Rice Leaf Diseases Detection Using Deep Learning Ensemble Model

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ABSTRACT

Rice leaf blast and bacterial blight disease are one of the most serious diseases that directly affect rice cultivation. Due to this reason, managing and keeping rice plants away from many diseases are very important to improve their production. In this study, we propose an approach to identify rice leaf diseases using deep learning methods. The proposed approach includes two steps: classification of diseases and detection of diseases via analyzing the classified images. In the first step, we use DenseNet121, which separates the diseases in the dataset to increase the accuracy of the model. In the second step, YOLOv5 algorithm is applied in order to detect diseases. The proposed approach is evaluated on 4141 images from many sources, including on Kaggle, Google, Mendeley and outperforms state-of-the-art methods. Experimental results show that the accuracy of the proposed model in this study when combining DenseNet121 and YOLOv5 has reached 79.45% and it is greater than compared to using only the YOLOv5 model is 78.5%.

1. INTRODUCTION

Rice is an important crop in agriculture. It is one of the most popular foods in the world, especially in Asian countries. According to article [1], every year around 500 million tons of rice are produced worldwide. The monitoring of growth as well as disease control in rice has a great influence on the improvement of crop yield. The current detection of the disease in Vietnam is still carried out by manual methods and is usually done by farmers or local agricultural officials. Sometimes the assessment of diseases on rice is incorrect or it depends a lot on the qualifications and experience of the examiner.

The application of science and technology to agriculture, including the application of deep learning methods to detect and classify diseases on short-term crops in general and rice, is very necessary. Automated disease diagnosis through leaf imaging offers great potential for smart agriculture. The automatic detection of disease based on computer vision techniques saves time and reduces the labor of farmers. In some cases, the results are even as accurate as those of an experienced professional. However, image analysis still faces many difficulties such as the variation of disease on different leaves, position of disease on leaves and density between images.

Deep learning, also called neural networks, is a subset of machine learning that imitates the working of the human brain in processing data and creating patterns in decision making. It is applied in all aspects of life, especially in agriculture. Currently, there are several studies on the application of AI (Artificial Intelligence) models to detect diseases in short-term crops in general and rice in particular. Some typical studies related to this research direction can be mentioned as research on disease detection on cucumber plants based on the application of YOLOv4 network in leaf image analysis [2]. The research of these authors has resulted in accurate recognition of more than 80% with more than 7000 images. Because this study only uses a CNN (Convolutional Neural Network) model, the accuracy is still limited. Study [3] evaluated the methods of deep learning that can be introduced in the surveillance and detection of plant foliar diseases, with different levels of infection images. This study also proposed the inclusion of a model to evaluate the progression of leaf diseases according to the growth cycle, to assess the influence of factors affecting the quality of sample images such as: the classes and size of datasets, learning rate, illumination, and the like. Study [4] used YOLOv3 to detect brown spot and leaf blast diseases. But they only use images with a white background, so the practicality is not high and less flexible. Studies [5,6] used ResNet and YOLOv3 to detect diseases in tomatoes leaves. In study [7], the authors used their CNN model to classify leaf blight diseases. In study [8], authors made a comparison between the CNN models DenseNet-121, ResNet50, ResNeXt50, SE-ResNet-50, and ResNeSt50 and then combined these models to achieve better results. Study [9] used CNN model to detect brown spot and leaf

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blast disease in rice and has 0.91 accuracy overall result. Vimal K. Shrivastava et al in [10] used AlexNet and SVM to classify 3 rice leaf diseases and the result achieved is 91.37% accuracy. In study [11], authors have made a survey and compared some different models on rice leaf and seedlings diseases detection. Research [12] used VGG16 and InceptionV3 to classify 5 different diseases in rice. In research [13], authors use SVM combined with DCNN model. They correctly recognized and classified nine different forms of rice diseases with 97.5% accuracy. Study [14, 15] used YOLOv5 to detect some typical types of rice leaf diseases.

In this research, we use deep learning method combined from DenseNet121 and YOLOv5 models to detect two most popular diseases of rice leaves in Vietnam: Bacterial blight and blast leaf disease.

1.1. Bacterial blight

The bacterium Xanthomonas oryzae pv. oryzae causes bacterial blight disease in rice leaves. This bacterium causes seedling wilting and also causes dry and yellow leaves on adult plants [16].

Fig. 1. Bacterial blight disease.

The sign of this illness is wilting and yellowing of leaves. Lesions on older plants often show as water-soaked to yellow-orange stripes on leaf blades, leaf tips, or mechanically damaged leaf parts. The lesions have a wavelike border and progress to the leaf root. Bacterial oozing on new lesions that resembles a milky dew drop can be detected early in the morning. The bacterial fluid then dries and changes into tiny golden beads beneath the leaf. Furthermore, as a result of the formation of many saprophytic fungi, previous lesions transform from yellow to grayish white with black dots [16].

1.2. Leaf blast

Leaf blast disease is caused by the fungus Magnaporthe oryzae. It can affect all sections of the rice plant, including the leaf, collar, node, neck, panicle portions, and even the leaf sheath. Blast illness may develop anywhere there are blast spores [17].

Fig. 2. Blast leaf disease.

The way to identify the symptoms of this disease is by checking leaves and collars of rice plants. Initial lesions or spots are white to gray green with dark green borders, however later lesions are elliptical or spindle shaped with whitish to gray cores and a red to brownish or necrotic border. Another symptom is a diamond-shaped symptom, broad in the center and pointed toward either end. Lesions form in groups and then destroy whole leaves [17].

2. PROPOSED METHOD

2.1. Overview

Proposed Method

In this section, our proposed method will be introduced with two main parts, the first part is classification, and the second part is detection. At first the test images will be put through the DenseNet-121 to separate images contain class leaf blast and bacteria blight. If the DenseNet model predict that the image contains leaf blast disease, the image will be put inside folder name "Predicted as leaf blast", and if the DenseNet model predict that the image contains bacterial blight the image will then be put inside folder name "Predicted as bacterial blight". In the next step, images in each of these folders will be detected by the YOLOv5 that have the highest accuracy for that class. For example, to be able to pick out the best YOLOv5 model for class Leaf blast, the model will be trained on both bacterial blight and leaf blast but when we validate the model while training the validation set will only contain Leaf blast picture, the same process will be used on bacterial blight.

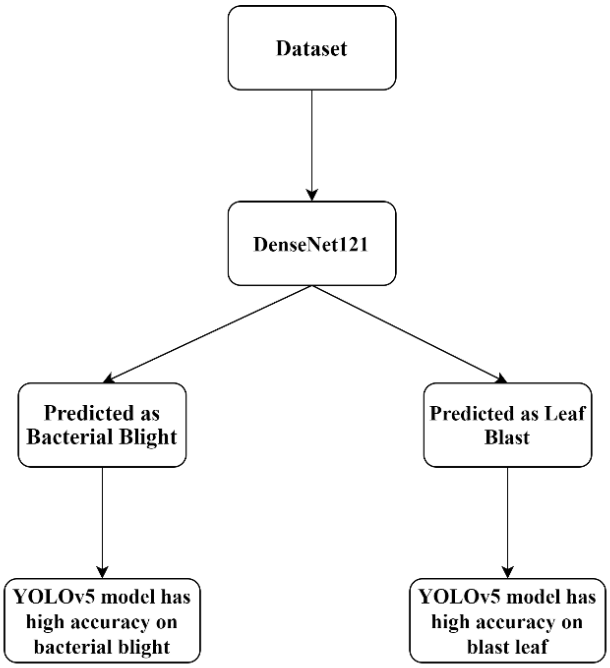

Fig. 1. Proposed method.

2.2. Data preparation

In this article, pictures of rice leaves were found and collected throughout internet sources. The pictures were taken from existing datasets and from various websites. The dataset includes picture of two diseases: bacterial blight and blast leaf, that are two typical types of rice diseases in Viet Nam. The pictures from the dataset contain one or more than one rice leaf that has disease.

This dataset is separated into three parts: train, validation, and test set. The validation set contains images like in the train set but have been fixed to not overlap with the existing image inside the train set. The test set includes pictures that do not have any relation with the picture in the train and the validation set. Pictures are labeled on the website Makesense.ai to draw the bounding box to the object. The output labels are taken in the YOLO format are TXT type files.

2.3. Motivation of proposed method

- *DenseNet-121:*

In study [7], the authors have shown the MCC results between five models on six different diseases in rice.

According to the results of the table, SE-ResNet-50 and DenseNet-121 illustrate the best results. However, in this article we choose DenseNet-121 because it has higher MCC value in class Leaf blast disease which we use in this article.

Table 1. Comparison between classification model on rice diseases

	ResNet-50	DenseNet-121	SE-ResNet-50	ResNeXt-50	ResNeSt-50
Leaf blast	0.978	0.995	0.994	0.978	0.995
False blast	0.986	0.996	0.995	0.985	0.996
Neck blast	0.977	0.997	0.993	0.976	0.994
Sheath blight	0.979	0.996	0.997	0.982	0.990
Bacterial stripe	0.989	0.993	0.996	0.983	0.992
Brown spot	0.949	0.994	0.988	0.950	0.991

- *YOLOv5*

In this project, my team uses the YOLOv5 model, a cutting-edge deep learning model that balances accuracy and inference speed for detection and tracking issues. The fifth generation provides greater precision, recall, and mAP@0.5 when compared to YOLOv3 and YOLOv4. On the same hardware, GPU or without GPU, the inference time is also quicker.

In this research, we combined and applied the strengths of these two models to create and test a completely new model.

2.3. DenseNet121

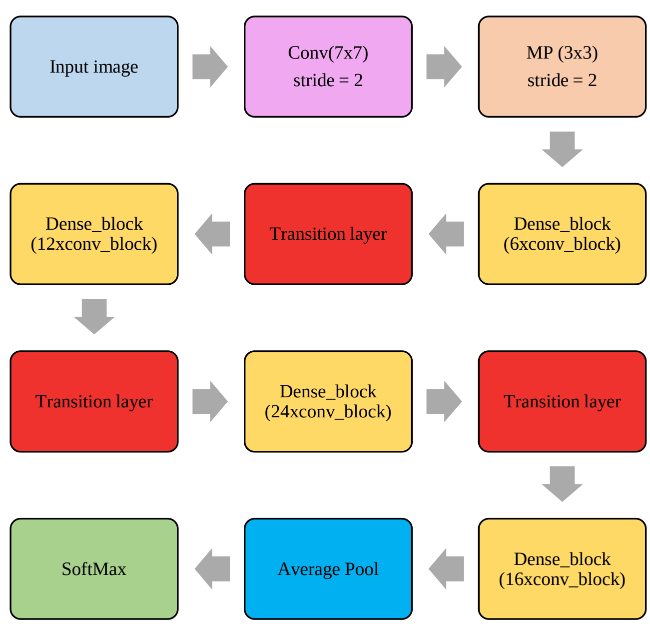

Fig. 2. DenseNet121 model.

Connection between the convolutional layer inside Dense block.

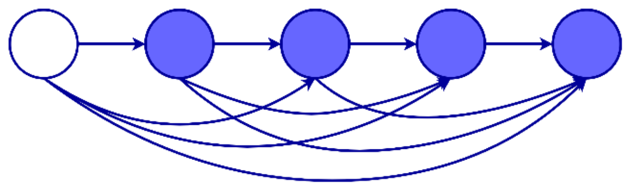

Fig. 3. Dense block

Convolutional block

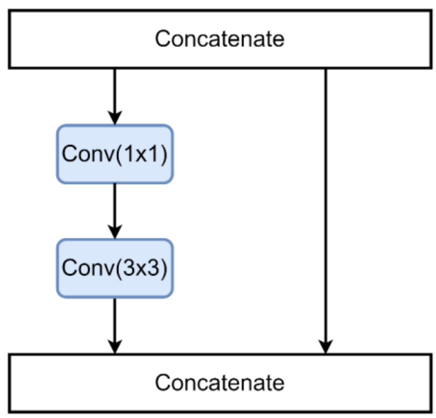

Fig. 4. Conv block

Transition layer

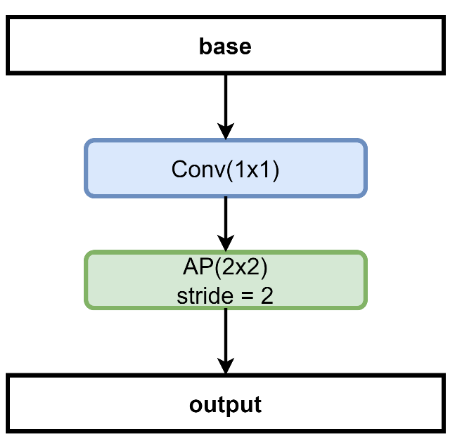

Fig. 7. 5Transition layer.

DenseNet 121 is an improved model based on the method of ResNet to avoid the problem of vanishing gradient. Vanishing gradient problem happens when the number of CNN model increase. The different between DenseNet and ResNet is that DenseNet concatenate every Convolutional layer inside a Dense block together which will help further reduce the risk of vanishing gradient. DenseNet 121 contains 2 main blocks: Dense block and Transition layer.

Dense block

For each Dense block it will contain a number of pair of Conv 1x1 and Conv 3x3 layers (6 for the first block, 12 for the second block, 24 for the third block, 16 for the fourth block). Feature maps learned from the previous layer will be concatenated with every feature map of other layer. Thus, from the previous layers, the n^{th} layer takes all of the feature-maps, $x_0, \dots, x_{n-1}$, as input:

$$x_n = H_n([x_0, x_1, \dots, x_{n-1}])$$

where, 'K' is mentioned in relation to the network's growth rate, which controls how much information is added in each network layer. If every function 'H' generates 'k' feature maps, then the 'n-th' layer will have:

$$k_n = k_0 + k * (n - 1)$$

To be able to perform concatenate from layers to layers, the size must be preserved which means padding is needed in this process.

Transition layer

The Transition Layer is applied for down sampling to lower the size of the data but keep the important feature by using bottleneck (Conv 1x1) and using drop out to reduce the chance of getting over fitted. Decreasing the size of the data will help lower the number of calculations. The average pooling will then be used to select features.

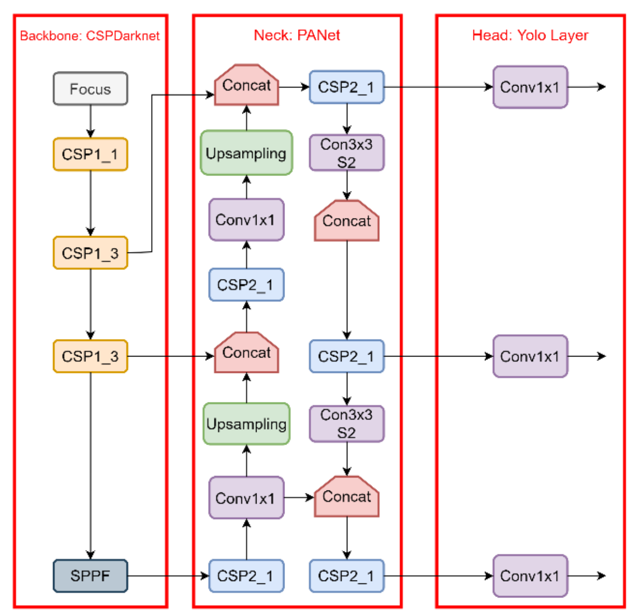

Fig. 6. YOLOv5 model.

2.4. YOLOv5

YOLOv5 is an improved model from YOLOv4 used on Pytorch. This fifth version has the same structure as the fourth version but lighter and faster. The structure of this version has three main parts: Backbone, Neck, Head.

2.4.1. Backbone

- *CSP Darknet*

The backbone of YOLOv5 is implies with CSP DarkNet53 pre-trained through ImageNet. The model itself is an improved version of DenseNet which helps prevent the risk of vanishing gradient. The main purpose of the backbone is for feature extraction.

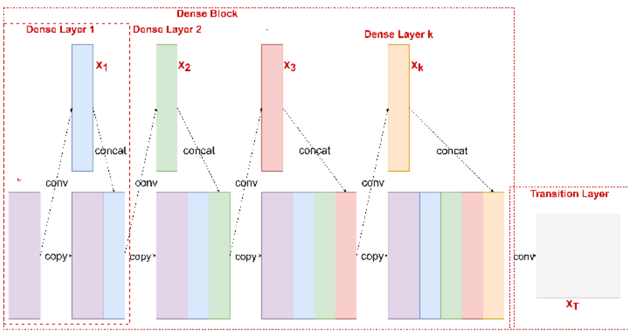

Fig. 7. DenseNet.

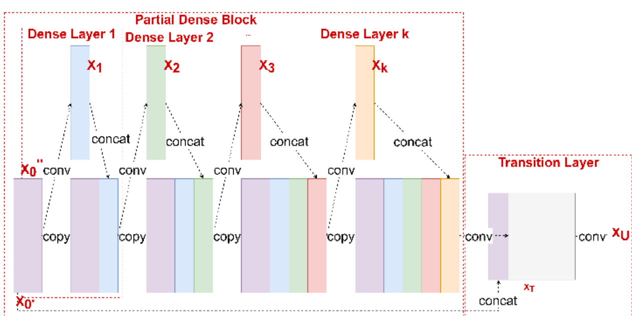

Fig. 8. Cross Stage Partial DenseNet.

Different from DenseNet, CSPDarkNet separates the original input into 2 parts. The first going through a Dense block just like in DenseNet. Meanwhile, the second part goes directly into the transition layer and then gets concatenated with the first part. CSPDarkNet has erased the downside of DenseNet which is complicated and hard to train.

2.4.2. Neck

In Neck different parts of features maps from backbone are collected.

- *SPPF*

One of the most noteworthy disadvantages of a CNN network (CSPDarkNet is also included) is that it must be a fixed size input image which means if the input has different size other than the fixed one, the network will fail to work. Two main parts of a CNN network are the Convolution layer and the fully connected layer. CNN network must have a fixed size image, this is inconvenient. To overcome this problem, SPP will be applied as it can have different input sizes and a fixed output.

With improved SPPF, it uses a Maxpooling layer on three different sizes of the features map, the input feature maps will stay the same and then be concatenated with three different sizes of feature maps that have been Maxpooling. In result, this will improve the speed of the model.

- *PANet*

Path Aggregation Network, or PANet using encoder and decoder architecture. First, the feature map from the SPPF is fed up with a bottom-up pathway and get up-sampling, after this it will be concatenate with the features map from the backbone of the model. After that a number of layers is added to the structure to increase the quality of feature maps, the feature maps in this part are also concatenated with the feature maps from the previous bottom-up pathway.

2.4.3. Head

The head of YOLOv5 is reused from YOLOv3, instead of applied the detection on just one size of the image, it will detect the objects on three different sizes of the images, this will help the model detect small objects much better.

3. RESULT AND DISCUSSION

In this article, evaluation metrics are used were Precision, Recall, F1, mAP50.

$$Precision = \frac{TP}{(TP+FP)} \quad (1)$$

$$Recall = \frac{TP}{(TP+FN)} \quad (2)$$

$$F_1 = \frac{2*Precision*Recall}{(Precision+Recall)} \quad (3)$$

$$AP = \sum_{k=0}^{k=n-1}[R(k) - R(k-1)] * P(k) \quad (4)$$

$$mAP = \frac{1}{N}\sum_{i=1}^{N} AP_i \quad (5)$$

P and R are Precision and Recall. TP (True Positive) is the number of correct detections of leaves that contain diseases. FP (False Positive) is the number of leaves that contain diseases but are diagnosed as healthy leaf. FN (False Negative) is the number of leaves that are healthy but diagnosed as leaf that contains diseases. The number of IoU threshold is n. AP is the average precision and AP_i is the average precision of the i^{th} class. N is the number of classes.

There is a total of 109 images in the test set, containing 120 bacterial blight leaves and 93 leaf blast. The result after being processed through the DenseNet121 is shown in the below confusion matrix.

Table 2. YOLOv5 result

YOLOv5	Precision	Recall	F1	Map@50
Bacterial Blight	89.9	66.6	76.5	75.4
Leaf Blast	79	77.1	78	81.6
All	84.39	71.1	77.1	78.5

As the result 63 images were predicted as leaf blast including 4 blight images were mistake as blast and 46 images were predicted as bacterial blight including 2 blast images were mistake as blight. The result of the purposed model is compared with method of using only YOLOv5.

The final result was determined after 100 training epochs of both DenseNet121 and YOLOv5 and showed in Table 2.

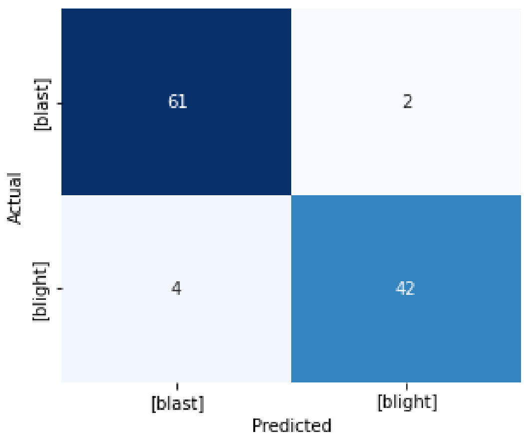

Fig. 11. DenseNet121 confusion matrix.

Fig. 12. Blast leaf detection.

Fig. 13. Bacterial blight detection.

4. CONCLUSION AND FUTURE WORK

With the use of the standard data set in this study, the accuracy achieved of our proposed model for bacterial blight is 74.9% and it is lower than compared to using only the YOLOv5 model. For the leaf blast, our purposed model gives an accuracy of 84% and it is higher than in the case of using YOLOv5. When we consider both diseases, the accuracy of the proposed model reaches 79.45% and higher compared to when using only a single model. These initial results show a positive and promising impact in the use of artificial intelligence in the field of smart agriculture. This leads to a faster and low-cost solution for the farmer while obtaining a high identification accuracy.

Table 3. Proposed method result

Proposed method	Precision	Recall	F1	Map@50
Bacterial Blight	95.7	55.5	70.3	74.9
Leaf Blast	90.5	76.3	82.8	84
All	92.9	64.6	76.2	79.45

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