# Rice Leaf Disease Classification and Severity Evaluation using Convolutional Neural Networks and Image Segmentation Models

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## Abstract

The study developed a deep learning system to detect and evaluate the severity of four major rice diseases in the Philippines using rice leaf images. The optimal model for classifying the disease achieved 93% accuracy and increasing the training epoch significantly improved the model's accuracy as well. Image segmentation models were trained and used to localize the Regions of Interest (RoI) which in this case is the leaf and the infected areas from a subject leaf. The researchers recommends adding more rice diseases for the model to be more applicable for real-life usage and deploying the model as a web application accessible through mobile phones for farmers to quickly assess the health of their crops, improving efficiency and accuracy and mitigating the negative impact of rice diseases on production and food security in the Philippines.


## Introduction

The agriculture industry is crucial for providing food and raw materials and has a significant impact on a nation's economy. The Philippines is an agriculture-dependent nation, and the agriculture sector is divided into four common sectors: horticulture, aquaculture, forestry, and livestock. The main crops cultivated in the Philippines include rice, corn, coconut, sugarcane, bananas, pineapples, coffee, mangoes, and tobacco. Rice is a staple food in the Philippines and a key intervention point for agricultural development and poverty alleviation. Rice-related illnesses negatively affect crop yield and disrupt the agricultural sector, directly impacting consumer welfare and food security. The usage of AI technology in agriculture has revolutionized the industry, and researchers aim to develop a system using a deep learning model to assist farmers in detecting and assessing the severity of rice diseases quickly.

## Methodology

### Data Acquisition

The dataset was collected from Mendeley Data, an online repository. To make the model more suitable for the rice cultivars in Kalilangan, Bukidnon, the researchers incorporated locally captured image data from the area to improve its adaptability.

### Model Training

For the RoI (Leaf and Disease) segmentation, the researchers used UNET architecture with ResNet-50 and ResNet-34 as a backbone. For the Classification Model, the researchers conducted experiments to get the model with the optimal performance, these models consist of the MobileNet and DenseNet family of models.

### Model Evaluation

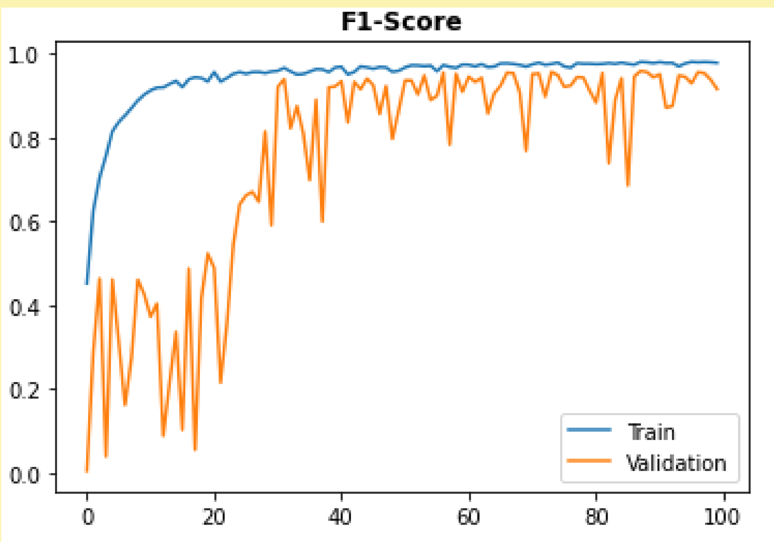
Machine Learning models have to be evaluated before further procedures. For the segmentation tasks, the researchers used the F1 score and IoU scores as metrics to indicate how well the model performs. For the classification task, the researchers used the confusion matrix and derived some of its components such as accuracy and precision.

### Prototype Deployment

The researchers used the Flask API server to deploy the models in the local machine, this type of local deployment mimics how the project will look and operate if deployed for production.

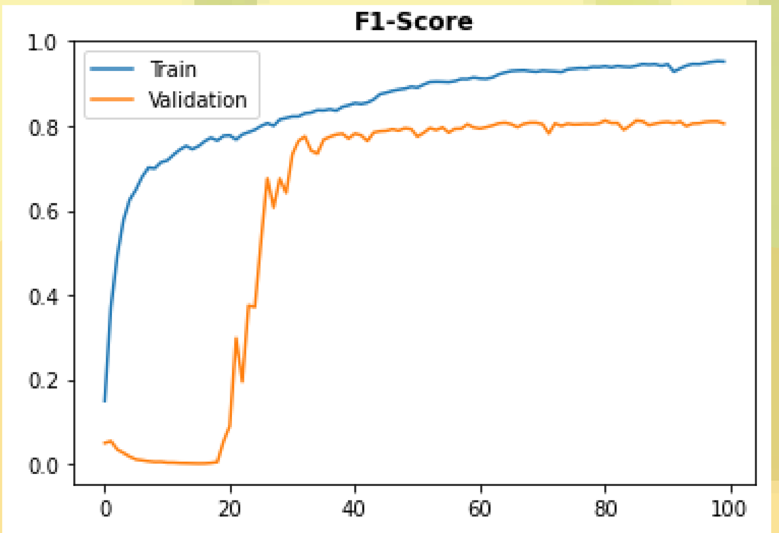
## Results and Discussion

### Leaf Segmentation



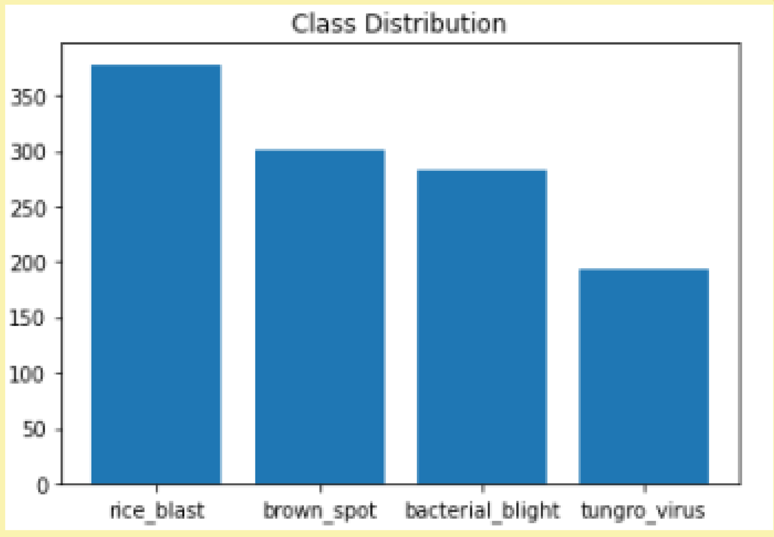

The researchers trained 3 deep learning models to achieve three tasks, the first task is to localize the leaf which is one of the two Regions of Interests (RoI), this is done through a segmentation model using UNET as the architecture and ResNet-34 as the backbone, the model achieved a test F1-score of 96% which is a good indicator that the model can predict the leaf mask well.

### Disease Segmentation




The researchers also take into account the severity of the disease that is present in the subject leaf, this is done by training another segmentation model. The process is quite identical from the leaf segmentation task, only that the training data that were used are disease masks that are annotated from the dataset. The model achieved a test F1-Score of 81%.

### Disease Classification




| Class | Precision | Recall | F1-Score |
|---|---|---|---|
| Bacterial Blight | 0.93 | 0.81 | 0.87 |
| Brown Spot | 0.78 | 0.94 | 0.85 |
| Rice Blast | 0.86 | 0.86 | 0.86 |
| Tungro Virus | 0.89 | 0.77 | 0.83 |

*Table 7.* DenseNet-169 Classification Report (SMOTE)

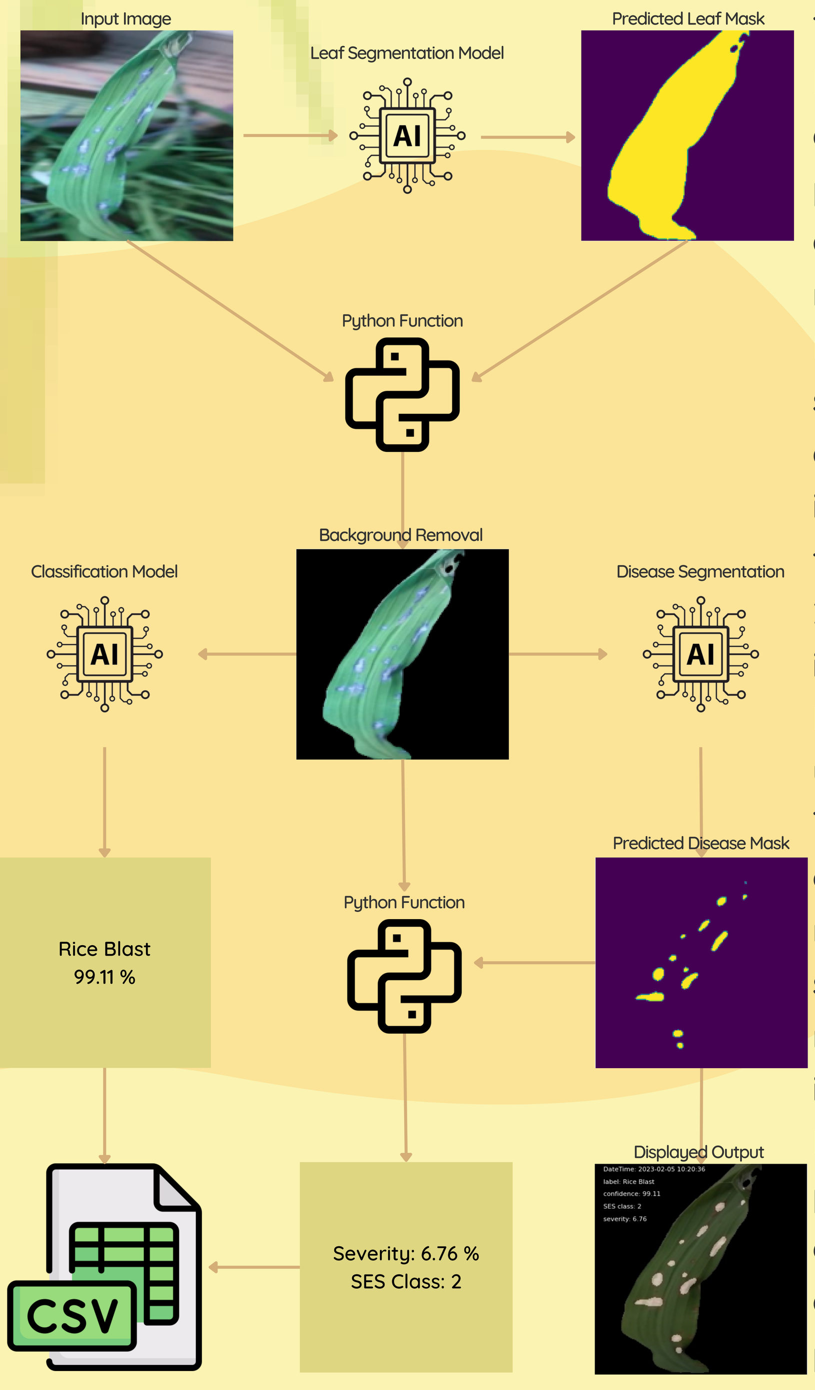
| Class | Precision | Recall | F1-Score |
|---|---|---|---|
| Bacterial Blight | 0.86 | 0.94 | 0.90 |
| Brown Spot | 0.97 | 1.00 | 0.99 |
| Rice Blast | 0.95 | 0.91 | 0.93 |
| Tungro Virus | 1.00 | 0.91 | 0.95 |

*Table 8.* DenseNet-169 Classification Report (Imbalanced)

After segmentation, the image data will be passed to a classification model to predict the manifesting disease. For this purpose, the researchers experimented on simulating MobileNet and DenseNet variations. The optimal model is the DenseNet-169. After getting the optimal model, the researcher conducted another test to see if there is a difference between the model trained to the original imbalanced data or the dataset where it was augmented with SMOTE algorithm, the researchers found out that the model performed well with the imbalanced dataset.

Precision measures the proportion of correct positive predictions made by the model. When the data is imbalanced, and the class of interest is under-represented, a model may achieve high accuracy by simply predicting the majority class most of the time. Based on the classification results, higher precision is achieved in the imbalanced data, and recall and F1-Score also have higher performance when trained with the imbalanced dataset.

## System Diagram




The system flow of the project is depicted in the layout on the left, which effectively handles the input and processes it through a series of procedures. The processes are encapsulated in a python script with all the requisite functions written in an organized manner.

Initially, the input image is read as a BGR image, and subsequently, the leaf segmentation model accurately predicts the leaf mask for the input image. This is followed by the execution of a python function that uses the input image and the predicted 2D leaf mask to remove the background of the input image with precision.

Next, the resulting image without the background undergoes classification and segmentation models. The classification model accurately predicts the type of leaf disease present, while the segmentation model generates a mask of the infected areas. The severity of the infection is evaluated based on the number of pixels tagged as infected (yellow) and is included in the output of the severity status.

Finally, the results are stored in a CSV file for future purposes, such as time-series analysis and exploratory data analysis. The system flow design and execution were performed with high levels of professionalism and academic rigor.

## Recommendations

- >> Fine-tuning of deep learning parameters for future improvement
- >> Add new data points and implement more robust models.
- >> Expand the scope of the study, include other rice diseases.
- >> Deploy to production or real-world use

## Conclusion

- >> Good model performance acquired.
- >> Optimal classification model: DenseNet-169, 93% Accuracy.
- >> Higher value for epoch makes the model learn well.
- >> Implementation of transfer learned data points implementation against the original dataset gained a significant result.