Rice Leaf Diseases Classification Using CNN With Transfer Learning

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***Abstract* — Rice is one of the major cultivated crops in India which is affected by various diseases at various stages of its cultivation. It is very difficult for the farmers to manually identify these diseases accurately with their limited knowledge. Recent developments in Deep Learning show that Automatic Image Recognition systems using Convolutional Neural Network (CNN) models can be very beneficial in such problems. Since rice leaf disease image dataset is not easily available, we have created our own dataset which is small in size hence we have used Transfer Learning to develop our deep learning model. The proposed CNN architecture is based on VGG-16 and is trained and tested on the dataset collected from rice fields and the internet. The accuracy of the proposed model is 92.46%.**

***Index Terms* —Convolutional Neural Network, Deep Learning, Fine-tuning, Rice leaf diseases, Transfer learning.**

I. INTRODUCTION

Rice is the staple source of food in India as well as across the world. It is attacked by a variety of diseases in various stages of its cultivation. Therefore, early detection and remedy of such diseases are beneficial to ensure high quantity and best quality but this is very difficult due to the huge expanse of land under individual farmers and the huge variety of diseases as well as the occurrence of more than one disease in the same plant. Agricultural expert knowledge is not accessible in remote areas and it is a time taking process. Therefore, the Automated Systems are required. To aid the plight of the farmers and provide improved accuracy of plant disease detection, research work using various machine learning algorithms including Support Vector Machine(SVM)[1]–[3], Artificial Neural Networks[4] have been done.

However, the accuracy of such systems is highly dependent on feature selection techniques. Recent researches on convolutional neural networks have provided great breakthrough in image based recognition by eliminating the need for image preprocessing as well as providing inbuilt feature selection. Another challenge is that it is very difficult to obtain large sized dataset for such problems. For cases where size of the dataset is relatively small, it is more preferable to use a model which is pretrained on a large dataset. This is called Transfer Learning and it can be utilized to create a model that can be used as a fixed feature extractor removing the last fully connected layer or by fine-tuning the last few layers that will work more specific to the concerned dataset.

Nowadays, mobile phones are accessible to everyone and so we have come up with the idea of an automated system where the farmers can upload the diseased leaf image and post it to our server where the neural network will be used to identify the disease and the disease classification along with the remedy can be sent back to the farmer. In this work we have proposed the architecture for the disease classification part of the automated system. Inspired by the work in [5]–[8] and [14] on convolutional neural networks, in this work, we have developed the deep learning approach on our rice disease dataset that we have collected over past several months. We have used the pre-trained VGG-16 model (Trained on the huge ImageNet data) and using Transfer Learning we have fine-tuned the fully connected layers so that we can accommodate our own dataset and at the end we have done some error analysis and tried to explain the reasons for the error.

II. RELATED WORK

A lot of research has been done using traditional classifiers but the results are dependent on the feature selection techniques and image preprocessing is a major step [9]. Therefore CNN has attracted multiple researchers to take advantage of high recognition accuracy.

A. Plant Disease Detection using CNN

In paper [10], CNN is trained using 87,848 images, with 25 plant varieties having 58 classes which includes healthy plants. Different types of models were trained, of which the best model provided 99.53% accuracy in correct identification. In [11], CNN was used to train 54306 images of 14 crop types, with 26 diseases and healthy leaves. The success rate of 99.35% reduced to 31.4% when tested on another dataset collected from real life scenario. In [12] the problem of disease severity and the reason for it being more challenging than disease classification is discussed. The high intra-class similarity among the various images belonging to same class makes its identification even more difficult.

B. Rice Disease Detection using CNN

Convolutional neural network classifier is used on a dataset of 227 images of snail-bitten, diseased and healthy rice plants in [8].The classifier is transfer learning based using AlexNet. Training the above architecture an accuracy of 91.23% is achieved but it can only predict whether plant is diseased or not. In [13], the authors collected 500 images of 10 different rice diseases of leaf and stem. They developed an architecture inspired by Le-Net and AlexNet and achieved 95.48% on the test set. Since the data is very less they used various preprocessing step like image resizing to 512*512, normalization, PCA and whitening. They used stochastic pooling instead of max pooling and stated that it prevents over fitting.

III. Rice Disease Types And Dataset Description

The rice image dataset has been collected over the past few months mostly from the cultivation fields of Madarat village (District: South 24 Parganas) in Baruipur, Dharinda village (District: Purba Medinipur) in Tamluk and Basirhat (District North 24 Parganas), belonging to the state of West Bengal, India as well as from the Internet. The images were taken using Motorola E4 Plus and Redmi 5A mobile camera. The symptoms and knowledge about the diseases have been collected from the International Rice Research Institute (IRRI) Rice Knowledge Bank website. There were limited number of images for training our system, so we have used a few data augmentation techniques with the help of Keras Documentation to get a considerable number of images. The dataset consists of 1649 images of diseased leaves of rice consisting of three most common diseases namely Rice Leaf Blast, Rice Leaf Blight, and Brown Spot. There are 507 images of Healthy leaves. We have not done any step to remove noise from the raw data. There were a number of difficulties faced while collecting the data like poor illumination and more than one disease in the same plant. We have tried to overcome them by using image preprocessing steps like resizing and zooming. The number of images that could be collected from the fields are very less for training CNN so we have used a number of augmentation techniques like zoom, horizontal and vertical shift, and rotation which are discussed in the Implementation Section later. The below sections describe the classes of Rice Leaf diseases on which we have worked.

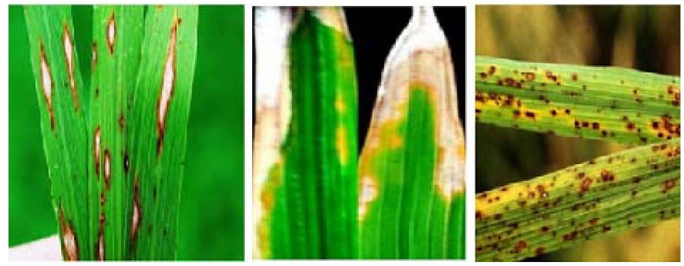

Fig. 1. (a)-(c) From Left to right. (a) Leaf Blast (b) Leaf Blight and (c) Brown Spot

A. Leaf Blast

It is a fungal disease caused by Magnaporthe oryzae. The initial symptoms are white to grey-green spots which are elliptical or spindle-shaped with dark red to brownish borders. Some have diamond shape with broad centers and pointed ends. In the Figure 1 (a) the spindle shaped lesions with white spots and dark brown border can be seen.

B. Leaf Blight

It is a bacterial disease caused by Xanthomonas oryzae. The infected leaves turn greyish green and roll up followed by yellowing and then it turns straw colored and finally dies after wilting. The lesions have wavy margins and progress towards the base. On young lesions bacterial ooze resembling morning dew drop can be observed. Figure 1 (b) shows leaves affected by Leaf Blight.

C. Brown Spot

It is a fungal disease. The infected leaves have numerous big spots on the leaves which can kill the whole leaf. At the initial stage, small, circular, dark brown to purple-brown lesions can be observed in the leaves. Fully developed lesions are circular to oval with light brown to gray center, surrounded by a reddish brown margin caused by the toxin produced by the fungi. Shown in Fig 1 (c) are the small dark brown lesions of the Brown Spot affected leaves.

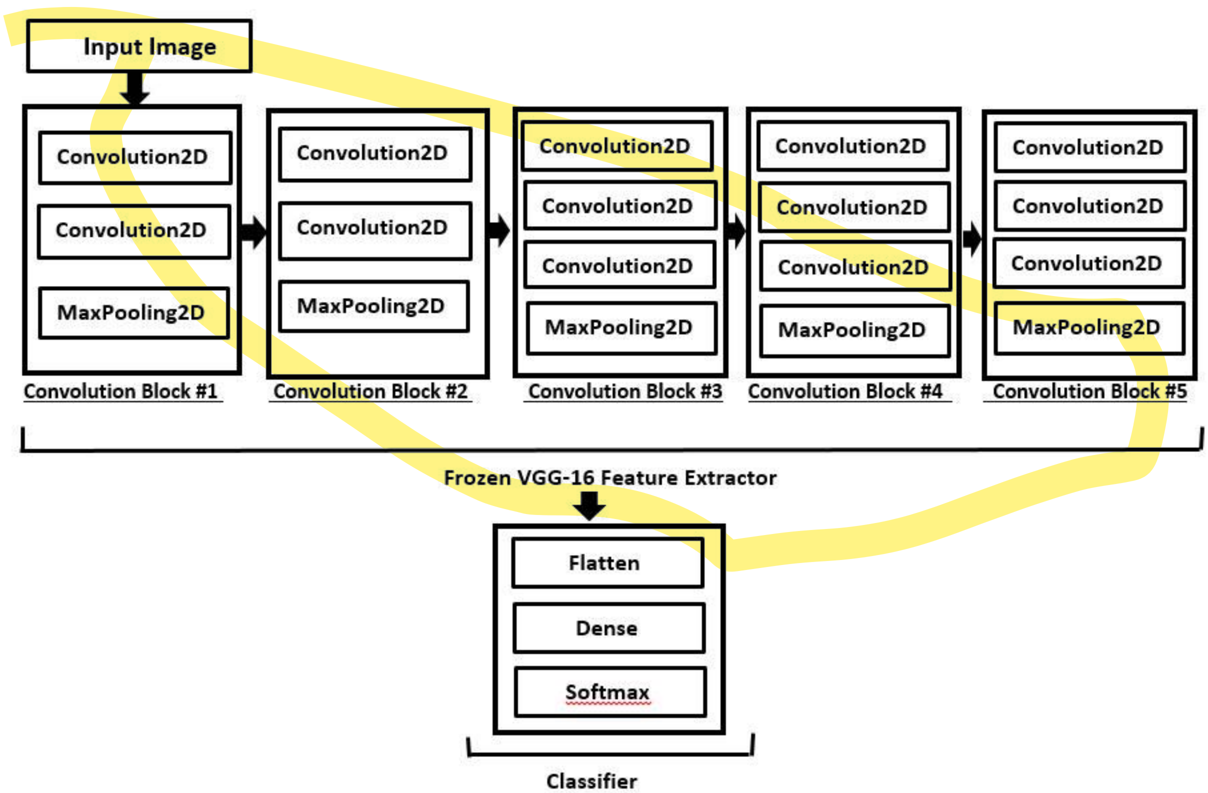

Fig. 2. VGG-16 Architecture fine–tuned with the last two layers with 128 Dense FC Layer and 4 Dense Softmax Layer as the output

IV. METHODOLOGY

Convolutional neural networks (CNNs) are multi-layered networks whose architecture determines the performance of the network. It consists of three parts namely, convolution layer, pooling layer and fully connected layer. The first two together forms the feature extractor and the third layer acts as a classifier. The pooling layer reduces the dimensionality of the features extracted by the convolutional layer. The fully connected layer followed by softmax uses the feature extracted to classify the images. The convolution layer takes input image and extracts the features using a set of learnable filters. The dot product of each filter with the raw image pixel in sliding window manner provides the 2-D feature map. The rectified linear unit (ReLU) is one of the most popular activation function. The max pooling layer is a sub-sampling layer that reduces the size of feature map. Then the fully connected layer provides a full connection to each of the generated feature map. Softmax assigns decimal probabilities to each class in a multi-class problem to classify the images.

As shown in Figure 2, VGG-16 architecture is a deep convolutional network with weights pre-trained on the ImageNet Database which contains 3.2 million clearly annotated images of 5247 categories [14]. Thus knowledge in form of weights, architecture and features learnt on one domain can be transferred to another domain by Transfer Learning on such pre-trained models. The features are generic in the early layers and more dataset-specific in the later layers. In our model, the initial 5 blocks of convolution layers are frozen for behaving as a feature extractor which is the advantage of CNN over traditional techniques and the last dense layer of size 128 followed by softmax layer of size 4(since number of classes is 4) is used for classification. The pre-trained VGG-16 model is again trained on our dataset and fine-tuned to get the classifications. Keeping in mind the size of new dataset and its familiarity with the original dataset, there can be 4 approaches of transfer learning:

- New dataset is small and familiar to original dataset..
- New dataset is large and familiar to the original dataset.
- New dataset is small but dissimilar to original dataset.
- New dataset is large and dissimilar to original dataset.

Since we have small dataset and it is different from the ImageNet dataset, our model falls in the third scenario so we

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have fixed the layers of the VGGNet to use it as feature extractor until the last fully connected layers which we have fine-tuned according to the number of classes in our dataset. In Figure 2 the architecture of proposed model is depicted.

We have also developed a CNN model without transfer learning with 4 Convolution layers each of which is followed by ReLU, Maxpooling and dropout layer followed by 2 Fully Connected Layer and SoftMax. But the performance was not as good as the above mentioned model. The comparison of the same has been mentioned in the result section.

V. Implementation

A. Experimental Setup

The experiment was performed on a Windows 10 PC equipped with GPU card P4000, 64-bit Operating System. The CNN-based model was implemented in the Keras 2.2.4 deep learning framework with TensorFlow 1.13.1 backend and python 3.7.2.

B. Image Acquisition

The images are collected from the cultivation fields as well as from internet. As discussed in the dataset description, data consists of 4 classes namely Leaf Blast, Leaf Blight, Brown Spot and healthy plant images.

C. Image Preprocessing and Augmentation

The images collected are resized to 224*224 pixel and a number of augmentation techniques like zoom, rotation, horizontal and vertical shift are applied using ImageDataGenerator in Keras to generate new images.

D. CNN Model Training

The image data set is loaded for the training and testing. The class labels and the corresponding images are stored in respective arrays for training. 70 percent of data is used for training and 30 percent of data is used for testing using train_test_split function. The 70 percent data is further split and 20% of it is used for validation. The class labels are encoded as integers and then, one-hot encoding is performed on these labels making each label represented as a vector rather than an integer. Next, the VGG-16 model is loaded from keras and the last fully connected layers are removed. The remaining layers are made non-trainable. We have flattened the output of feature extractor part, followed by fully connected layer and output layer with softmax. Then we have compiled our model using the Adam optimizer with categorical_crossentropy as the loss function for classification.We have stopped at 25 epochs since after this the results were stable. Figure 3 shows the steps we have executed for the classification process.

E. Justification For the Chosen Model

Transfer learning refers to the situation where what has been learned in one setting is exploited to improve generalization in another setting. Transfer learning has the benefit of decreasing the training time for a neural network model and thus is very useful since most real-world problems typically do not have millions of labeled data points to train such complex models. Usually, a lot of data is needed to train a neural network from scratch but access to that data isn't always available. With transfer learning a solid machine learning model can be built with comparatively little training data because the model is already pre-trained. Hence we have used the pre-trained VGGNet and fined tuned it to classify using our own small dataset.

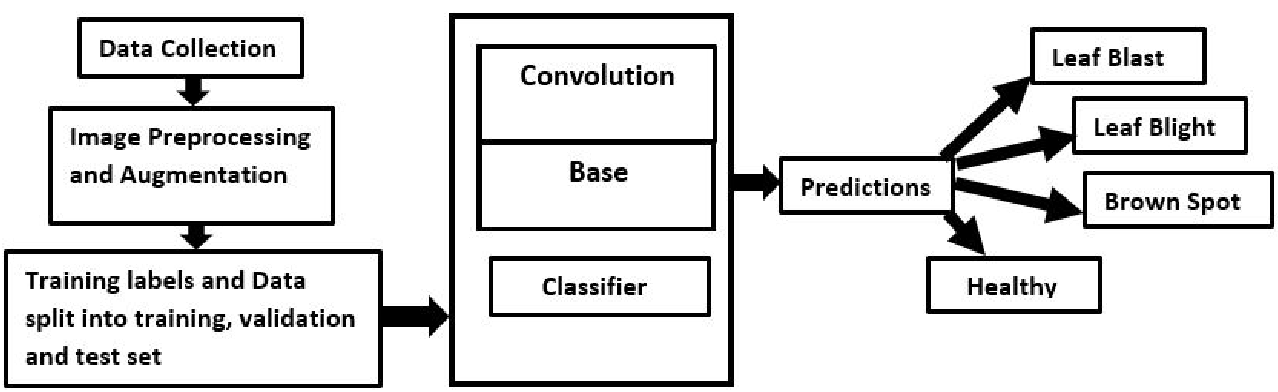

Fig. 3. Overview of the steps of the proposed model

VI. RESULTS

A. Calculations

The proposed model is executed for 25 epochs over 1509 training data followed by 647 test data and the accuracy of training set is 97% and the test accuracy of 92.4%. We have also executed the same data using the same split ratio into train, validation and test set on another CNN model without transfer learning. The batch size, number of epochs, optimizer was fine-tuned and 16, 30, rmsprop respectively along with dropout 0.4 provided the best result yet the best accuracy was 74%. The CNN model without transfer learning has 4 Convolution layers each of which is followed by ReLU, Maxpooling and dropout layer followed by 2 Fully Connected Layer and SoftMax. Table I in Figure 4 shows the comparison in accuracy of the proposed CNN model with Transfer Learning and CNN without Transfer Learning. Figure 5 illustrates the Training and validation accuracy versus the number of epochs for the CNN with Transfer Learning.

TABLE I. PERFORMANCE OF COMPARISON OF CNN WITH AND WITHOUT TRANSFER LEARNING

Model	*Test Accuracy*
CNN With Transfer Learning	**92.46%**
CNN Without Transfer Learning	74%

Fig. 4. Performance comparison of CNN model with and without Transfer Learning

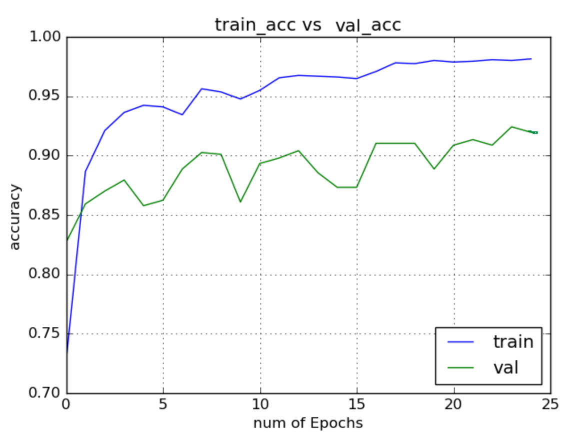

Fig. 5. Plot of Accuracy versus Epochs

B. Error Analysis

The Figure 6 (a)-(f) illustrates images that are misclassified by the proposed CNN model. The misclassifications are described in details in the below section for each of the disease type.

Rice Blast: Image (a) belongs to Rice Blast but (a) is classified as Brown Spot as the image is blurred. The reason could be the presence of small brown spots in the same rice leaf.

Leaf Blight: Images (d) and (e) are classified as Healthy but they belong to Blight category. The reason could be poor illumination and blurring of image.

Healthy: Image (f) is healthy but it is classified as Brown Spot probably because the image is blurred and contrast is poor.

Brown Spot: Images (b) and (c) belong to Brown Spot but are classified as Blast. One reason could be the presence of small blast lesions on the leaf. In (d) the brown spot lesions resemble the blast lesion.

Fig. 6. From left to right (a)-(f) Rice disease images that are misclassified by the model. (a) Rice Blast disease (b) and (c) Brown Spot (d) and (e) Leaf Blight (f) Healthy

VII. CONCLUSION

In this paper we have proposed a deep learning architecture with training on 1509 images of rice leaves and testing on different 647 images and that correctly classifies 92.46% of the test images. Transfer Learning using fine-tuning the predefined VGGNet has greatly improved the performance of the model which otherwise did not produce satisfactory results on such small dataset. The number of epochs used was stopped at 25 because we had received a cut point after which the accuracy was not improving and the loss was not decreasing on both training and validation data.

In future work, we would like to collect more images from agricultural fields and Agricultural Research institutes so that we can improve the accuracy further. We would like to add cross-validation process in future in order to validate our

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results. We would also like to use better deep learning models and other state-of the art works and compare it with the results obtained. The developed model can be used in future to detect other plant leaf diseases, which are important crops in India.

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