RICE PLANT DISEASE CLASSIFICATION USING TRANSFER LEARNING OF DEEP CONVOLUTION NEURAL NETWORK

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ABSTRACT:

Early and accurate diagnosis of plant diseases is a vital step in the crop protection system. In traditional practices, identification is performed either by visual observation or by testing in laboratory. The visual observation requires expertise and it may vary subject to an individual which may lead to an error while the laboratory test is time consuming and may not be able to provide the results in time. To overcome these issues, image based machine learning approach to detect and classify plant diseases has been presented in literature. We have focused specifically on rice plant (*Oryza sativa*) disease in this paper. The images of the diseased symptoms in leaves and stems have been captured from the rice field. We have collected a total of 619 rice plant diseased images from the real field condition belong to four classes: (a) Rice Blast (RB), (b) Bacterial Leaf Blight (BLB), (c) Sheat Blight (SB) and (d) Healthy Leave (HL). We have used a pre-trained deep convolutional neural network (CNN) as a feature extractor and Support Vector Machine (SVM) as a classifier. We have obtained encouraging results. The early identification of rice diseases by this approach could be used as a preventive measure well as an early warning system. Further, it could be extended to develop a rice plant disease identification system on real agriculture field.

1. INTRODUCTION

Crop plant disease identification and classification, in the early stage is one of the most vital activities in agricultural practices. Infection by diseases results in great loss to economic to the farmers in every year. Therefore, quickly, timely and accurate diagnosis of the disease prevents the loss of product and improves the quality of the product as well (Phadikar *et al.*, 2013). As a consequence, it helps in economic growth of the country. In traditional practices, identification of these diseases are based either on the visual symptoms caused by the pathogens or identification of pathogens in the laboratory (Barbedo, 2016). The visual assessment of the disease lesion is that it is subjective matter and may fail to diagnosis the disease successfully. On the contrary, pathogen identification in laboratory becomes a cumbersome process as it is time taking process for pathogen culturing which may fail to provide results in appropriate time (Barbedo, 2016). Moreover, both of the above mentioned procedures require professionals along with paper, we have considered the images of three common rice plant
diseases: Rice Blast (RB), Bacterial Leaf Blight (BLB) and Sheath Blight (SB) along with the healthy (HL) images.

Rice plant disease identification and classification are dependent on the symptoms and signs produced by the pathogens. Many a time, the identification of disease on the basis of symptoms becomes very difficult. Therefore, identification based on digital images has been increasingly growing (Barbedo, 2013). Multispectral and hyperspectral images provide more information, but they are more expensive for farmers. While the conventional cameras and in-built cameras in mobile phones are easily available with almost all farmers with affordable cost to capture images. This has prompted the researchers in developing systems based on RGB

rich experienced experts to identify the diseases. These limitations have encouraged the researchers to explore automatic methods that detect and classify plant diseases in a simple and reliable way with high accuracy. In addition, it will help the farmers to select the correct pesticides. Along this line, image based plant disease identification and classification models have been developed in literature for various plants such as (Liu *et al.*, 2009; Phadikar *et al.*,2013; Joshi *et al.*, 2016; Jia *et al.*, 2013; Hu *et al.*, 2016; Cao *et al.*, 2012). Among different crops, rice is the major crop in Asian country (Liu *et al.*, 2010) including India (Shah et al., 2016). In this paper, we have focused specifically on rice plant disease identification and classification.

According to statistics, 10-15% of rice production in Asia is destroyed because of rice plant disease (Gianessi *et al.,* 2014).
The fungus and bacteria are believed to be the main reason for rice plant diseases. There are various rice plant diseases. In this

color images *i.e.* in the visible range. Hence, we have used RGB color images in this study as well.

In this new era of science and technology, many computer-aided diagnosis (CAD) systems has been developed for agricultural sciences along with plant disease recognition CAD systems (Hu *et al.*, 2016; Baldi *et al.*, 2017; Chaki *et al.*, 2015). Among different methods, traditional machine learning techniques is one; which have been used in literature for rice plant disease classification. In traditional approaches, the characteristic features from the diseased images are extracted by applying various image processing techniques and then different classification techniques such as discriminant analysis, decision

tree, neural network and support vector machine are applied for disease recognition.

Suresha *et al.*, 2017, applied the global thresh holding methods to extract disease part of rice leaves. Further, the authors used k-nearest neighbour (k-NN) classifier to recognize rice blast and brown spot. Prajapati *et al.*, 2017, proposed centroid feeding based K-means clustering for segmentation and further removed the ineffective spots and used SVM to classify the rice disease. Sanyal *et al.*, 2008, proposed the method of extracting features of the rice diseases *i.e.* color and texture and these features were fed to multilayer perceptron (MLP) to detect different rice plant diseases. Joshi *et al.*, 2016, extracted the color and shape features of the leaf and used these features to minimum distance classifier (MDC) and k-NN Classifier to detect the diseases. In the same line, Yao *et al.*, 2009, proposed the combination of texture and shape features of the rice leaf to detect the different rice diseases using the SVM classifier. Majid *et al.*, 2013, used fuzzy entropy and probabilistic neural network classifier to identify diseases. Xiao *et al.*, 2018 explored principal component analysis (PCA) for dimensionality reduction of features and used back propagation (BP) neural network model to classify the different rice diseases.

Now days, deep learning techniques have attracted the attention of researchers due to its great performance in image classification. The advantage of deep learning technique is that it avoids extraction of complex hand-crafted features unlike traditional machine learning techniques and provides end-to-end learning. Among different deep learning techniques, the deep convolutional neural network (CNN) has been used mostly for image classification (Krizhevsky *et al.*, 2012; Lu *et al.*, 2017). The CNN model provides a relationship between layers and spatial information of the image and hence it is convenient for the classification of image (Arel *et al.*, 2010). Along this line, there are limited works on rice plant disease classification using CNN. Lu *et al.*, 2017, investigated the ability of deep CNN technique for classification of different rice diseases. A total of 500 images belonging to 10 categories have been considered and used CNN model with three convolution layers, three stochastic pooling layers and softmax layer at the end. The classification accuracy of 95.48% has been reported. Rajmohan *et al.*, 2018 have explored the deep CNN for de-noising images and used SVM for rice disease classification using shape and color features. A total of 200 images belonging to seven categories have been considered. They reported a classification accuracy of 87.50%. However, CNN requires massive training data for proper training and collection of rice diseased images is a challenging task. This limitation can be overcome by the application of transfer learning. The transfer learning technique uses previously trained networks on large dataset to update the weights for current small dataset (Bengio, 2012). In this paper, we have used AlexNet (Krizhevsky *et al.*, 2012) which is a deep CNN model pre-trained on large ImageNet dataset (Deng *et al.*, 2009). To the best of our knowledge, this is the first paper which explores the application of transfer learning technique for rice plant disease classification.

2. 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), natural language processing (Young *et al.*, 2018), emotion recognition (Mohammadpour *et al.*, 2017), recommendation system (Zhang *et al.*, 2017) etc. 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. Otherwise, the performance of CNN is not encouraging on small datasets because of over fitting (Hnoohom *et al.*, 2018). Transfer learning is a technique, where the initialization of CNN weights occurs from pre-trained network (Oquab *et al.*, 2014; Hu *et al.*, 2015; Ng *et al.*, 2015; Hoo-Chang *et al.*, 2016). It has been observed that the performance of transfer learning is better as compared to training the network from scratch on the small dataset. We have used AlexNet (Krizhevsky *et al.*, 2012) which is a deep CNN model pre-trained on large ImageNet dataset (Deng et. al, 2009). ImageNet dataset contains 1.2 million images of 1000 classes and AlexNet consists of five convolutional layers, three pooling layers and two fully-connected layers as shown in Figure 2. The first layer of any CNN model defines the input dimensions. The AlexNet CNN model used in this paper requires input dimension to be 227x227x3. Hence, all the input images of rice plant diseases have been resized to this dimension. The final layer of any CNN model is the classification layer. However, we have used AlexNet CNN model as a feature extractor here and not for classification task. Therefore, we have removed the last layer of AlexNet model. The extracted image features from previous deep layers are fed to Support Vector Machine (SVM) (Wang *et al.*, 2005) classifier for training.
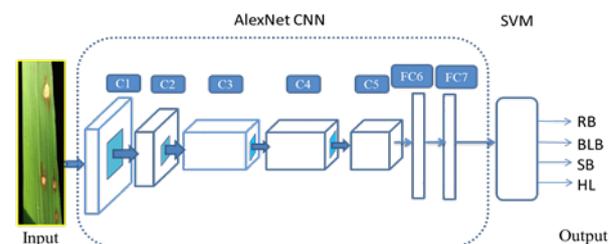

Figure 2. AlexNet Architecture

3. Results and Discussion

3.1 Data Description

The image samples used in this paper were collected from rice field of Indira Gandhi Agricultural University, Raipur, Chhattisgarh, India. These images were collected between 6.30am to 9.30 am and 4.00 pm to 5.30 pm. The image acquired during this period gives more clarity than other sunny time of the day. The images are acquired using Canon Powershot SX530HS digital camera, Gionee and LYF mobile set. The image background is prepared to be black to reduce the background complexity as a result to reduce the computation cost. There are 619 images belong to four classes: (i) Rice Blast (RB); (ii) Bacterial Leaf Blight (BLB); (ii) Sheath Blight (SB); and (iv) Healthy Leaves (HL). This is the first time when such a large rice disease dataset has been collected from Indian agriculture field. Table 1 shows the description of considered rice diseases with sample images of each class and the details are given below:

A. **Rice Blast (RB):** RB disease is incited by Magnaporthe oryzae (Couch *et al.*, 2002). The symptoms of this disease are grayish green circular and a spot with dark green border in the leaves (Padhikar *et al.*, 2013). The lesions are elliptical or spindle shaped. It is one of the most devastating diseases of rice in different countries of the world (Kumar *et al.*, 2016). A total of 88 images of RB disease has been collected for this study. An example of infected leaf with RB disease is shown in Table 1.

B. **Bacterial Leaf Blight (BLB):** BLB is incited by Xanthomonas oryzae. The symptoms of this disease contain a lesion that generally starts from the tip of the leaf and spread towards the base of the leaf with several inches (Rice Doctor, 2003; OU, 1985). BLB is one of the destructive diseases that affect considerable loss in the rice production (Patil *et al.*, 2017). A total of 240 images of BLB disease have been collected for this study. An example of infected leaf with BLB disease is shown in Table 1.

C. **Sheath Blight (SB):** SB disease is incited Rhizoctonia solani (Nandakumar *et al.*, 2001). The symptoms of this disease start from lower sheath of the plant and then spread towards the upper sheath and leaves. It communicates from plant to plant in the field (Zhou *et al.*, 2015). SB has become the most economically destructive disease in major rice growing countries in the world (Zhou *et al.*, 2015). A total of 100 images of SB disease has been collected for this study. An example of infected leaf with SB disease is shown in Table 1.

Rice Disease Class Name	Total Number of Images	Sample Image
RB	88	
BLB	240	
SB	100	
HL	191	
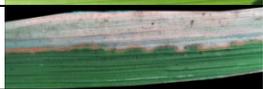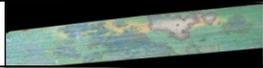
Table 1. Details of Four Rice Diseases in the Dataset with Sample Images from Each Class

3.2 Experiment Setup and Performance Analysis

This paper investigates the use of transfer learning of deep CNN for rice disease classification. We have used AlexNet for extraction of features and SVM for classification. The MatConvNet toolbox (Vedaldi *et al.*) is used for implementation of AlexNet CNN model. The considered dataset has been randomly partitioned into training and testing set. To analysis the effect of partitioning, three sets of training-testing partition has been done: (i) 60%-40%; (ii) 70%-30%; and (iii) 80%-20%. The experiment was carried out for 10 trails (10 times) by choosing samples randomly for each partition from whole dataset. Further, the classification accuracy was calculated by averaging the accuracy for 10 trails. The results are shown in Table 2. All of our experiments were performed on Intel Core i5-6200U CPU @2.40 GHz with 8GB RAM and NVIDIA GeForce 940M GPU. The classification accuracy of 91.37% has been achieved with training-testing partition of 80%-20%.

Training-Testing Division (%)	Classification Accuracy (%)
60-40	89.45
70-30	90.39
80-20	91.37

Table 2. Classification Accuracy with Different Training-Testing Partition.

4. Conclusion

In the Indian scenario, a limited works has been done on automatic classification of rice plant diseases. In this paper, transfer learning of deep CNN was explored first time to classify rice plant diseases. Moreover, the experiments were conducted by partitioning the whole dataset into different ratio of training-testing set. The proposed model is able to classify rice diseases with classification accuracy of 91.37% for 80%-20% training-testing partition. However, benchmarking of proposed model with literature is not appropriate because of unavailability of standard labelled rice disease images. The performance of proposed model can be further improved with large dataset of rice diseased images.

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