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Object Detection for Diagnosis Rice Leaf Diseases Using YOLO Method

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Abstract

Rice plants have been attacked by various diseases. The leaves of rice plants can be used to identify rice diseases because they have a wide cross-section, besides that the discoloration and spots are more visible than the stems, panicles, and roots of rice. This study presents the detection of rice leaf disease using transfer learning methods from the Convolutional Neural Network, namely Yolo to predict bounding boxes and identify objects. This experiment uses a public dataset from the Indonesian rice leaf dataset and the experimental results shown that the proposed scheme achieves a high accuracy value of 94% with a detection speed of 1 image of 0.028 seconds.

Keywords: CNN, Deep Learning, Rice Leaf Disease.

1. Introduction

Rice is one of the staple food crops that is very important to support food security for the majority of people in the world, making rice farmers one of the spearheads of food sources in various countries, including Indonesia[1].The agricultural sector, especially rice production, is often at risk of uncertainty including crop failure caused by climate change such as the impact of floods, droughts, pests and even diseases or plant-disturbing organisms that have an impact on losses suffered by farmers [2], [3]. If the disease is not immediately eradicated, it will easily spread to other rice plants and have an impact on decreasing the quality of the rice produced and even causing crop failure. Diseases in rice plants also affect social changes in society in a country, especially in developing countries, so that it has an impact on changes in the type, level of attack, development, and rate of spread of disease in the plant itself. Dozens of these diseases are also reported to threaten various cultivated food crops, including rice plants [4], [5].

Diseases that infect rice plants will show symptoms in the form of spots with certain patterns and colors. Where these symptoms are seen in several parts of rice including panicles, leaves, stems, and roots. However, the symptoms of rice disease are more often identified through rice leaves because they have a wide cross-section, besides that discoloration and spots are more obvious. Therefore, rice leaves are used as an early stage in the identification of rice diseases [6], [7].

The technology used by farmers in developing rice production currently requires several improvements in accordance with the threatening problems, it also takes into account resources and the environment, including plant diseases that can develop over time. Disease management in rice plants is important as an effort to maintain food stability, because diseases that attack plants will develop rapidly from time to time so that they can threaten the growth of rice plants and even have the potential to cause crop failure [8].

The Indonesian Center for Rice Research (BB Rice) in 2018 has planned several programs to control rice pests and diseases. However, based on the annual report made by BB Rice, they face several obstacles where the condition of the Human Resources (HR) of BB Rice, most of whom have entered retirement age, in addition to the equipment used in the laboratory and in the field, is still using old equipment, as well as the activities carried out in the field, depending on the growing season, climatic conditions, rainfall, pest disturbances, as well as diseases and weeds that attack so that BB Rice requires cooperation in the form of research with other institutions that already have modern equipment [9], [10].

Industrial revolution 4.0 technology in the agricultural sector currently utilizes high-precision agricultural application technology to overcome problems in agriculture, such as a combination of bioinformatics and genetic algorithms to find superior seeds and the process of chromosomal crossing. On the other hand, the use of an intelligent image interpretation system is also used for land use planning, as well as a fuzzy system for diagnosing pests and plant diseases [11]. Crop damage is also avoided automatically by using quality testing tools, optimization of the shortest route in commodity distribution, and transparency of the flow of goods and money with block-chain technology and big data [12].

One of the trends in the use of technology in agriculture in detecting diseases in rice plants is the use of the classifier method to detect diseases of rice plants. This is expected to help farmers to classify rice plant diseases based on their class or type, control the spread of disease in rice plants, and provide solutions in overcoming rice plant diseases [13], [14].

2. Related Works

Many researchers have worked on the automated identification of rice leaf diseases through typical means that akin to pattern recognition techniques using CNN [15], using Support Vector Machine (SVM) [16], digital image process associated computer vision [5] for enhancing the accuracy and celerity of diagnosing the results. In an earlier study, planned a rice disease identification approach wherever the unhealthy rice pictures were classified utilizing Convolutional Neural Network [16] during which the train images were obtained by extracting the options of the infected components of the leave whereas four differing types of images were applied for testing purposes. A somewhat satisfactory classification results were reported. In a completely different study, planned an automatic approach to classify the rice plant diseases, specifically leaf brown spot and also the leaf blast diseases supported the morphological changes. A complete of 1,000 spot pictures captured by Nikon COOLPIX P4 photographic camera from a rice field were used. The results obtained were 79.5% and 68.1% accuracies from the Bayes' and SVM classifiers, respectively [17], [18].

The research was carried out by Bari, Bifta Sama and friends, which was published in 2021 with the title "A real-time approach of diagnosing rice leaf disease using deep learning-based faster R-CNN framework". This research shows that the Faster R-CNN method using 4 classes (Rice Blast, Brown Spot, Hispa and Healthy) taken from public and private with a total dataset of 16,800 images and a learning-rate of 0.0002 is able to detect diseases in rice leaves with a high degree of accuracy. which is very good with an average accuracy of 98.50% with a detection speed of 2 seconds per image [76] with computer specifications for the train model namely K40 @ 875 MHz, Intel Xeon CPU E5-2650 v2 @ 2.60GHz and 8GB GPU memory [19].

Then the research was carried out by Sethy, P. K. and friends which was published in 2020 with the title "Rice Diseases Recognition Using Effective Deep Learning Models Sex Nitrogen Defciency Prediction of Rice Crop Based on Convolutional Neural Network". The method used is transfer-learning, namely GoogleNet and compares it with other transfer-learning methods and uses 2 classes (Healthy and Unhealthy) taken from private datasets with a total dataset of 5790 images and is able to recognize / recognize diseases in rice leaves with a high level of accuracy with 99.40% accuracy for GoogleNet [20].

There is also research that has been done by Mathulaprangsan and Patarapuwadol which was published in 2020 with the title "Rice Diseases Recognition Using Effective Deep Learning Models of Sex". The method used is transfer-learning, namely ResNet and compares it with DensNet [21] using 4 classes (Blast, Brown Spot, Blight, Bacterial leaf streak) taken from a private dataset with a total dataset of 12223 images and able to recognize diseases on leaves. rice with a good level of accuracy with an average accuracy of 91% for DensNet and 95% for ResNet.

Then from Ghosal, Shreya and friends, which was published in 2020 with the title "Rice Leaf Diseases Classification Using CNN with Transfer Learning". The method used is transfer-learning, namely VGG16 and compares it with standard CNN using 3 classes (Rice Blast, Brown Spot, Blight) taken from public and private with a total dataset of 1649 images and 25 epochs capable of recognizing / recognizing diseases in rice leaves with a good level of accuracy with an average accuracy of 92.46% for VGG16 and 74% for standard CNN with computer specifications for the train model, namely Windows 10 PC with GPU card P4000, 64-bit Operating System [16], [22].

The research was conducted by D. Bandar and B. Mayurathan which was published in 2021 with the title "Detection and Classification of Rice Plant Diseases using Image Processing Techniques". From this research, it shows that the SVM method is combined with K-Nearest Neighbors using 3 classes (Rice Blast, Brown Spot, Blight) taken from private with a total dataset of 400 images where the image is resized first, then remove the background and change the image. to HSV color [23] able to recognize disease on rice leaves with a good level of accuracy with an average accuracy of 89.19%. And the research was conducted by Ma. Kristin Agbulos and colleagues published in 2021 with the title "Identification of Leaf Blast and Brown Spot Diseases on Rice Leaf with YOLO Algorithm". This research shows that the YOLO method uses 2 classes (Blast, Brown Spot) taken from a private dataset with a total of 200 images with an accuracy rate of 90% for Blast and 70% for Brown Spot with an average accuracy of 75.33% [24].

The development of automatic rice leaf disease detection techniques encountered many difficulties. It should be emphasized that the recognition and detection requires procedures that can precisely segment the area in the rice plant where sometimes one leaf has two or more diseases. Shooting settings are difficult to manage, making image prediction more difficult and disease diagnosis with object detection more challenging. Furthermore, symptoms caused by different diseases may appear physically identical. Differences in the distribution of features of the data used to train the model as well as the data that can be used to validate the model is another common problem. Overfitting is a problem in these circumstances. When plant diseases are automatically detected, this is very important because symptoms can differ depending on geographic location, resulting in overfitting problems [25]. Many of the suggested rice leaf disease diagnostic designs are also off-line, with only a few tests performed in real-time. In most cases, the image resolution is increased in real-time, which increases the computational complexity [26]. In addition, with various disease features, diverse backgrounds, and blurred disease symptom boundaries, real-time surgery becomes more difficult. To overcome this problem, the current study aims to use a new deep learning approach based on You Look Only Once (YOLO) to identify rice leaf diseases, as proposed in a previous research paper as a comparative and additional reference material [27].

The present investigation is sought to mitigate the lingering problems in the process of developing a system of diagnosing rice disease. The key contributions of the research are summed up as follows:

1. Identification of disease spots is considered the basis for recognizing rice leaf diseases, therefore the accuracy of spot identification has a direct impact on the accuracy of rice leaf disease recognition. Therefore, when choosing a target detection algorithm, recognition accuracy should be used as a key indicator. Faster R-CNN, SSD, YOLO are the main algorithms for detecting deep learning targets. Among them, the YOLO algorithm creatively proposes an RPN structure to generate candidate regions, making precise target positioning. In addition, YOLO also has strong advantages in detection accuracy and detection speed compared to Faster R-CNN. The proposed study uses YOLO as the main research algorithm due to its efficacy in reliably detecting disease points.
2. The natural diseased rice leaf image is processed to produce adequate training data through data augmentation and image contrast technology so that the object in the image is more focused to overcome the insufficient complexity of the diseased rice leaf image and to avoid model over-fitting in the training phase.
3. YOLO is used for real-time detection of rice leaf disease. With the proposed deep learning method, the discriminatory features of sick rice images will be automatically classified, and the three main types of rice leaf diseases are recognized with high accuracy. Furthermore, the proposed method can manage all rice leaf images collected from rice farmland in real conditions.

3. Method for Improving The Model Algorithm

Figure 1. Below describes the research procedure starting from the origin of the dataset which is then annotated to fit the classification which is then pre-processed after that divided by 70% for training, 20% for validation, and 10% for testing. Then the Yolo architectural model is used from training and validation and then a data test is carried out with data testing and detecting disease. After that, a performance evaluation's carried out for the architectural model used.

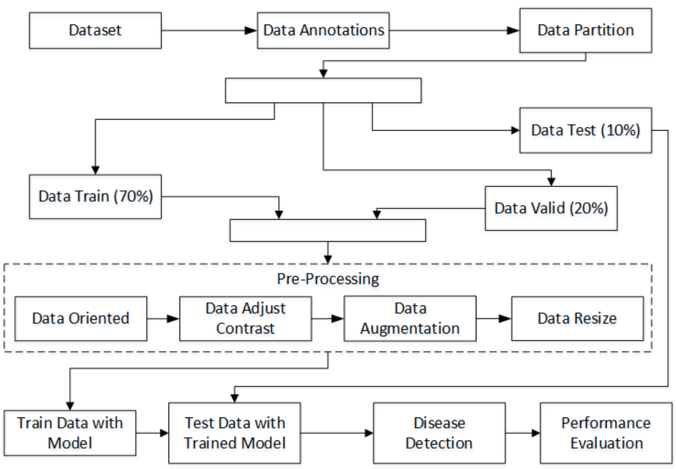

Figure 1. Workflow Research

Data Colection

In collecting the dataset, the author uses public dataset and the dataset can be accessed from Website Kaggle with the link at [Rice Leaf Diseases Dataset](). This dataset is in the form of Healthy, Brown Spot, Hispa, Blast, Blight with a total of 110 images each for a total origin dataset of 550 images. The following is an explanation of each type of diseases can be seen below:

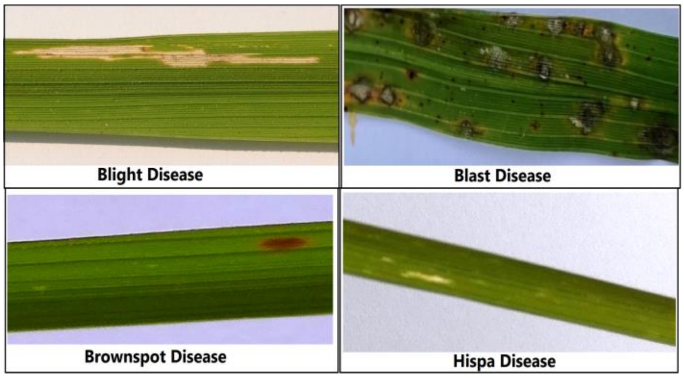

Figure 2. Types Rice Leaf Diseases

Data Preprocessing

Preprocessing is the stage before the execution of the algorithm model, it is needed to speed up computing and add data so that more datasets are used for training.

1. Auto Oriented
   Auto Oriented has done so that the image is oriented more clearly.
2. Modify Classes
   Modified Label from 0, 1, 2, 3 be Healthy, Brown Spot, Hispa, Blast, Blight.
3. Augmentations
   To increase the number of datasets in order to avoid overfitting, the authors perform several augmentations in the form of:
   Flip – Flip right, and left, 90 Degree Rotate – 90 degree Rotation, Rotation – Rotation of 30 degrees left and right, Hue, Saturation, Exposure, Brightness.
4. Resize Images
   To get the same size of pixel images, author resize images to width= 416 pixel and height = 416 pixel.

Image Annotations

Image annotations are used for position and class labeling on objects in disease and healthy images for multiclass object detection. In computer vision, XML is a method that stores annotations in a XML file and a separate annotation file is stored for each image. The application used for this labelling is: LabelIMG which was developed in python. XML files provide a standard image dataset for object detection. The author creates a file for each image from the dataset in YOLO. The XML file that is created includes information such as:

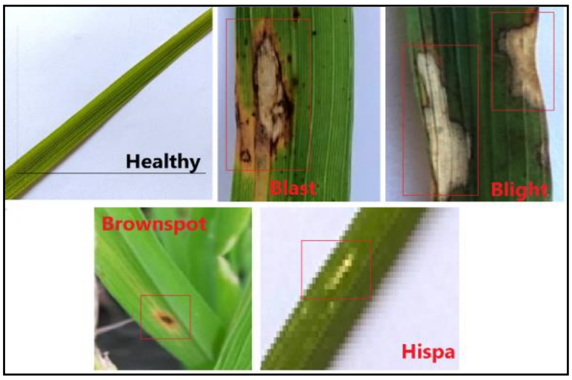

Figure 3. Bounding Box for Types Rice Leaf Diseases

Figure 3 shown bounding-box coordinates and disease class. For training purposes, 550 images were annotated for each class (Healthy, Brown Spot, Hispa, Blast, Blight) from the origin dataset. Sometime 1 figure there were 2 classes, an example like healthy and brownspot.

Model Architecture

At present, the main object recognition algorithms are R-CNN series and YOLO series. The R-CNN series has superiority in target detection with higher accuracy requirements, but its detection speed is lower than that of the YOLO series. In actual scenarios, the real-time performance of target detection cannot be met. In this context, the YOLO series of algorithms use the idea of regression, which makes it easier to learn the generalized characteristics of the target and solve the speed problem. The YOLO series of algorithms use a first-level neural network to directly locate and classify the detected object [27].

YOLO treats image detection as a regression problem with a simple pipeline and fast speed. It can process streaming video in real time with a delay of less than 25 seconds. During the training process, YOLO can view the entire image and pay more attention to global information in target detection. The core idea of YOLO is to use the entire picture as the input of the network, and directly return to the position of the bounding box and the category to which the bounding box belongs at the output. In YOLO, each bounding box is predicted by the characteristics of the entire image, and each bounding box contains five predictions and confidences, which are relative to the grid unit in the center of the bounding box of the boundary.

The basic frame of YOLO is as follows: w and h are the predicted width and height of the entire image (relative to the entire image). The YOLO is mainly composed of three main components:

- Backbone: A convolutional neural network that aggregates and forms image features on different types of image granularity;
- Neck: A series of network layers that mix and combine image features and pass the image features to the prediction layer;
- Head: It can predict image features, generate bounding boxes, and predict categories. The confidence indicates the accuracy of classification under the specific condition.

YOLOv2 [28] uses a new training algorithm. YOLOv2 uses the k-means clustering method to cluster the bounding boxes in the training set. As the main purpose of setting, the a priori box is to make the IOU between the prediction box and the ground truth better, and the IOU value between the box and the cluster center box is used as the distance indicator in the cluster analysis. Compared with YOLOv1, it significantly improves the accuracy and recall rate. YOLOv3 [29] uses a better basic classification network-class ResNet and classifier Darknet-53.

The detection accuracy and speed are greatly improved, and the false background detection rate is effectively reduced. YOLOv4 [30] retains the head of YOLOv3, changes the backbone network to CSPDarknet53 [31], uses the idea of SPP (spatial pyramid pooling) to expand the receptive field, and uses PANet [32] as the neck. The structure of CSPNet can achieve richer gradient combination information and reduce the amount of calculation.

YOLOv5 [33] continues to use the three main components of the YOLO series. The network structure is shown in Figure 4 below.

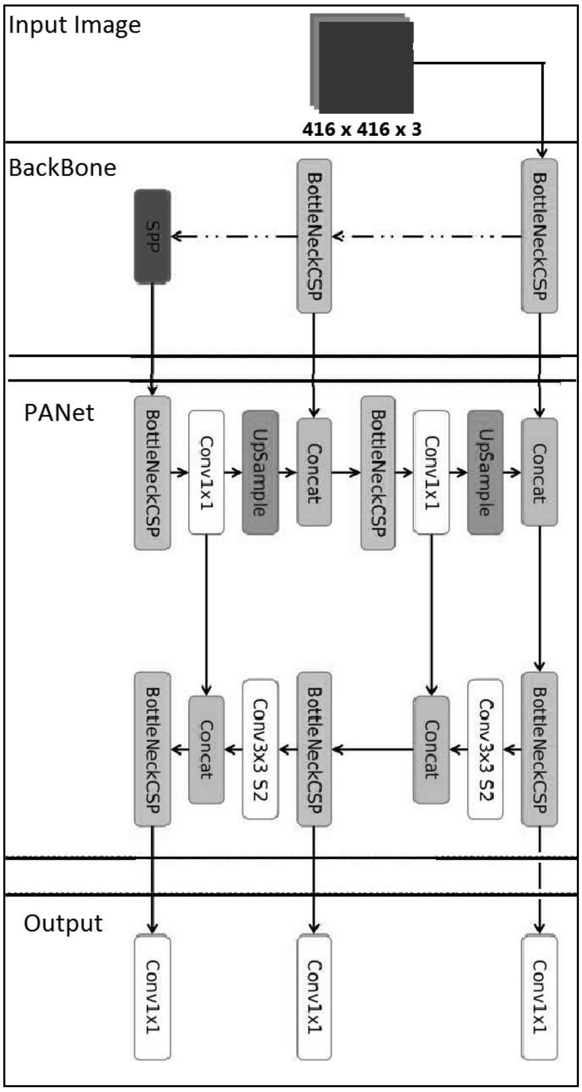

Figure 4. Yolov5 Network Structure Diagram

1. Input

YOLOv5 adds the function of adaptive anchor frame calculation. During each training, the value of the optimal anchor frame in different training sets is calculated adaptively.

2. Backbone

YOLOv5 adds the Focus structure to realize the slicing operation. Taking the structure of Yolov5 s as an example, the original 640 x 640 x 3 image is input into the Focus structure, and the slicing operation is used first to form a 320 x 320 x 12 feature map, and then after a convolution operation of 32 convolution kernels, it finally constructs a feature 320 x 320.

3. Neck

Yolov5 uses the FPN-PAN structure, CSP2 structure designed by CSPNet, and PANET as Neck to aggregate features. The neck is mainly used to generate feature pyramids, enhance the model's detection of objects of different scales, and realize the recognition of the same object of different sizes and scales. The feature extractor of the network uses a new FPN structure, which enhances the bottom-up path and improves the propagation of low-level features.

Evaluation Indicator

The detection accuracy of each category in the detection of rice leaf diseases is very important. False positive and false negative tests may lead to the risk of further spread of the disease. Therefore, this study selects Average-Precision (AP) and Mean-Average-Precision (mAP) as the evaluation indicators of the target detection algorithm. These two evaluation indicators consider accuracy (Precision, P) and recall (Recall, R):

$$Precision = \frac{TP}{TP + FP} \quad [15]$$

$$Recall = \frac{TP}{TP + FN} \quad [15]$$

Table 1. Selection of Key Parameters

Parameter name	Parameter value
Batch size	32
Learning rate	0.001
epoch	400

$$AP = \int_0^1 P(R)dR \quad [19]$$

$$mAP = \frac{\sum_{i=1}^{N} APi}{N} \quad [19]$$

Taking the category of gray mold in the detection object of this study as an example, the TP in the above formula means that the detection model detects that the correct target of gray mold is the number of gray mold diseases, and FP indicates that the number of misdetected objects of other categories is gray mold. , FN indicates the number of times that the correct Botrytis cinerea object is falsely detected as an object of other categories.

Take the values of recall rate and accuracy rate as the abscissa and ordinate respectively, draw a P-R curve, and the area under the curve is AP. For all categories (the number of categories is denoted as N), the average accuracy is obtained by calculating the AP and taking the average value. mAP is an important indicator for evaluating model performance, which can reflect the overall performance of the network model, avoiding extreme performance of certain categories and weakening the performance of other categories in the evaluation process.

4. Experiment Result and Analysis

Below at table 2, we did Comparism with Other Pre-trained Model to get the performance evaluation. Our proposed model was trained with total time: 9 hours with 550 images origin and was augmented (1.320 images) for training and 330 images for data test. Therefore, by considering the strong dataset, real-time disease detection ability and detection accuracy, our proposed method is somewhat superior to that of other related approaches for rice leaf disease identification reported in the literature. This table explained about time speed, accuracy, precision, recall.

Table 2. Comparism Other Pre-trained Model

MODEL	Kelas	ACC	PRE	REC
VGG16 [16]	Healthy	0.65	0.63	0.6
	Brown Spot	0.66	0.64	0.61
	Blast	0.63	0.61	0.58
	Blight	-	-	-
	Hispa	0.63	0.612	0.58
ResNet50v2 [21]	Healthy	0.7	0.69	0.19
	Brown Spot	0.69	0.69	0.17
	Blast	0.7	0.67	0.17
	Blight	-	-	-
	Hispa	0.7	0.68	0.165
GoogleNet [20]	Healthy	0.59	0.53	0.3
	Brown Spot	0.5	0.54	0.34
	Blast	0.54	0.53	0.32
	Hispa	0.53	0.512	0.35
Faster R-CNN [19]	Healthy	0.99	-	-
	Brown Spot	0.98	-	-
	Blast	0.98	-	-
	Blight	0.98	-	-
	Hispa	0.99	-	-
Yolo Improved	Healthy	0.94	0.89	0.83
	Brown Spot	0.94	0.88	0.81
	Blast	0.93	0.88	0.80
	Blight	0.93	0.88	0.86
	Hispa	0.94	0.88	0.85

The proposed method is YOLO, this method is used to detect objects by providing boundary-boxes on objects infected with diseases in rice leaves, this is done because sometimes one rice leaf can identify more than one disease on its leaves, boundary-boxes are very helpful to determine the type disease is detected by giving signs so that the disease can be identified better. An example as shown in Figure 5.

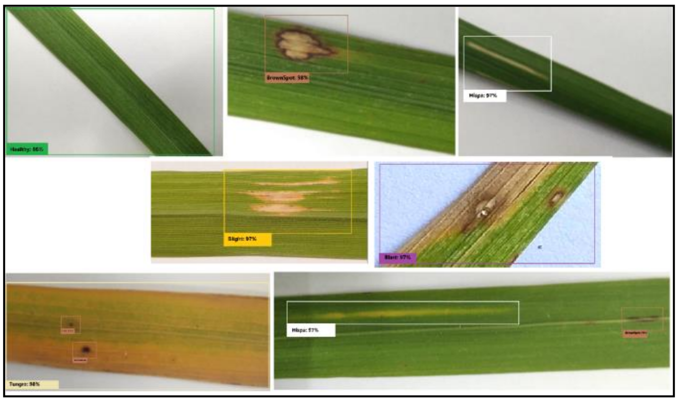

Figure 5. Type of Detection Results

In Figure 5, it can be seen that the results of the detection with the boundary-box using the Yolo model where in one leaf sometimes there are two or more diseases as shown above are detected efficiently but if the detected image has small pixels, the disease cannot be detected as in Figure 5 bottom right, where there is one undetected Brown Spot.

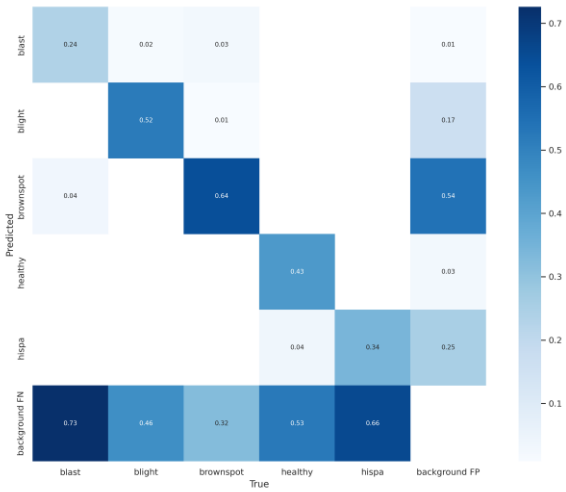

Figure 6. Confusion Matrix

Confusion Matrix

When dealing with multiple classes of similar shape, classifiers may be confused. Infected rice leaf images on different levels or backgrounds can cause high complexity which leads to lower performance for the patterns displayed in the same class. The classification accuracy of a model can be visually tested using a confusion matrix. The entire dataset of our study is split into a training set and a testing set randomly in order to train and test the model. To evaluate the proposed model, the 70% dataset is used to train and the remaining 20% dataset is used to validation and 10% to testing. Total images observations are utilized for training the model, whereas another images (test dataset) observations are utilized for testing the model. Figure 6 displays the final test results confusion matrix. The deeper the color in the visualization results, the greater the model's accuracy in the respective class. All correct predictions are located diagonally, whilst all wrong predictions are off diagonal. The classification accuracy can be visually assessed based on these findings.

5. Conclusions

The signs of infection appear in various sections of the plant, and leaves are widely used to diagnose the plant disease. The advanced computer vision technology encourages researchers around the world to carry out extensive experiments on plant disease recognition using leaf image analysis techniques. In the past few years, deep learning methods have notably been utilized to recognize plant leaf infection. This paper proposes a real-time rice leaf disease diagnosis framework based on the You Look Only Once (YOLO) technique.

The rice leaf infected image database consists of healthy leaf and three diseases, including healthy, blight, blast, brown spot, and hispa. In order to enhance the robustness of the proposed system, our own captured rice leaf image is combined with a publicly available online database. Moreover, we have used several image augmentations schemes to enrich the dataset, which familiarizes the model with the different possible conditions of the image. This strategy also enhances the model's performance and generalization capability.

The obtained results of the proposed study are very encouraging to diagnose healthily and the different types of infected leaves in both laboratory-based images and real-field images. However, an additional study should be carried out to make segmented the infected portions of the leaf image by minimizing the surrounding interference. The existing rice leaf disease diagnosis systems are designed using laboratory-based captured images. Although we have implemented real-time disease recognition architecture using real field rice leaf images, the proposed system is still not fully automated. Therefore, further study should be carried out to implement a dynamic and automatic system to recognize large-scale rice leaf diseases. This system could be made up of a mobile terminal processor and agricultural Internet of Things that may be favorable to modernize the agricultural industry.

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