MICROSOFT RICE DISEASE CLASSIFICATION

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1   Problem statement

Rice is a staple crop in Egypt, but despite Egypt's position as the top rice producer in Africa, it still relies on imports to meet the demands of its population. One of the main causes of this gap in Egypt is rice blast disease, which is responsible for 30% loss in rice production worldwide. Early detection is the best way to manage crop diseases like rice blast, but rice blast is easily misclassified as brown spot disease - both are fungal diseases and have similar appearances in their early stage. With the current scarcity of experienced agricultural extension officers in the country, there is a clear case for recent technological advances in computer vision to help in early diagnosis, particularly by using multi-spectral images of crops.

2   Objective

The objective of this challenge is to predict the classes of disease of a rice plant in RGB and Infrared images.

3   Hypotheses

In order to achieve our objective, we try a set of hypotheses such as data augmentation, test time augmentation (during post-processing) and model fine tuning (using transfer learning approach).

4   Data exploration Methodology

4.1   Data exploration

The data contains images of rice plants in Egypt where a single sample consists of a pair of Red-Green-Blue (RGB) and Red-Green-NearInfrared (RGNIR) images (Figure 1). RGB images are captured using a mobile phone camera and a survey camera was used to capture the multispectral RGNIR images. The train data is composed of approximately 5340 images (with 2670 been RGNIR and the rest RGB). The test data on the other hand contains 2290 images.

Figure 2 shows the distribution of the different classes (blast, brown, healthy). The class **healthy** has a lower representation than the blast and brown labels.

In most cases, the images of rice are barely visible. We noticed that several of these images depict primarily soil and water. In such cases, we resize the images. In addition, the following pre-processing procedures are carried out:

- Random cropping of images
- Image flipping and resizing
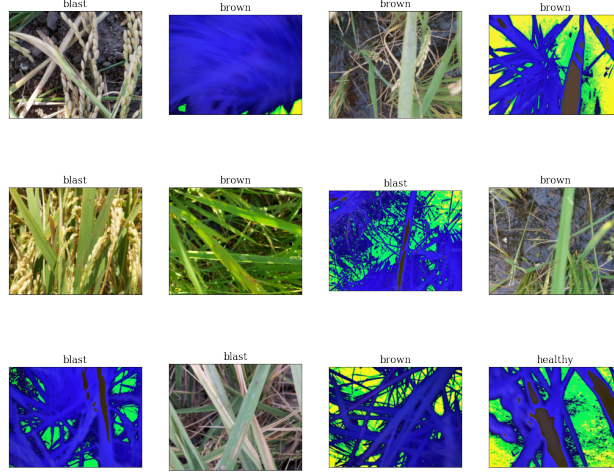- Hue augmentation (color jitting) in order to mimic the spectral nature of the RGNIR images.

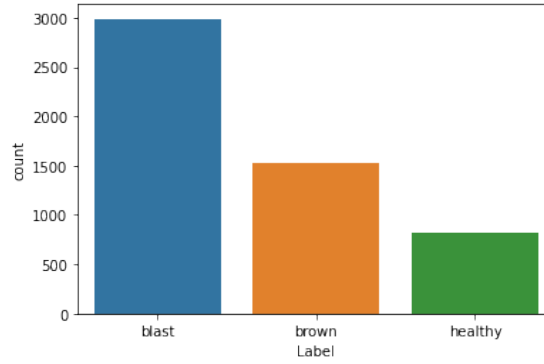Figure 1: Data visualization of the **healthy**,**blast** and **brown**

Figure 2: Distribution of the different classes.

4.2 Methodology

Fastai [1] is a deep learning library which provides practitioners with high-level components that can quickly and easily provide state-of-the-art results in standard deep learning domains, and provides researchers with low-level components that can be mixed and matched to build new approaches. We used Fastai to load and easily train pre-trained models under a transfer learning framework [2]. The pre-trained models used in our experiment include $resnet50$ and $resnet34$ [3]

5 Related papers

Several research have been carried on rice disease detection. Yang Lu et.al[4] used deep convolutional neural networks (CNNs) techniques to detect natural images of diseased and healthy rice leaves and stems. Kawcher Ahmed et.al [5] used a range of different machine learning algorithms including that of KNN(K-Nearest Neighbour), J48(Decision Tree), Naive Bayes and Logistic Regression to detect rice plant diseases namely leaf smut, bacterial leaf blight and brown spot diseases.

6 Results

Table 1 presents our result for the two sets of models, under different configurations; firstly we trained the models using only the **RGB** images, secondly we trained using the **RGNIR** images and compared both results. We also consider post-processing using test time augmentation (TTA) [6]. The training was done using varying number of **epochs** and **image size**. The learning algorithm used was stochastic gradient descent [7] and the evaluation metric was the

cross-entropy loss (**Log loss**) as defined in equation 6:

$$logloss \quad = \quad -\frac{1}{N} \sum_{i=1}^{N} \sum_{j=1}^{M} y_{ij} log\left(p_{ij}\right) \tag{1}$$

Where, y_{ij} is 1 if class belongs to j or 0 if not and p_{ij} is the predicted probability of the observation to belong to class j.

Models	Image-size	number of epochs	TTA	Image-type	Log-loss
$ResNet34$	224	5	No	(RGB)	0.252
$ResNet34$	224	5	yes	(RGB)	0.221
$Resnet50$	224	10	yes	(RGB)	0.134
$Resnet50$	400	15	yes	(RGB)	0.166
$Resnet50$	400	5	yes	$(RGNIR)$	1.674

Table 1: Model comparison simple bench-marking to choose the best model

Varying the number of epochs, significantly changes the $logloss$ of the model with an optimal number of epochs been 10 and providing a logloss of 0.134 when submitting the result in the public leaderboard . Throughout the experiment, we noticed that post-processing with TTA, gave slightly better results (smaller log-loss). A change in the image type from RGB to $RGNIR$, gave a drastic increase in the error of the model (around 1.674) . We suspect that $RGNIR$ images are not informative enough to characterise the different classes of diseases.

Base on our findings, we conclude that $Resnet50$ was able to detect the classes of disease with an error of **0.134** on the test set.

References

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