Paddy Disease Classification

Ababacar Dioukhané (adioukhane@aimsammi.org) Mouhamadou Mansour Sow (msow@aimsammi.org)
Habib Mbow (hmbow@aimsammi.org) Paul Sanyang (psanyang@aimsammi.org)

Team: SeneGambia |**Public score:** 96.80% | **Private score:** not available
https://github.com/mm230/paddy-desease-classification.git

1 Introduction

Rice is an important crop in agriculture. However, crop diseases can significantly reduce its yield and quality, which is a great threat to food supplies around the world. Thus, disease control is critical for rice production. The key for successful disease control is a correct and fast diagnosis of diseases, so that pesticide control measures can be applied timely. With the limited availability of crop protection experts, manual disease diagnosis is tedious and expensive. Now days, deep learning techniques have attracted the attention of researchers due to its great performance in image classification Thus, it is increasingly important to automate the disease identification process by leveraging computer vision-based techniques that achieved promising results in various domains.

2 Objective

Classification is a classical machine learning problem, and much progress has recently been observed. The goal of this data challenge is to develop a machine learning model to classify the given paddy leaf images accurately. In this challenge we experiment with the resnet50 pretrained model to classify whether a given paddy has a particular disease or not.

3 Methodology

In recent times, the deep learning techniques have obtained very high performance in almost all aspects of the problems, such as image recognition (Litjens et al., 2017), image segmentation (Long et al., 2015; Garcia et al., 2017), speech recognition (Abdel-Hamid et al., 2014). In general, deep learning technique is end-to-end learning and thus avoids complex hand-crafted feature extraction. It learns features at different levels of abstraction as layer increases. The deep convolutional neural network (CNN) is the most popular and extensively used for image recognition (Lu et al., 2017). It mainly comprises of convolutional, pooling and fully-connected layers. However, CNN requires large labelled dataset such as ImageNet (Denget al., 2009) to train efficiently which is a challenging task in the field of agriculture.

4 Related Work

Several researchers have proposed an automated identification system for rice disease detection . In another study , the infected area was extracted using K-means clustering from the diseased leaf surface (Petchiammal et al., 2022). the authors proposed an Attention-based Depthwise Separable Neural Network - Bayesian Optimization (ADSNN-BO) model that has achieved an accuracy of 94.65 percent. In (Bharathi, R.J., 2020), AlexNet model was used for rice disease identification and achieved an accuracy of 96.5 percent. In (Patil, R.R, Kumar, S.), CNN and Multilayer Perceptron (MLP) models were proposed to achieve 81.03 percent and 91.25percent accuracy.

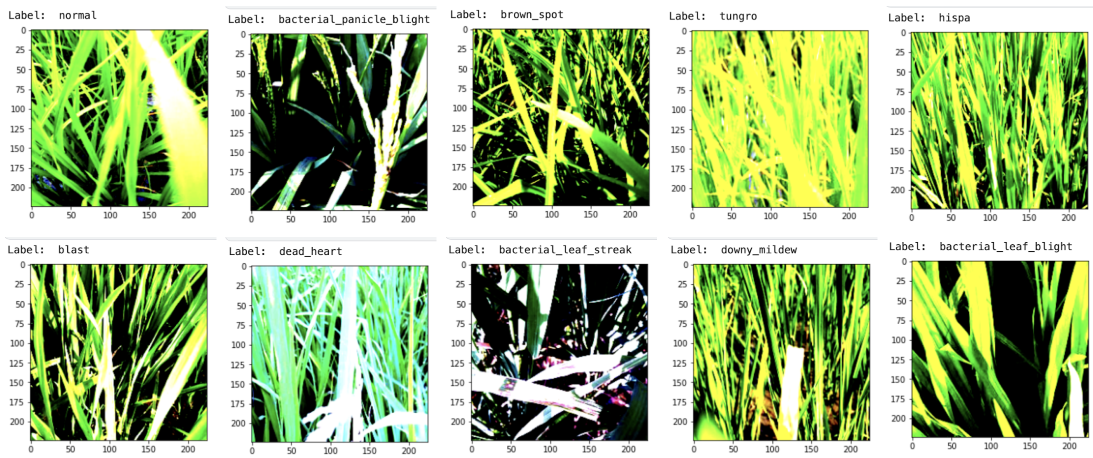

Figure 1: Sample of the ten different classes

5 Data Description

The dataset provided for the training is 10,407 (75 percent) labeled paddy leaf images across ten classes (nine diseases and normal leaf).Additional metadata for each image, such as the paddy variety and age was provided.

5.1 Experiment Setup and Performance Analysis

In This challenge we use pre-trained models for rice disease classification. Moreover, all images were normalized. We used also data augmentation in order to deal with unbalanced classes. All models used a learning rate of 0.0001, 10 epochs, and 16 batch sizes for training. We use the standard classification accuracy to measure and compare the performance of the models.
We used Google's Colab framework using GPU to conduct all the experiments. The training process took approximately 180 minutes for each model. The results showed that resnext101_32x8d achieved the highest classification accuracy of 96.80% . This is followed by resnet50, achieving 95.42%. In comparison, the resnet152 model achieved the lowest accuracy of 92.90% . These results demonstrate the usability of the dataset for automated paddy disease classification tasks. We plan to evaluate additional pre-trained models based on different transfer learning strategies before the end of the competition. However, we would like to inform you that we are unable to obtain the score on the private leaderboard because the competition is still in progress.

6 Conclusion

As described in the overview of the competition, manual disease diagnosis is tedious and expensive due to the limited availability of crop protection experts. That's why, it is very needed to increase automated solutions that can scale to many diseases and plants. In this competition, we used the Paddy Doctor dataset for automated paddy disease detection. It contains 10,40 annotated paddy leaf images across ten classes (nine diseases and normal leaf). The presented dataset was benchmarked using three deep learning-based models and we compared their performance across each other. The results demonstrate that resnext101_32x8d achieved a superior accuracy of 96.80% followed by 95.42% with resnet50 based model and finally 92.90% with resnet152 based model.

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