 million, respectively[1][2].Factors that affect the level of production are very important to consider, one of which is the cause of rice plant diseases. Many types of rice leaf diseases appear on rice farms, including brown spot and leaf blight [3][4][5]. Brown spot disease is commonly found in rice crops, especially in marginal soils that are less fertile or lack certain nutrients [6]. Leaf blight is one of the major diseases that limit paddy rice production. This disease infects rice from the vegetative phase to the generative phase and can reduce paddy rice yield by 30-40% [7]. Global solutions are very important, and a method is needed to formulate the problem. The technique used is digital imagery by processing images of disease in rice plant leaves using the YOLO (You Only Look Once) algorithm. YOLO uses a single Convolutional Neural Network (CNN) for classification and object localization using bounding boxes [8][9][10]. Research on CNN has been widely used to identify images and provides convincing results. Recent research on CNN was conducted by Z. Fan, Y. Wu, J. Lu, and W. Li [11]. This research identifies cracked road images and normal roads. By using 3 types of datasets and several types of training and testing data division, the highest precision of 96% was obtained. Other research on the application of Yolo has been carried out to identify rice plants; the main conclusion of the previous study on the application is that the Yolo method can quickly and accurately identify swiftly and accurately based on digital image data processed to get the right results [12][13][14]. The application of YOLO algorithm to date has been widely applied in image identification. YOLO is proven to be more efficient than other machine learning algorithms. Therefore, this research uses the YOLO algorithm to create a diagnosis system for rice leaf diseases. This system helps provide options for users of rice cultivation techniques to classify diseases in rice plants by taking pictures of rice affected by the disease so that the images can be processed and entered into the system.[15][16][17].

2. RESEARCH METHOD

In this study, the data used is 200 data in the form of image files, from these data including 100 images of Brown spot disease and 100 images of Leaf Blight disease; data collection is done by downloading rice image datasets from the Kaggle.com website, where the Kaggle website itself is one of the largest data scientist communities in the world. In Kaggle, data scientists can compete to solve scientific problems based on complex data. The data obtained in this research is secondary data, namely data from existing sources. The data used in this research is Rice Leaf Diseases Dataset collected by a bookshelf, taken from the site https://www.kaggle.com/vbookshelf/rice-leaf-diseases.

YOLO makes the object detection process a single regression problem, which processes directly from image pixels into bounding box coordinates and class probabilities. The first thing done in the YOLO algorithm is input; the input referred to here is an image, only an image that has gone through pre-processing, such as cropping, resizing, and annotation. The first thing done in the YOLO algorithm is input. The input referred to here is an image, only an image that has gone through pre-processing processes such as cropping, resizing, and annotation. The processed image is an image that has been converted to an RGB matrix. The following is an example of an image and an example of an RGB matrix from Figure 1.

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Fig 1. Rice leaf input image

The image conversion result from Figure 1 is 3 RGB matrices (Red, Green, and Blue). One of them is the red matrix as in Table 1. Due to the limitations of writing media, the example matrix taken is 10x10 from 416x416; taking a 10x10 matrix is also more likely in manual calculations than using a 416x416 matrix.

Table 1. Red RGB matrix conversion results

71	61	60	59	60	60	60	58	59	60
48	48	48	49	49	49	49	50	49	49
60	48	49	49	49	49	49	49	50	49
60	49	49	49	49	49	50	48	47	48
59	51	49	49	49	50	50	48	47	50
59	51	49	49	49	50	51	48	50	49
60	52	51	49	50	50	51	51	49	49
60	51	52	49	50	50	50	50	51	50
63	51	51	50	51	50	49	50	51	51
63	50	49	51	52	52	50	50	51	53

The second stage of the Yolo algorithm is the CNN process Yolo has its own CNN architecture, as shown in Figure 1. The Yolo architecture is divided into the convolution process, max pool and Fully Connected Layer.

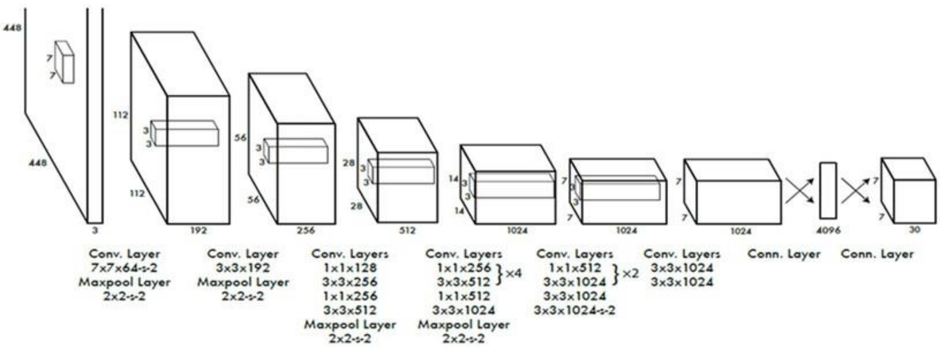

Fig 2. Basic Architecture of YOLO [18]

The RGB input matrix will be convolved into the CNN architecture in the convolution stage. As an example of this research, the calculation takes one red table in Table 1. to be convolved into one of the layers in the CNN architecture. In the first layer of the convolution stage, the filter used is a 7x7 filter, so the first step of the convolution stage is that the RED 10x10 matrix will be multiplied by the 7x7 filter matrix horizontally to the right. The filter is also called a kernel. The values in the kernel are random. The kernel in this study can be seen in Table 2.

Table 2. 7x7 Filter Kernel Matrix

3	**2**	**1**	**2**	**3**	**1**	**3**
3	**2**	**1**	**1**	**2**	**2**	**2**
2	**1**	**3**	**3**	**2**	**1**	**1**
2	**1**	**3**	**1**	**2**	**2**	**3**
2	**1**	**3**	**2**	**1**	**1**	**3**
3	**1**	**3**	**2**	**1**	**3**	**1**
2	**3**	**2**	**1**	**3**	**2**	**1**

The next step is to perform the shift from Table 1 to get the convolution result value. The first phase of sliding windows.

Table 3. Fase sliding window.

71	61	60	59	60	60	60	58	59	60
48	48	48	49	49	49	49	50	49	49
60	48	49	49	49	49	49	49	50	49
60	49	49	49	49	49	50	48	47	48
59	51	49	49	49	50	50	48	47	50
59	51	49	49	49	50	51	48	50	49
60	52	51	49	50	50	51	51	49	49
60	51	52	49	50	50	50	50	51	50
63	51	51	50	51	50	49	50	51	51
63	50	49	51	52	52	50	50	51	53

(71*3) + (61*2) + (60*1) + (59*2) + (60*3) + (60*1) + (60*3) +(48*3) + (48*2) + (48*1) + (49*1) + (49*2) + (49*2) + (49*2) +(60*2) + (48*1) + (49*3) + (49*3) + (49*2) + (49*1) + (49*1)+(60*2) + (49*1) + (49*3) + (49*1) + (49*2) + (49*2) + (50*3) +(59*2) + (51*1) + (49*3) + (49*2)+ (49*1) + (50*1) + (50*3) +(59*3) + (51*1) + (49*3) + (49*2) + (49*1) + (50*3) + (51*1) +(60*2) + (52*3) + (51*2) + (49*1) + (50*3) + (50*2) + (51*1) = 5047.
The convolution results will be put into a 4x4 matrix, as shown in Table 3.

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Table 4. Sliding window First step results

5047			

The sliding stage is performed up to sliding 16 (sixteen) to produce a 4x4 convolution matrix, as shown in Table 4. and generate the convolution values in Table 5.

Table 5. Sliding window to 16

71	61	60	59	60	60	60	58	59	60
48	48	48	49	49	49	49	50	49	49
60	48	49	49	49	49	49	49	50	49
60	49	49	49	49	49	50	48	47	48
59	51	49	49	49	50	50	48	47	50
59	51	49	49	49	50	51	48	50	49
60	52	51	49	50	50	51	51	49	49
60	51	52	49	50	50	50	50	51	50
63	51	51	50	51	50	49	50	51	51
63	50	49	51	52	52	50	50	51	53

Table 6. Convolution Result

5047	4896	4871	4881
4896	4750	4739	4739
4959	4767	4760	4749
4193	4035	4022	4013

These steps will be repeated in as many layers as listed in the YOLO network architecture as in Figure 1. The previous actions can be used to calculate the RGB green and blue matrices. After obtaining a 4x4 matrix from the 10x10 matrix convolution stage with a 7x7 kernel, the YOLO CNN architecture must do max pooling, taking the highest value of each filter (2x2). Furthermore, in the matrices in the table described, the max pooling value is obtained as follows:

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Table 7. Maxpooling Process

5047	4896	4871	4881
4896	4750	4739	4739
4959	4767	4760	4749

→

5047	4881
4959	4760

The result of max pooling will be three layers because it has three colour matrices that are calculated, namely Red, Green, and Blue. Suppose in convolutional and max pooling calculations three RGB matrices are produced, namely:

Table 8. RGB Red Matrix Maxpooling Result

5047	4881
4959	4760

Table 9. RGB Green Matrix Maxpooling Result

7791	7631
7753	7566

Table 10. RGB Blue Matrix Maxpooling Result

1720	1549
1605	1401

The results of the three matrices will be organized into a one-column matrix, and this process is also called *flatten*; it will be like Table 10.

Table 11. Flatten Matrix

5047
4881
4959
4760
7791
7631
7753
7566
1720
1549
1605
1401

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The results obtained from the CNN process are in the form of bounding boxes and probability levels. The bounding box is the output that is issued at the CNN stage. A bounding box is an object marker that has gone through the detection process, and the bounding box is usually in the form of a box with a colored outline. An example of a bounding box from this research can be seen in Figure 2.

Fig 3. Output Bounding Box

Probability is the probability level of an image containing a class, and probability is usually defined in per cent. The probability level depends on how much in a fully connected layer matrix there is a matrix that characterizes the test image.

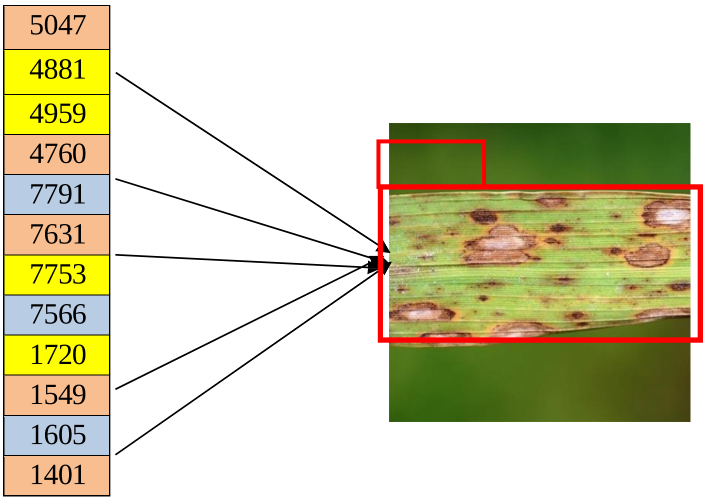

Fig 4. Output Probability

The evaluation in this study using Intersection over Union (IOU), Precision, Recall, Average Precision, Mean Average Precision[19].

Intersection over Union (IOU) is a measurement to measure the overlap or intersection between the predicted bounding box and the actual bounding box[19]. The equation of IoU is:

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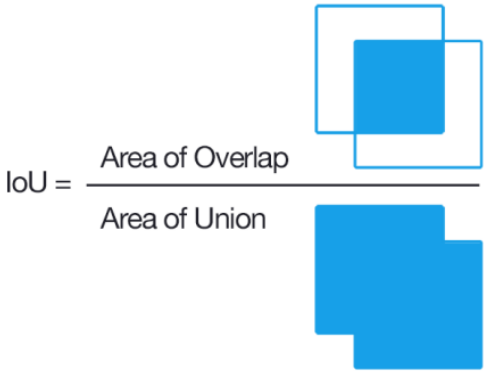

Fig 5. Intersection over Union Formula

The Area of Overlap is the intersection of the ground truth box with the predicted box, and the Area of Union is the combination of the ground truth box and the expected box. Meanwhile, an equation is needed to calculate the Area, as in Figure 5.

Fig 6. Area Formula

$$Area = (x\_right - x\_left + 1) \text{ x } (y\_bottom - y\_top + 1)$$

Precision is the level of accuracy between the information requested by the user and the answer given by the system[19]. Precision measures how accurate the prediction is. The equation of precision can be seen in Figure 6.

$$Precision = \frac{TP}{TP + FP}$$

Fig 7. Precision formula

TP = True Positif (IoU>50%) and FP = False Positif (IoU<50%).

The recall is a ratio of a positive value to the total number of relevant objects[19]. For example, if a model correctly detects 75 brown spot diseases in an image and 100 diseases in the image, then the recall is 75%. The recall equation can be seen in Figure 7.

$$\textbf{Recall} = \frac{\textbf{TP}}{\textbf{TP + FN}}$$

Fig. 8 *Recall formula*

TP = True Positif (IoU>50%) FP = False Positif (IoU<50%) FN = False Negatif
TP + FN = ∑*Ground-Truth*

Average Precision (AP)[19]. There are several ways and equations for calculating the AP value, one of which is using 11 Point Interpolated Precision. To use this method, the equation needed is shown in Figure 8.

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$$AP = \frac{1}{11} \sum_{r \in \{0.0,\ldots,1.0\}} AP_r$$
$$= \frac{1}{11} \sum_{r \in \{0.0,\ldots,1.0\}} p_{interp}(r)$$

Fig 9. Average Precision formula

It takes a precision value that intersects with the recall value, the precision value is only the value right at the recall point (0.0,0.1,0.2...1.0), and the interpolation stage has been carried out on the precision. The precision interpolation stage is the stage of taking the best precision value.

Mean Average Precision is the average of all APs from each class.

$$\text{mAP@}\alpha = \frac{1}{n} \sum_{i=1}^{n} \text{AP}_i \quad \text{for n classes.}$$

Fig 10. Mean Average Precision (mAP) [19]

Description (AP and the number of classes): AP is calculated individually for each category. There are as many AP values as classes (loosely speaking). These AP values are averaged to get the average metric of Average Precision (mAP) [19].

In this research, two classes are used, namely Brownspot and leaf blight. So, to find the mAP value, the next step can see the AP value of each class first.

3. RESULTS AND DISCUSSION

In the training stage using the YOLO algorithm, the initial weight of the YOLO algorithm is needed to train the data to produce new consequences. YOLO algorithm for data training to produce new weights, this weight is useful for detecting brown spot disease and leaf blight. At the detection stage, input data is required to image rice leaves affected by pests. Affected by pests, this stage can be done in 2 ways: by inputting image data from the system storage or image data from the system storage. Image data from the system storage or inputting image input directly from the camera is commonly called Real-Time Object Detection. The disease detection stage produces a probability value and bounding box to show the probability level and location of the detected pests. Probability and location of detected problems.

The implementation of the YOLO algorithm was tested on an Android system by producing an application for diagnosing Brown spot and Leaf Blight diseases named "Diagnosis of Rice Diseases". This application can detect the probability level of rice disease detection. Figure 10 is the interface of the Android-based application for detecting diseases in rice plants based on leaf images.

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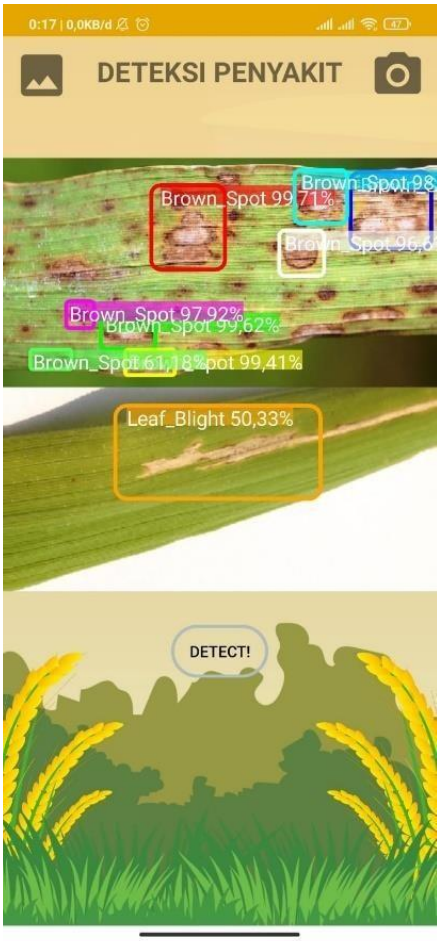

Fig 11. Diagnose Leaf Blight and Brown Spot in the Detection Menu

Determination of IoU and TP/FP Class Brownspot The first step in accuracy testing is to determine the Intersection over Union (IoU) and whether a predicted box predicts correctly or not.

Sorting by Probability Class Brownspot After determining the IoU and TP/FP, the results must be sorted based on the probability level.

Accumulation of TP and FP of Brownspot Class After sorting by probability, the next step is calculating the collection of TP and FP. The expansion of TP and FP is calculated based on adding the TP/FP values from the previous rows. Next will be the calculation of Precision and Recall Class Brownspot. From the resulting precision and recall values, the average precision of the brownspot class is 94%, and the average value of the brownspot recall class is 48%. The results obtained precision and recall curves as in Figure 11.

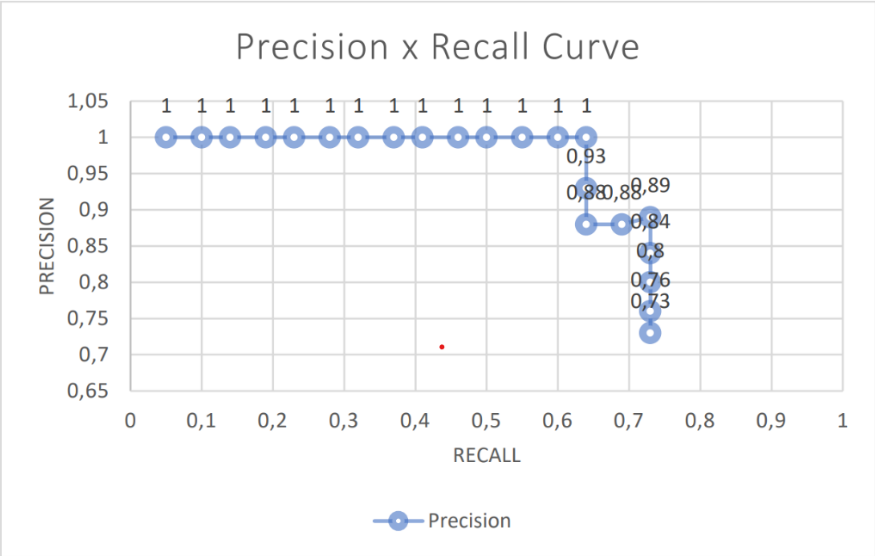

Fig 12. Brownspot Class Precision x Recall Curve

11-Point Interpolated Precision Class Brownspot This step in the process obtained the results of the interpolated precision process in Figure 12.

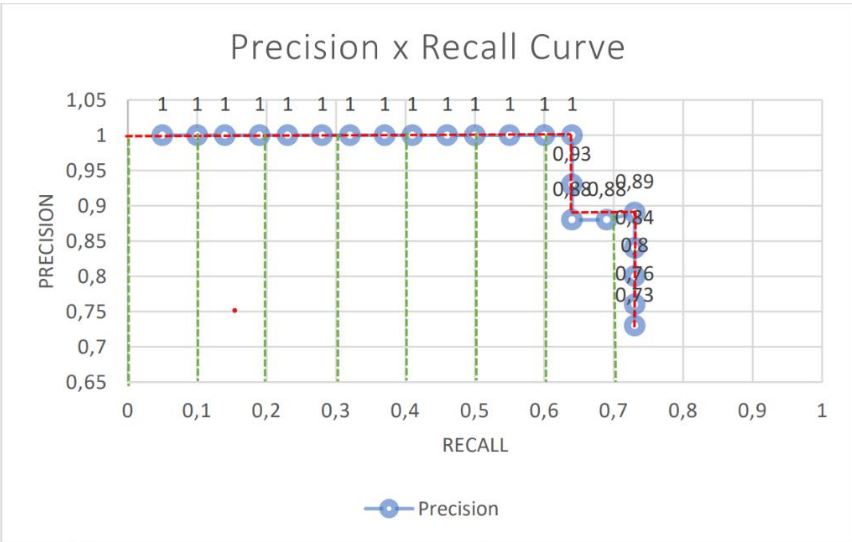

Fig 13. Interpolated Precision Class Brownspot

The precision value that intersects with recall (0.0, 0.1, 1.0) is needed at the AP calculation stage, which can be seen in Figure 12 and is represented by a dashed green line.
They were testing on Leafblight Disease.
The steps applied to obtain Precision, Recall and Average Precision in leafblight disease testing are the same as in brownspot disease testing. Fromthe resulting precision and recall values, it can be calculated that the average precision of the leafblight class is 84%, and the average recall value of the leafblight class is 46%.

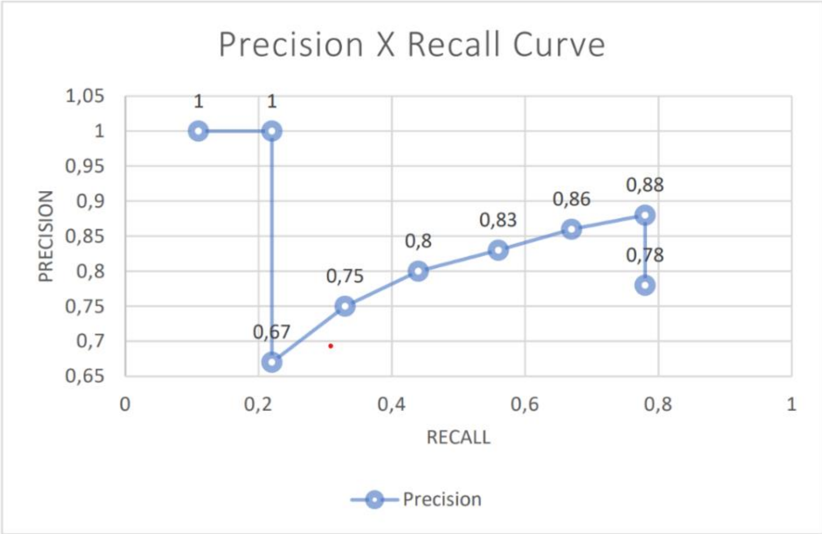

Fig 14. Precision X Recall Class Leafblight

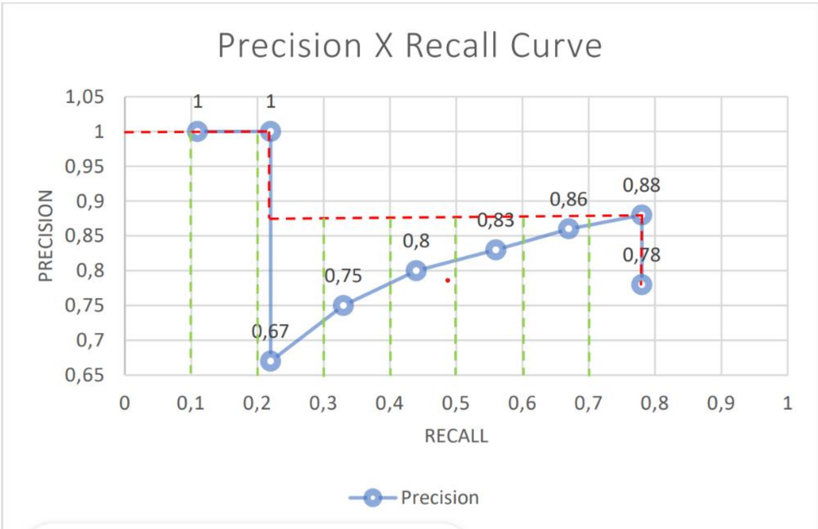

Fig 15. Interpolated Precision Class Leafblight

By using the Average Precision (AP) equation on Class Leafblight, the Average Precision calculation obtained is:

AP = 1/11x(1+1+0,88+0,88+0,88+0,88+0,88+0,88+0,88+0+0+0) = 0,66

Resulth the Average Precision (AP) obtained on Class Leafblight is 66%.

The evaluation calculation is done using mAP. To calculate the mean Average Precision (mAP) value, the Average Precision (AP) value of each class is needed. In this research, only two classes are used, so using the equation in Figure 4, the calculation will be as follows.

mAP = (0,71 + 0,66) / 2
= 0,69
= 69%

The brown spot and leaf blight disease diagnosis system on the leaves of rice plants with the YOLO algorithm are designed to help system users, in this case, the community, especially farmers, to find out the type of disease or pest on the leaves of rice plants based on the selected image, so that

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treatment can be done quickly to other rice plants so as not to contract the pest. The algorithm used in designing this system is the YOLO algorithm. YOLO is an algorithm that uses CNN (Convolutional Neural Network) architecture. The YOLO algorithm has several stages in the training and testing process, starting from the pre-processing step to the detection stage. In certain cases, two adjacent bounding boxes detect one disease (multiple bounding boxes). This is because the YOLO algorithm must predict a certain probability only; YOLO will only run its calculations for each bounding box in each cell in the image and produce output. A Non-Max Suppression process is carried out from the multiple bounding boxes, which can eliminate various Bounding Boxes, but the process is not 100% accurate.

The accuracy test carried out is divided into several difficulties. In testing the brownspot class, the precision value is 94%, the recall value is 48%, and the AP is 71%. While testing, the leafblight class obtained a precision value of 84%, a recall value of 46% and an AP of 66%. So that the mean Average Precision (mAP) accuracy value obtained from the two classes is 69%.

4. CONCLUSION

Based on the results of the research that has been done, it can be concluded; Making the application of the disease diagnosis system of Brown Spot and Leaf Blight on rice leaves provides options for users in determining and classifying pests, especially for Brown Spot disease (Leaf Blight) and Leaf Blight disease (Leaf Blight). YOLO algorithm to calculate the probability value on the detection system of Brown Spot disease (Leaf Spot) and Leaf Blight disease (Leaf Blight) on the leaves of rice plants. The system output is a probability value accompanied by a bounding box. The output of several bounding boxes in one disease (Multiple bounding boxes) because the process of removing multiple bounding boxes, commonly called non-Max suppression, is inaccurate. Testing on the diagnosis system for Brown Spot and Leaf Blight on the leaves of rice plants is divided into several tests, and in testing, the brown spot class obtained a precision value of 94%, a recall value of 48% and an AP of 71%. While testing, the leaf blight class obtained a precision value of 84%, a recall value of 46% and an AP of 66%. %. So that the average Precision (mAP) accuracy value obtained from the two classes is 69%.

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