ISSN 2229-5518

Identification And Classification Of Rice Plant Disease Using Resnet 50

K.M. Faisal, Md. Eftiaz Hossien, Mohammad Tauhidul Islam

Abstract— In this research image system for detection and classification of rice diseases from the pictures of infected rice plants. This image recogntion system is developed when careful experimental analysis of assorted techniques is employed in image process operations. This paper cosiders three rice plant diseases namely, Bacterial leaf blight, Brown spot, and Hispa. This paper tends to capture some pictures of infected rice plants with a mobile phone from a rice field. This paper tends to apply four techniques of background removal and three techniques of segmentation by default. To alter the correct extraction of options, this paper tends to propose center feeding based mostly on K means agglomeration for the segmentation of disease portion from a leaf image. This paper tends to enhance the output of K means agglomeration by removing inexperienced pixels within the disease portion. This paper tends to extract various options categories: color, shape, and texture. This paper tends to use a Support Vector Machine (SVM) for multi-class classification. This paper accomplishes 93.33% accuracy on the training dataset and 73.33% accuracy on the test dataset. Future researchers will be developing an android app for faster recognition and related information and suggestion.

Index Terms— Image Processing, Image Detection, Image classification, Disease classification, Disease Identification, Objects Detection, AI, Resnet 50, Plants Disease classification, Plants Disease Identification, Colab, Tenorflow.

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1 Introduction

Capturing the photographs of infected leaves and matching information of the data is a way to induce eliminates loss of crop production from infection. As an automatic resolution of this downside, cameras may be deployed at sure distances within farm to capture pictures sporadically. These photographs may be sent to a central system for analysis of information; the system will sight the diseases and provides suggestion concerning the disease and chemical choice. The alternative way is, farmer can collect the image by smart phone and send data to central system for analysis. At the core of such system would be to automatically detect the disease and insects. Authors tend to address this downside during this thesis work. Objective of this work is to indicate that the machines learning field may be helpful for agriculture as Authors. Applying machine learning is another best option in agriculture for maximum production. Disease and infection can be detected when segmenting disease or infection with natural healthy leaf. An important work is a separate healthy leaf portion from disease portion that Authors tend to believe that's an important step when making acceptable decision by machine learning, that define the quality of our features. Moreover, the ideas can be applied to detect different diseases that can be found on different plants. Authors tend to resolution the matter elaborately of automatic detection and classification of rice plant diseases. Authors tend to collect the diseases leaves from rice fields and ready a dataset of rice plant diseases, with white background. Our system initially removes the background from a picture then applying K-means cluster it separates the disease parts of the leaf image. By using threshold technique unnecessary green part can be removed from leaf, as Authors inside the disease portion. Finally, Support Vector Machine (SVM) is used to classify the diseases.

2 Prolegomenon

2.1 Objectives

The objectives of the analysis are undertaken during this thesis is to develop effective and high accuracy image recognition techniques. The knowledge can be applied in any fields i.e.

ISSN 2229-5518

detection anything from images and determine what it is. Also, this analysis focuses on classifying of rice diseases with CNN that is most promising algorithmic in deep learning. The objectives of this thesis include: To implement Tensorflow and ResNet50, To identify disease portion from a rice leaf accurately, To classify the types of disease accurately, To improve the output results by adjusting parameters, To Evaluate the performance of the network.

2.2 Outline of the paper

This article is divided into seven sections. Section 2 presents a study on different types of rice plant diseases and discusses overall process of disease classification and data collection. Section 3 presents data preprocessing Authors carried out in implementation and evaluation of our work. Section 4 presents the brief discussion on system development and prepare artificial neural network and specially ResNet 50 that Authors have used in model. Section 5 presents the brief discussion on training ResNet 50 that Authors have used in our model. Section 6 presents the results analysis and comparison. Finally, Section 7 summarizes the work in form of conclusion.

2.3 Overview Survey

In 2019, Preetom Saha Ark [1], Mohammed Eunus Ali, Sajid Hasan Apona, Abu Wasif of People's Republic of Bangladesh University of Engineering and Technology (BUET) had supervised an exploration on rice disease identification and recognition with six rice diseases and 3 pests of rice. They have research and deployed 5 models like VGG16, InceptionV3, ResNet50, Exception and InceptionResnetV2. From all of them VGG16 had provided the simplest accuracy rate. Secondly, among all the six diseases, one is Neck Blast disease that isn't found in Bangladesh; whereas Leaf Blast disease is often found however authors, they didn't attach it in their dataset. Thirdly, a number of their dataset includes large background from that distinctive many disease affected space is hard and eventually will cut back the accuracy proportion.

Santanu Phadik [2] and Jaya Sil of Authors, Bengal University of Technology, Bengal Engineering and Science University had created a Pattern Recognition Techniques by deploying SOM neural network for classifying 2 rice diseases only. Leaf Blast, and Brown Spot among of their classes. They used four cases for the classification, and therefore, the highest classification among these four cases was 90% successfully.

From Google Inc. Yuan Xue [3] Authors, Chong Wang et al. had used ResNet-v2-50 constructively as their image model in their analysis supported distinguishing and localization of Thoracic Disease exploitation restricted direction. The result ware considerable.

2.4 Data Collection

To gather the necessary data of the different rice pests and diseases, the researchers conducted interviews to the personnel of the Department of Agriculture specifically to the faculty of Agriculture Department and some students and friends. Images of different rice pests and diseases Authors collected using the available image captureing devices such as digital camera and smart phone. Due to corona virus lockdown, more required data cannot be collected, and use alternative of downloading dataset from internet. After collecting, all image Authors preprocessed and encoded as a part of the dataset.

3 Data Pre-Processing

Data Preprocessing could be a predominant section for our analysis. The accuracy of our machine learning based model is clearly addicted to this step. The 2 major footsteps of Data preprocessing are Data Augmentation and Resizing. Authors tend to flip and turned the images to bring out of the simplest angle from them. Microsoft built in paint 3d software was used to process some images. The input data was divided into two parts; the training set and test set. For training data, 920 of the total images Authors used. For test data set

ISSN 2229-5518

used the remaining 120 of the images.

Diseases and healthy leaf image data was annotations with labellmg software. Rectangle boundary box was created on each image of disease portion and healthy portion. labellmg software create (.XML) file that consist the coordinate of selected boundary box that Authors created earlier. Finally, all data was uploaded in Google Drive. After install required all library file in COLAB, the (.XML) of test and training data was converted to (.CSV) file. From that (.CSV) file (. record) was created.

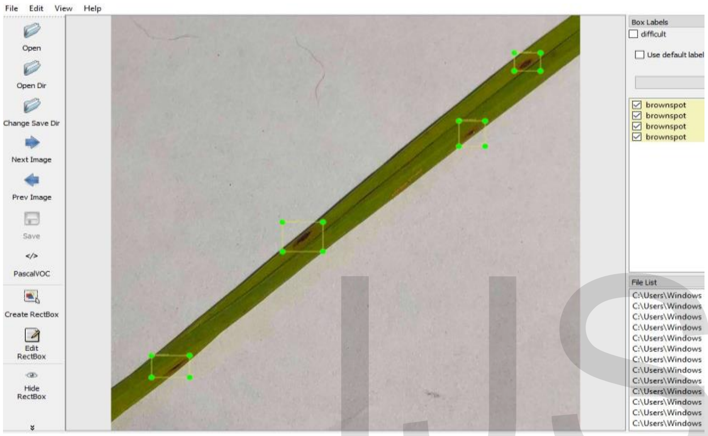

Figure: Labellmg Software Interface

The (.PBTX) file was created based on our classes, and it was Bacterial leaf blight, Brown spot, Hispa and Healthy leaf. For tracking training process and output Tensor Board is deployed.

4 System Development

Google cloud computers (COLAB) ware use in whole process of training and output was on Tensor board, due to corona virus outbreak and personal computer was Pentium four processor (very old). Selected batch size was 10 for limited provided ram of 35 GB for limited time. Google Drive was used to store data 15 GB and save model data.

Figure: Colab Interface with Google Drive mount

5 Training the Model

Authors utilized transfer learning, to develop the model. Transfer Learning is the improvement of learning during a new task through the transfer of information from a connected task that has already been learned [4]. It had been incontestable that transfer learning will be used once it's insufferable together thousands of the latest pictures [5]. Transfer learning is the use of already trained deep learner to new complication. During this study, Authors used of a model already trained on another issue rather than developing a model from scratch. Applying Python and TensorFlow, Resnet 50 was retrained to predict completely different classes of rice diseases and pests. The ImageNet large Visual Recognition Challenge, trained for ResNet 50. The final layer of the model was retrained from scratch from the provided images.

```
I0923 07:48:20.200990 139865148630784 supervisor.py:1050] Recording summary at step 3649.
INFO:tensorflow:global step 3650: loss = 0.2851 (11.657 sec/step)
I0923 07:48:21.657739 139869454120832 learning.py:512] global step 3650: loss = 0.2851 (11.657 sec/step)
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I0923 07:50:03.826052 139869454120832 learning.py:512] global step 3660: loss = 0.2277 (10.064 sec/step)
INFO:tensorflow:global step 3661: loss = 0.4593 (10.167 sec/step)
I0923 07:50:13.994265 139869454120832 learning.py:512] global step 3661: loss = 0.4593 (10.167 sec/step)
INFO:tensorflow:Recording summary at step 3661.
```
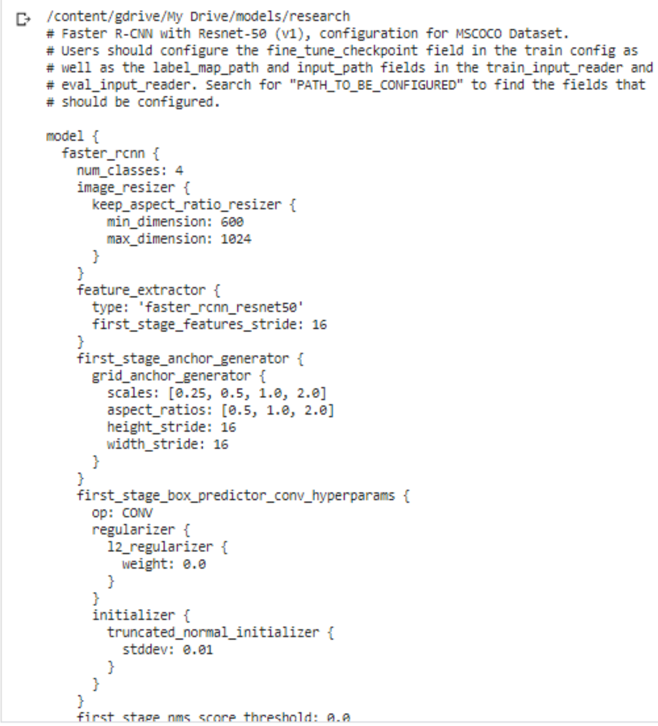

Figure: Training is in progress

ISSN 2229-5518



```
/content/gdrive/My Drive/models/research
# Faster R-CNN with Resnet-50 (v1), configuration for MSCOCO Dataset.
# Users should configure the fine_tune_checkpoint field in the train config as
# well as the label_map_path and input_path fields in the train_input_reader and
# eval_input_reader. Search for "PATH_TO_BE_CONFIGURED" to find the fields that
# should be configured.

model {
  faster_rcnn {
    num_classes: 4
    image_resizer {
      keep_aspect_ratio_resizer {
        min_dimension: 600
        max_dimension: 1024
      }
    }
    feature_extractor {
      type: 'faster_rcnn_resnet50'
      first_stage_features_stride: 16
    }
    first_stage_anchor_generator {
      grid_anchor_generator {
        scales: [0.25, 0.5, 1.0, 2.0]
        aspect_ratios: [0.5, 1.0, 2.0]
        height_stride: 16
        width_stride: 16
      }
    }
    first_stage_box_predictor_conv_hyperparams {
      op: CONV
      regularizer {
        l2_regularizer {
          weight: 0.0
        }
      }
      initializer {
        truncated_normal_initializer {
          stddev: 0.01
        }
      }
    }
    first_stage_nms_score_threshold: 0.0
```

Figure: Configuring ResNet 50 Model

6 RESULT DISCUSSION

6.1 Outcome Consideration

The model employed in detecting rice diseases and pests was supported by Convolutional Neural Network (CNN). CNN area unites at the core of most progressive machine vision solutions for a good type of tasks [6]. A Convolutional Neural Network (CNN) comprises one or additional convolutional layers, and so follow Authors by one or additional totally connected layers as in a very normal multilayer neural network. CNN area unit generally comprised of various sorts of layers, as Authors as convolutional, pooling, and fully-connected layers. By stacking several of those layers, CNN will automatically learn feature illustration that's extremely discrimination while not requiring modified features [7]. The structure of a CNN is composed of associate degree Input, Output Layer and multiple hidden layers. The hidden layers will either be a convolution layer, pooling or totally connected layers. The Input layer can hold the raw pixel values of the photographs whereas the convolution layer computes the output of neurons that area unit connected to the native region of the input. The pooling layer can perform a down sampling operation on the spatial dimensions. The totally connected layer can analyses the category scores.

The model for identify rice pests and diseases was supported CNN. However, Authors the model predicts pictures, a picture should be import to the classifier as an input then the convolution layer computes the output of the neuron cell to the logical region of the input. Down sampling of the operation on the spatial dimensions are analyses within the pooling layer. The operation is performed over and over on the quantity of layers until it reaches the ultimate layer that could be a totally connected layer which can analyses various categories as basis for creating prediction.

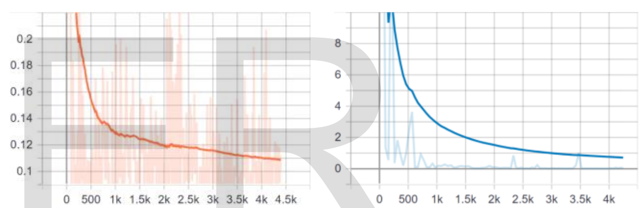


Figure: Train Classification Loss and Test Classification Loss

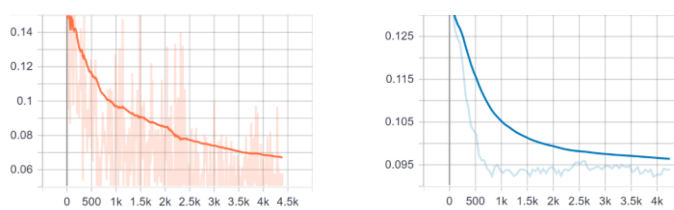


Figure: Train Localization Loss and Test Localization Loss

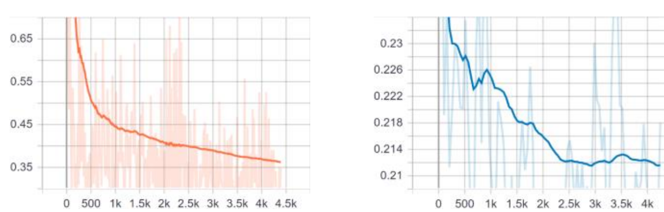


Figure: Train Objectness Loss and Test Objectness Loss

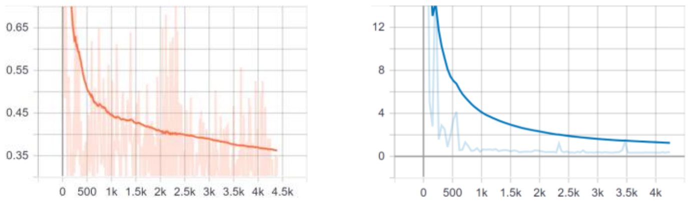


Figure: Train Total Loss and Test Total Loss

```
Average Precision  (AP) @[ IoU=0.50:0.95 | area=   all | maxDets=100 ] = 0.166
Average Precision  (AP) @[ IoU=0.50      | area=   all | maxDets=100 ] = 0.439
Average Precision  (AP) @[ IoU=0.75      | area=   all | maxDets=100 ] = 0.096
Average Precision  (AP) @[ IoU=0.50:0.95 | area= small | maxDets=100 ] = 0.020
Average Precision  (AP) @[ IoU=0.50:0.95 | area=medium | maxDets=100 ] = 0.157
Average Precision  (AP) @[ IoU=0.50:0.95 | area= large | maxDets=100 ] = 0.177
Average Recall     (AR) @[ IoU=0.50:0.95 | area=   all | maxDets=  1 ] = 0.153
Average Recall     (AR) @[ IoU=0.50:0.95 | area=   all | maxDets= 10 ] = 0.351
Average Recall     (AR) @[ IoU=0.50:0.95 | area=   all | maxDets=100 ] = 0.385
Average Recall     (AR) @[ IoU=0.50:0.95 | area= small | maxDets=100 ] = 0.233
Average Recall     (AR) @[ IoU=0.50:0.95 | area=medium | maxDets=100 ] = 0.366
Average Recall     (AR) @[ IoU=0.50:0.95 | area= large | maxDets=100 ] = 0.395
```

Figure: Evaluation results at 4500 steps

Using the photographs of rice pests and diseases because the training dataset, authors are able to retrain the model and create the results. The output of the training is recorded for each of the ten steps of the result. The result contains data concerning the training accuracy, validation accuracy and cross-entropy. The training of the dataset was able to gain 90.9% accuracy that is high considering that some categories have limited range of pictures. This suggests that the trained model will perform correct prediction supported pictures that may be fed to the system.

As the training of the model progresses, the results Authors conjointly being documented and are plots on a graph. Accuracy scalar graph of the training as documented apply on Tensor Board. The orange-colored line represents the coaching accuracy whereas; the blue colored line represents the validation accuracy. At 4.5K steps within the training, the model already achieved 75% accuracy on training.

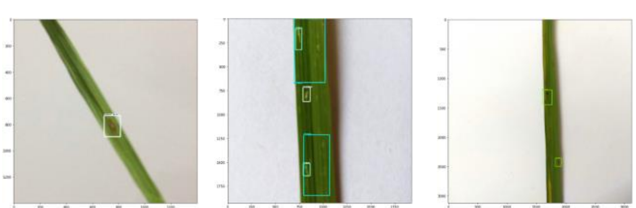


Figure: Train (Left) Leaf Blast (white rectangular box) Detect 100% accuracy. (Middle) Healthy (Cyan rectangular box) Detect 75% and 70%, Leaf Blast 85%, Hispa (Cyan green rectangular box) Detect 70% accuracy. (Right) Brown Spot (green rectangular box) Detect 99% and 95% accuracy.

6.2 Comparison of segmentation techniques

Authors use ground truth primarily based approach to check results of assorted segmentation techniques. Ground truth Image is a picture during which segmentation will be done manually. In ground truth primarily based approach, the results of segmentation are match with the ground truth image [8]. Authors tend to create the ground truth images by manually segmenting the infected portion from the leaf disease with Labellmg software.

Authors conjointly got to evaluate however Authors sensible a model will work for every class label. The class wise accuracy of every disease for ResNet50. Authors tend to observe that for Hispa disease category, the testing accuracy is 50% that is low. The attainable reason for this low testing accuracy may Authors the reason was confusion between Authors Healthy and Hispa diseases. Authors will see that each Brown spot and Leaf smut have spots or regions of brown color. For machine learning the training step incredibly low and only 4500, but that's gives impressive results.

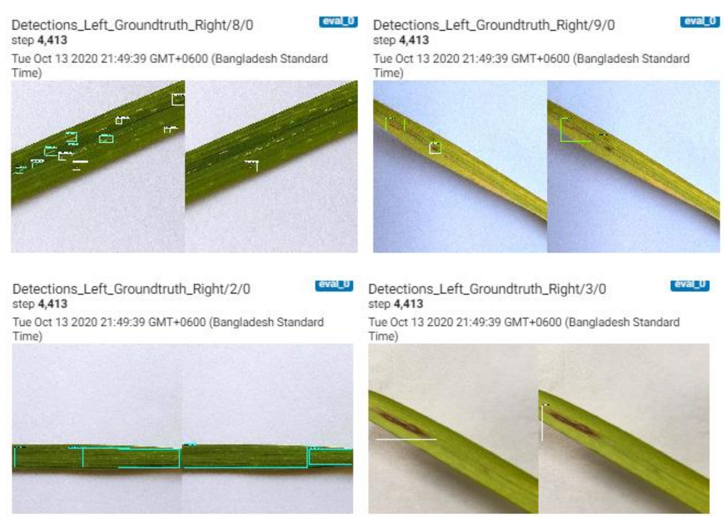


Figure: Ground truth, each image set has (Left) detected compare with (Right) given rectangle boundary box.

7 Conclusions

7.1 Decision

Rice plant diseases will create an enormous quantity of loss within the agriculture domain. This article demonstrates the system identification of 3 rice plant diseases and healthy leaf. In this paper, Authors are able to develop a rice diseases and pests detection application applying convolutional neural network. To accurately predict the diseases and pests in rice, a pre-trained model was trained applying transfer learning technics. This permits us to train the model quicker instead of building the model from beginning. The trained model has achieved high accuracy with minimum error in predicting results. So that, now the model can predict or identify rice diseases and pests with high accuracy. This same model again can be used to train rest of the rice disease and pest. Not only Rice disease, any plant disease can be included with this model in future. Our trained model now can be transfer on mobile device also. These developed mobile app or other alternative devices can be provided farmers to assist them to control all rice disease, nutrition deficiency and pest for maximum production. These will also help the others researcher and workers of Department of Agriculture to provide help to farmers once the disease or pests area identify and reported to their office.

7.2 Limitations

In colab has limited time and hardware access, it's difficult to research more area. Corona outbreak is the main problem that prevents to gather data from rice fields. Authors did not get enough time and suitable environment to develop mobile app.

7.3 Future Works

Many research organizations working on a deep learning-based machine learning that encourages us to use deep learning on medical pictures. Very recent corona virus will be detected with chest x-ray only. Expecting the brighter side of machine learning, authors to tend to hope the earlier human is going to be replaced in most of the medical application particularly diagnosis. Knowledge that authors have gain from this research can be applied in a wide application. After Developing mobile app for fast and easy detection, our next goal is working with chest x-ray for detect all chest disease along with corona virus.

Acknowledgment

Throughout the writing of this dissertation, Authors have received a great deal of support and assistance. Authors would first like to thank to supervisor, **Md. Abu Bakr Siddique**, whose expertise was invaluable in the formulating of the research topic and methodology in particular.

Completing this work would have been all the more difficult Authors it not for the support and friendship provided by the other members of the College of Science and Engineering, and the Department of Electrical and Electronic Engineering, IUBAT. Also, Authors would like to thank our parents for their wise counsel and sympathetic. Finally, there are our friends, who Authors of great support in deliberating over our problems and findings, as Authors as providing a happy discussion to rest our minds outside of our research. Special thanks to our parents who motivated and supported us throughout our entire study period. It would have not possible to cope up without their support and guidance.

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