Rice Paddy Disease Detection and Disease Affected Area Segmentation Using Convolutional Neural Networks

Md Naimul Islam Suvon
Electrical & Computer Engineering
North South University
Dhaka, Bangladesh
naimul.suvon@northsouth.edu

Ibne Farhan Ishrak
Electrical & Computer Engineering
North South University
Dhaka, Bangladesh
farhan.ishrak171@northsouth.edu

Sajan Mahmud Alvee
Electrical & Computer Engineering
North South University
Dhaka, Bangladesh
sajan.alvee@northsouth.edu

Afrida Jahan
Electrical & Computer Engineering
North South University
Dhaka, Bangladesh
afrida.jahan@northsouth.edu

Fahim Mashroor
Electrical & Computer Engineering
North South University
Dhaka, Bangladesh
fahim.mashroor@northosuth.edu

Shahnewaz Siddique
Electrical & Computer Engineering
North South University
Dhaka, Bangladesh
shahnewaz.siddique@northsouth.edu

***Abstract* — Bangladesh is the fourth largest rice-producing country in the world. Agriculture plays a vital role in the country's economy. One of the major obstacles in rice production is rice paddy diseases. In this paper, we develop a deep learning-based system to detect rice paddy diseases. In the first step, a rice paddy image dataset is analyzed and preprocessed for classification. To build the classifier, we use the Efficient Net B3 Convolution Neural Network (CNN) model. Next, we train a new model using segmented rice paddy disease-affected areas to detect affected regions using MASK Recurrent Convolutional Neural Network (Mask RCNN). For the classification methods, we obtain an accuracy of nearly ~99%. For Segmentation, the loss value of the class, bounding box, and mask are 0.09, 0.29, 0.30. The mean Average Precision(mAP) of the Segmentation is around ~89%.**

Keywords — convolutional neural network, recurrent neural network, lab color space, efficient net, confusion matrix, blast, tungro, blight, brown spot.

I. Introduction and Problem Statements

Agriculture is one of the core branches playing a significant role in the economy of a country. A wide variety of fruit and vegetable crops are grown by farmers at their discretion. Growing crops for optimum production and excellence is therefore quite feasible. As a result of technical advancement, it might be enhanced [1]. Bangladesh produces a large amount of rice every year since rice is the country's primary food source. Rice is a staple food of 135 million people of Bangladesh [2], which is cultivated by one-third of the population [3]. There were, however, significant problems with the rice plants, which resulted in a far lower than projected yield. Because this condition is contagious, it is crucial to discover them early and separate them from healthier ones. Some diseases are Rice Blast [4], Bacterial Blight [5], Brown Spot [6], RRSV, Tungro, Narrow Brown Blast, Hispa [7].

Fig. 1 shows some major rice plant diseases. Every year because of these diseases huge amount of rice products are lost [8]. Blast disease is the most severe disease. Symptoms appear on a leaf with a spindle shape spot with a brown margin, and the center of the spot is whitish grow.

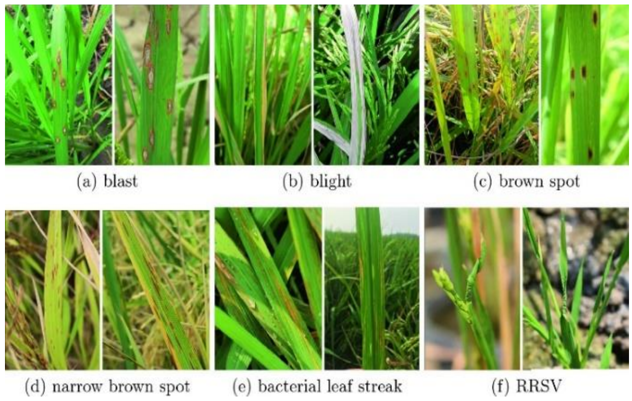


Fig. 1. Major rice plant diseases (taken from [8])

Among the leaf, neck, and node parts, the neck part infects the most. When it comes to brown spot illness, initial infections are greenish-grey in color and become greyish-white with a brown border, indicating the presence of sclerotic. Lesions may cluster and cause the entire leaf to die. Finally, in the Narrow Brown Spot, grains are partially full or empty. Lesions range in size from 2 to 10 mm in length and 1 mm in width. Short, thin, elliptical to linear brown lesions often affect leaf blades but can sometimes affect leaf sheaths, pedicels, glumes, or rice hulls. Resistant varieties' lesions are smaller, shorter, and deeper brown. On susceptible individuals, the lesions are larger and lighter brown, with grey necrotic cores. During the later stages of development, lesions become more common. Plant diseases can move from diseased to healthy sections of the plant [9].

The main *nobility* of this work is that there is no work done before on the Bangladeshi Rice Paddy Disease dataset to detect the rice paddy's disease and exact the location of the affected area so that farmers of Bangladesh can remove those areas from the plant to save the whole plant. Every year in Bangladesh, a huge amount of rice production is damaged because of this dangerous disease, and it is necessary to make an advanced method to get rid of it.

In this paper, related papers on paddy disease detection have been discussed briefly in Section II. In section III, we have discussed our proposed methodologies and show the procedure of methods. In section IV, we have shown the performance of our model and discussed them briefly. Finally, in section V, we have concluded our paper with future works.

II. RELATED WORK

Along with the South Asian subcontinent, rice is a major food worldwide. Scientifically known as “Oryza Sativa,” it is one of the main crops of Bangladesh. But some obstacles lessen the growth of the paddy plant, known as paddy diseases. Any uncertain state that affects the growth of the plant is called plant disease. Based on the symptoms, diseases are recognized. Paddy plants have various diseases like Paddy Blasts, Brown Spots, Narrow Brown Spots, etc. For agricultural works, both computer vision and image processing systems are pretty favorable [10]. As per statistics of the year 2014, approximately 20 million tons of rice are produced from around 10.5 hectares of land. The government aims to increase this production amount to 30 million tons more by the next 20 years.

In [11], Arnal et al., developed a technique for detecting, measuring, and categorizing agricultural leaf illnesses based on digit image magnitudes. This system is categorized based on the detection of objects in terms of severity and categorization. Plant diseases can be detected in a variety of ways. Some illnesses have no outward signs or symptoms. Multi and hyperspectral picture captures are investigated using remote sensing techniques. This method suggested training rates and efficient illness recognition, identification, and quantification.

In [12], S. Weizheng et al., presented a computer image processing-based system of eyeballing methods. The illness spot edges are extracted using the sobal operator. The technique proposes that plant illnesses be diagnosed by dividing two values, the disease spot and leaf area, and determining the ratio of the two. The technique for identifying leaf spot illnesses is too graded in terms of speed and accuracy.

Narmadha et al., recommended a study on identifying paddy leaf illnesses such as Blast Leave, Brown Spot disease, and Narrow Brown Spot disease, all of which disrupt paddy leaf growth and safety [13]. The illness affects the entire development of the border leaves at different stages. Microorganisms were used to examine the paddy disease's ignored regions. The model was designed to reduce the influence of paddy leaf disease by automatically ejecting noise, social blundering, and alerting the duration occupied. The K-means clustering method is used in this study to identify paddy leaves. The K-means clustering technique was used for better precision in this study to examine the approaches in computerized picture processing for distinguishing, recognizing, and detecting yield leaf infections.

Latte et al., used an automated system to identify various nutritional component losses in paddy leaves [14]. As a result, the pattern analysis RGB characteristics were retrieved for the defective paddy leaf detection. The normal, nitrogen, phosphorus, and potassium infected leaf datasets were created first. The test is done with many current level’s techniques such as an ass numerous colors together with nitrogen, phosphorus, potassium, and phosphorous potassium to assure efficiency. This technique was developed using pattern detection and color feature testing for various photos with a variety of flaws. The system may be tweaked to detect the three faults in a single leaf and then applied to images of paddy fields. This method combed the services for the early occurrence of numerous faults and aided in yield enhancement.

All the related works guided us to make a classification model and segmentation model to recognize the paddy disease area and detect the disease class. This paper aims use different types of convolutional neural network to build a method for detect and recognize paddy disease. Data analysis and data pre-processing are executed before training the models. For training, different parameters are used in the model. Finally, many types of accuracy matrices [15,16] are shown to evaluate the models' performance.

III. PROPOSED SYSTEM METHODOLOGY

This project aims to develop and enhance an image processing system and deep learning techniques to advance the agricultural sector.

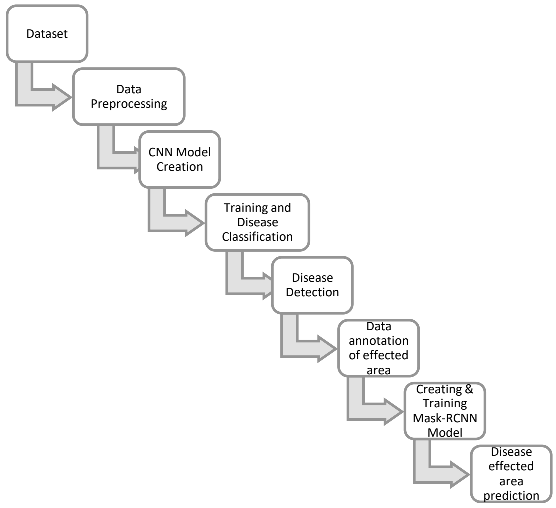


Fig. 2. Proposed System Diagram

In Fig. 2, a system diagram is proposed where firstly, the data collection and preprocessing will be done. After that, this preprocessed data will be trained using a pretrained CNN model. Finally, we can get the prediction and accuracy metrics of this model. After detecting the disease, it is important to separate the affected area of the disease, which will be done by using Mask RCNN. All the dataset images will be labeled by affected area by the VGG (Visual Geometry Group) image annotator and generate a JSON file that contains all the labeling information. This information is used in the Mask RCNN model training. So finally, we can get the affected area of the predicted disease.

A. *Dataset and Annotation*

The dataset used in this paper is called Dhan-Shomadhan [17], which was published in 2021. Dhan-Shomadhan is a dataset of rice leaf disease classification for rice grown locally in Bangladesh. It is a dataset of 4 different harmful diseases of rice leaf called Brown Spot, Bacterial Blight, Rice Blast, and Rice Tungro. It contains 5500 images. Brown Spot, Bacterial Blight, and Rice Blast have 1675 images in each class, and Tungro has 1575 images. All of the images are in 300X300 pixels. So Dhan-Shomadhan datasets can use for rice leaf disease classification and Segmentation. Fig. 3 shows some data for the Bacterial Blight disease class. To find out the affected area from the rice plant disease images, the dataset needs annotation of the affected area as there is no annotation file given with the dataset.

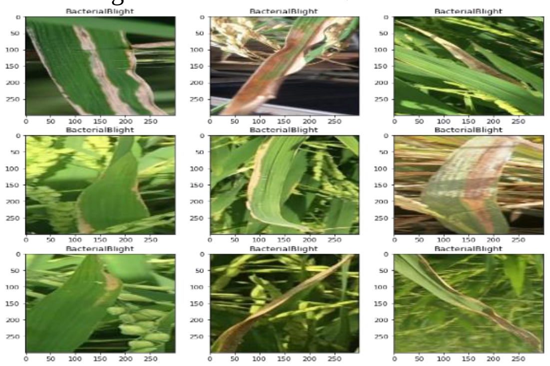


Fig. 3. Example data of disease class Bacterial Blight

Fig. 4(a) shows the affected area of Bacterial Blight, and Fig.4(b) shows the affected area of Tungro. Similarly, we have also annotated the affected area of Rice Blast and Brown Spot diseases. In total, 5500 images have been annotated using a VGG image annotator and saved the information's in a JSON file, which will need to train the segmentation model.

(a) *(b)*

Fig. 4(a,b). Annotation of the affected area of paddy disease

B. *Data Analysis using Lab Color Space*

Fig. 5, shows an image from the dataset is plotted into 3-Dimensional(3D) color view for analysis purposes which has done according to CIELAB color space system [18]. In this 3D plot, yellow is the affected part, the healthy and affected part of the leaves can be seen separately plotted by color value.

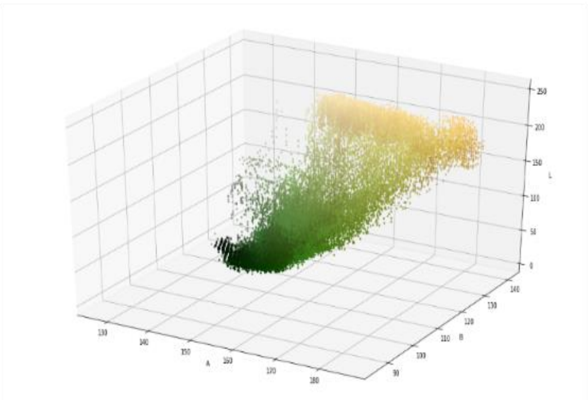


Fig. 5. 3D Color View of an example image

C. *CNN Model Creation & Transfer Learning*

CNN is usually composed of several convolution layers and max or average pooling layers. Here, Transfer learning [19] has been used to detect paddy diseases. There are many pre-trained models which are good, well known, and prepared with billions of pictures. In Fig. 6, all the accuracy of the pre-trained model can be seen. Drop the fully connected layer of the pre-trained models and merge it with a new model layer to train a pre-trained model. EfficientNet-B3 pretrained on the ImageNet dataset. The reason for choosing Efficientnet-B3 can be seen in Fig. 6, and it achieves both higher accuracy and better efficiency over exiting CNN. It reduces parameter size and FLOPS by order of magnitude. It uses the scaling method, which scales all the width, depth, and resolution dimensions using a compound coefficient. From Efficient Net B1 to B7 are made by scaling up the baseline network of B0. The main reason for choosing this architecture is that EfficientNet is 8.4x smaller than the best existing CNN and has high accuracy also. Although B7 has higher accuracy than B3, B3 was used as B7 is much complex than B3, and the maximum level of accuracy has already been obtained with the B3. Except for EfficientNet, some ground-breaking architectures are AlexNet, VGGNet, ResNet, etc. But the new state-of-the-art model is EfficientNet, whose accuracy is 8.4x smaller than the best existing CNN.

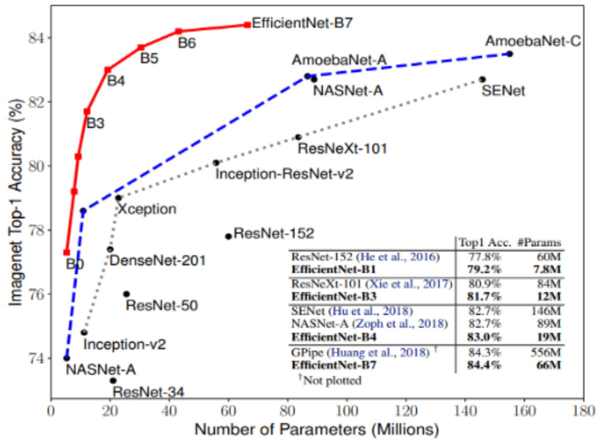


Fig. 6. Some Popular Pre-trained model [20]

In TABLE 1, there is the first convolutional layer which is the input. Then, there is the image input shape. The images are 300X300, so the input shape was 300,300, and 3 is the input image dimension. Then there are many convolutional layers which is the structure of efficientnetB3. Lastly, there is the dropout layer and predicted layer. The dropout rate of our dropout layer was 0.3. In the model, the total parameters were 11,397,939. From them, 11,310,636 are trainable, and the rest of them are non-trainable.

TABLE-1: Layers and Parameters of Efficient Net B3

Layer(type)	Output Shape	Parameters
Input Layer	[(None,300,300,3)]	0
Efficientnetb3	(None,10,10,1536)	10783535
Flatten	(None, 153600)	0
Dropout	(None, 153600)	0
Dense	(None, 4)	614404
Total Parameter		11,387,939
Trainable Parameter		11,310,636
Non-trainable Parameter		87,303

D. *Mask-RCNN Semantic Segmentation*

There are two types of Segmentation. One is instance segmentation, and another is semantic Segmentation. In this paper, Mask-RCNN is used, which is an instance segmentation method. The Mask RCNN is a hybrid recurrent convolutional neural network that handles instance segmentation issues in deep learning or computer vision. To put it another way, it can distinguish between distinct things in a picture or video. You may get the bounding object boxes, classes, and masks by giving it an input image. Mask RCNN is divided into two phases. Based on the input image, it first provides suggestions for locations where an item may be. Second, based on the first stage suggestion, it guesses the object's class, refines the bounding box, and creates a pixel-level mask. The COCO dataset is used to train Mask-RCNN models.

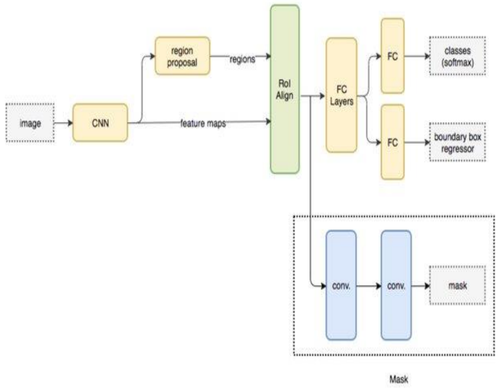


Fig. 7. The architecture of the Mask R-CNN framework.

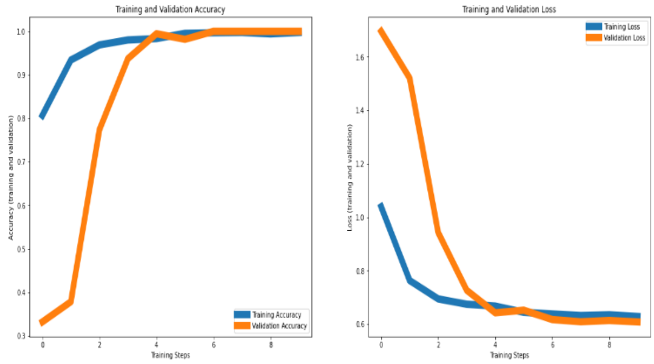
Mask-RCNN is a hybrid of a Faster R-CNN for object recognition (class + bounding box) and an FCN (Fully Convolutional Network) for pixel-wise boundary detection. In Fig.7, the two parts can be seen clearly. Here CNN represents the backbone used for the feature extraction. Mask-RCNN gives three outputs: the predicted class name, bounding box, and mask of the expected class. Here for the backbone CNN, resnet101 is used. This work [21] shows the configurations of our Mask-RCNN model.

IV. Result and Analysis

After performing all the necessary processing on our dataset and training, we can now evaluate our models. There are many ways to evaluate the model. The most common is to show the accuracy matrices. There are also many accuracy matrices: Precision, Recall, F1-score, confusion matrix, etc. We have tried to show all of this for our model.

A. *Performance of Efficient Net B3 CNN Detection model*

The dataset was separated into training and validation once the model was created, with an 80:20 percent split between the two. There were 4400 training pictures and 1100 validation images in all. The learning rate was set at 0.0001 at the start, and the batch size was 32, which means 4000/32=138 number of batched in total. Finally, the training started with 10 epoch or iteration



(a) (b)

Fig.8. (a) Accuracy graph of our model and (b) Loss graph of our model

Fig. 8 shows the training accuracy and loss graph of the trained model. As the epoch increases, the model's accuracy increases, and it can be seen that there is a little sign of overfitting. Nevertheless, the accuracy of the model is almost 100%. If the loss of a model decreases, then the accuracy increases as our model's loss decrease in each epoch. At the start of our training, the training accuracy started from 80%, and validation accuracy was only 30%, but as the epoch increased to 2, the validation accuracy changed dramatically and became 70%. Validation accuracy and Training accuracy intersect each other at epoch 4, which is near ~99%. We know the closer these two lines come, the better a model can predict. After epoch 4, there are no significant training and validation accuracy changes, and the exact opposite also happens to the loss graph. Fig. 9 shows the prediction of 9 images from our test dataset. In addition, it can be seen that the prediction and true labels matched for all the images, which means it predicts correctly for all the images. For example, the First perdition from the 9 images predicted 3, which is Tungro, and the actual label of this sample was also 3, so our model predicted it correctly. We have also predicted a single image where we generate a function that will take one image randomly from the test data and try to predict it. Fig. 10. shows that the image was taken from the brown spot folder, and it is predicting brown spot also with a confidence percentage of 87.57%, which means it is 87.57% sure that it is a brown spot affected disease plant image.

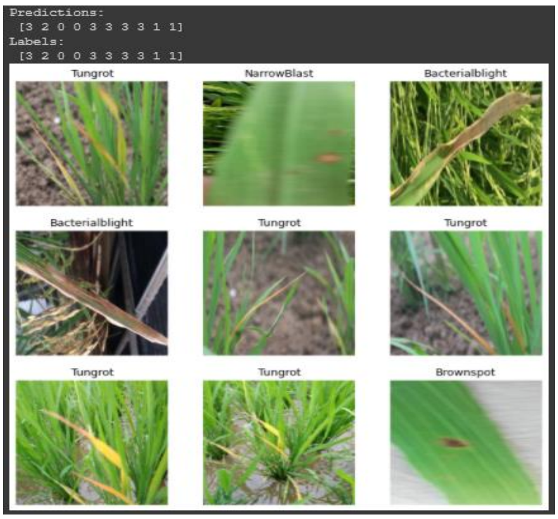


Fig. 9. Testing our model on 9 images from a testing sample

Fig. 10. Single Image Prediction

In Fig. 11, we have shown the confusion matrix for our model. A confusion matrix is essential for checking the accuracy of each class. We have generated a confusion matrix to show that our model is doing well in test data. As our dataset is huge after augmentation, it was about 15 thousand. We were not able to test all the test data at a time. That's why we have done the testing per batch. Our batch size is 32, which means we have done testing on 32 images from any batch. Here, we can see that all the true labels and predicting labels are the same that means our model has no wrong prediction for this test data batch. That's means for all the prediction classes, and the accuracy is 100%. By testing batch-wise, we can see that there is no False Positive (FP) and False Negative (FN) prediction on the confusion matrix. That means all the disease category has the same 100% accuracy, precision, and recall value.

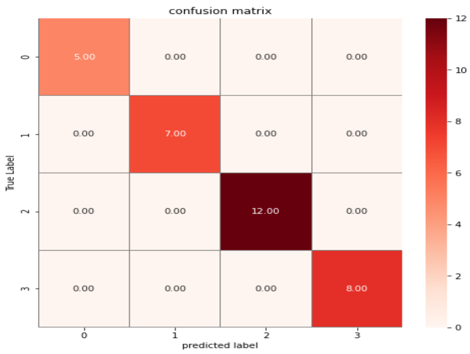


Fig. 11. Confusion Matrix of our model

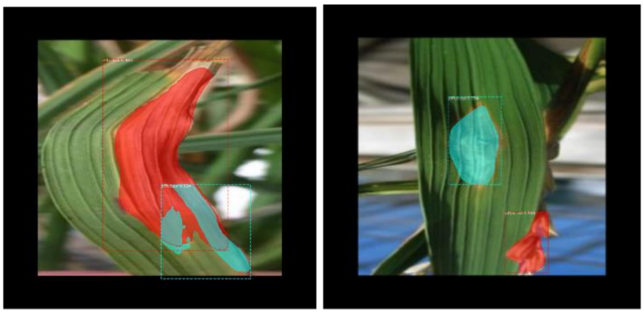
B. Performance of Mask-RCNN Segmentation Model

TABLE 2 shows the final MRCNN loss value for the segmentation model. From the loss table, we can see that all the loss values are below 0.5. As we know, the lower the loss value, the greater the model performs. The model's mAP (mean Average Precision) is around ~89% accuracy, a good result.

TABLE-2: Model Loss Table

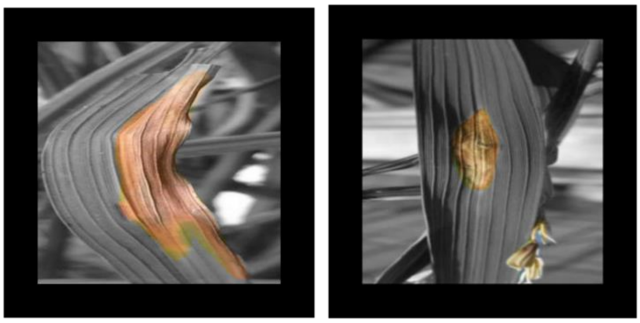
Loss Weights	Value
mrcnn_class_loss	0.0908
mrcnn_bbox_loss	0.2985
mrcnn_mask_loss	0.3046

Fig.12(a, b) showed the result when testing the trained MASK-RCNN model with validation data. Every run takes a random image from the validation dataset, makes a prediction, and gives three outputs: prediction class, bounding box, and mask (affected area). Fig. 13 shows two output results with two colors which are light blue and red. Here in these two output images, the portions marked with these two colors are the disease mask prediction or disease-affected area. In Fig. 13(a, b), color splash has been applied in the detected output of Fig. 12(a, b) for better result visualization. Form an image color splash generally keeps the detected mask (affected area) in RGB, and the rest of the image becomes black and white. By doing this, can mark the separation of the affected area from the healthier ones. As we know, the affected areas are generally the yellow areas of the leaf. By comparing Fig. 12(a) and Fig. 13(a), it can be seen that the light blue and red marks of Fig. 12 are the yellow regions in Fig. 13(a). Our purpose is to recognize the affected area, so it is not our concern how many detections the model found. Even if they overlap, this will not hamper the detection of the disease-affected regions. The same thing happens in 12(b) and 13(b). Our model has detected two affected areas marked with two different colors in 12(b), originally the affected yellow area.Fig.13 (b) shows the affected areas of 12(b) more clearly.



(a) (b)

Fig. 12 (a, b). Recognition result of MASK-RCNN



(a) (b)

Fig. 13 (a, b). Advance visualization of the predicted region

C. Model Comparison

Our study's Segmentation and classification model are compared with some previous work models with respect to mAP (mean Average Precision) for Segmentation and accuracy for classification in TABLE 3.

TABLE-3: Result comparison

Reference	Method Name	Segmentation mAP	Classification Accuracy
In study [12]	Remote sensing Techniques	83%	97%
In study [13]	Eyeballing methods	79%	90%
In study [14]	K-means Clustering	86%	None

Our Study	Mask-RCNN and EfficientNet B3 CNN	89%	~99%

TABLE 3 shows the comparison between different methods for the segmentation and classification of rice paddy disease. Most of them give good overall accuracy. They are pretty close to each other. For the agriculture field, most of these accuracies are quite good. For segmentation of the affected area, the previous state-of-the-art mAP was 86% obtained using K-means clustering but using Mask-RCNN segmentation, we have got much higher mAP which is 89%. For the classification, our model is far better than the others. The previous highest accuracy was 97%, but we got nearly 100% accuracy. For both of the models, it beats the previous related work model's performance.

V. CONCLUSION

This paper tried to detect and recognize paddy disease detection with Bangladeshi paddy disease data, which is unique and new. There is a lot of work on detecting paddy disease but very little work on recognizing the affected area of the disease. In total, there were four disease data in our dataset. So, for categorical classification, the model was trained using an EfficieantnetB3 pre-trained model. To recognize the disease-affected area, all the dataset images were labeled with “effected” and then trained with an instance segmentation model named Mask-RCNN. So, if we give an input image to our system, it will predict the disease. After that, it will go to our segmentation system, and the system will then recognize the affected area of that disease. The accuracy is nearly 100% for the prediction model, and for the segmentation model, we got an mAP of ~89%.

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