

PREDICTING THE RICE LEAF DISEASES USING NEURAL NETWORKS

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ABSTRACT

The rice leaf suffers from several bacterial, viral, or fungal diseases and these diseases reduce rice production significantly. To sustain rice demand for a vast population globally, the recognition of rice leaf diseases is crucially important. However, recognition of rice leaf disease is limited to the image backgrounds and image capture conditions. The convolutional neural network (CNN) based model is a hot research topic in the field of rice leaf disease recognition. But the existing CNN-based models drop in recognition rates severely on independent dataset and are limited to the learning of large scale network parameters. In this paper, we propose a novel CNN-based model to recognize rice leaf diseases by reducing the network parameters. Using a novel dataset of 4199 rice leaf disease images, a number of CNN-based models are trained to identify five common rice leaf diseases. The proposed model achieves the highest training accuracy of 99.78% and validation accuracy of 97.35%. The effectiveness of the proposed model is evaluated on a set of independent rice leaf disease images with the best accuracy of 97.82% with an area under curve (AUC) of 0.99. Besides that, binary classification experiments have been carried out and our proposed model achieves recognition rates of 97%, 96%, 96%, 93%, and 95% for Blast, Brownspot, Bacterial Leaf Blight, Sheath Blight and Tungro, respectively. These results demonstrate the effectiveness and superiority of our approach in comparison to the state-of-the-art CNN-based rice leaf disease recognition models.

INTRODUCTION

The detection of rice leaf diseases is quite a hard task for farmers and experts with naked eyes. Identifying the abnormality in plants with similar symptoms in different disorders is highly challenging. Moreover, these challenges are aggravated by the different backgrounds of images and image capturing conditions. Recent progress in computer vision and deep learning has made it possible to identify the deep features of numerous diseases irrespective of variety in image backgrounds and image capture conditions.

OBJECTIVE

The main objective is to identify the plant diseases using image processing. It also, after identification of the disease, suggests the name of pesticide to be used.

The CNN model is designed to suit both healthy and sick leaves; photos are used to train the model, and the output is determined by the input leaf.

Thus the main objectives are:

To design such system that can detect crop disease and pest accurately.

Create database of insecticides for respective pest and disease.

To provide remedy for the disease that is detected.

EXISTING SYSTEM

There exists many works on the detection and recognition of rice leaf diseases and pests using convolutional neural network (CNN). Moreover, plant leaf diseases have been identified in various works using state-of-the-art CNN architectures such as VGG16, GoogleNet, CaffeNet, ResNet50, ResNet101, ResNet152, Inception V4, ResNet34, Student-teacher CNN, AlexNet and DenseNet. Recently, a method for recognizing rice leaf diseases using two-stage custom CNN has been proposed on a dataset from Bangladesh. Most of the existing CNN-based plant leaf disease recognition models is limited to image capturing conditions and backgrounds. It restricts the disease recognition into the known dataset. For example, the works proposed in are limited to plain backgrounds. Moreover, tuning better network parameters of the model for recognizing plant leaf diseases still depends on the existing state-of-the-art CNN architectures. All of the architectures achieve better recognition rates, but researchers do not consider the effectiveness of large scale parameters in memory restricted devices such as mobile phones. This is particularly important for farmers living in the rural areas.

Disadvantages

1. The manual division process of symptom classes, which is laborious and may cause misclassifications.
2. CNN-based models are sometimes restricted to generalization whenever new data is included into dataset its accuracy falls down drastically.

PROPOSED SYSTEM

The data scientists at Big Mart have collected 2013 sales data for 1559 products across 10 stores in different cities. Also, certain attributes of each product and store have been defined. The aim is to build a predictive model and find out the sales of each product at a particular store. Using this model, Big Mart will try to understand the properties of products and stores which play a key role in increasing sales.

Advantages:

This is an easily scalable model to provide detailed information and accurate predictions for sales volume for different types of products as there is a lot of data out there.

It is the percentage of display space in a store given to that particular item. Looking at the average visibility of items given in each store type and outlet.

Goals

Building the regression models: linear and decision tree. Predicting the sales, cross validating the scores, calculating the R^2 .

Classifying the training data with a decision tree and a random forest and calculating the accuracy score and the R^2 .

We propose a novel CNN-based model by using a number of convolution and pooling layers followed by a dense layer and a softmax layer for recognizing rice leaf diseases. Our custom CNN-based model is designed to reduce the number of network parameters. We have prepared a novel dataset containing diverse image backgrounds and image capturing conditions, and augmented it to improve the generalization of our model. To verify the effectiveness and superiority of our model, it is tested on an independent set of rice leaf disease images.

The entire process is partitioned into different stages: beginning with the preparation of a novel training dataset, development of a novel CNN model, deep feature extraction for training the model and finally, classification of the rice leaf diseases.

Dataset

A total of 323 original RGB colored images of five common rice leaf diseases, including Blast, Bacterial leaf blight, Brownspot, Sheath blight, and Tungro are

Table 1. Dataset descriptions of rice leaf disease recognition

Disease Class	#Org. Images	Augmentation Techniques					# Aug. Images
		Rotations	Flipping	Shifting	Scaling	Zooming	
Blast	63	252	126	126	189	63	756
Bacterial Leaf Blight	70	280	140	140	210	70	840
Brownspot	70	280	140	140	210	70	840
Sheath blight	57	228	114	114	171	57	684
Tungro	63	252	126	126	189	63	756
Total	323	1292	646	646	969	323	3876

CNN has been proposed on a dataset from Bangladesh. Most of the existing CNN-based plant leaf disease recognition models is limited to image capturing conditions and backgrounds. It restricts the disease recognition into the known dataset.

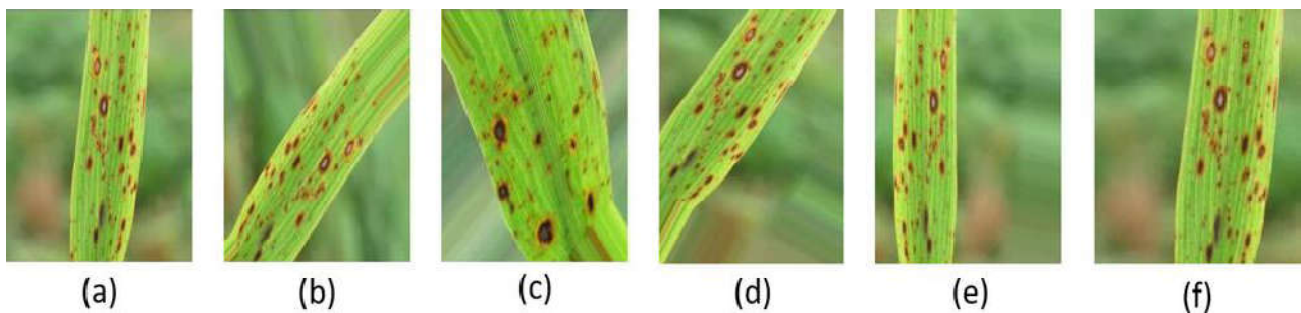
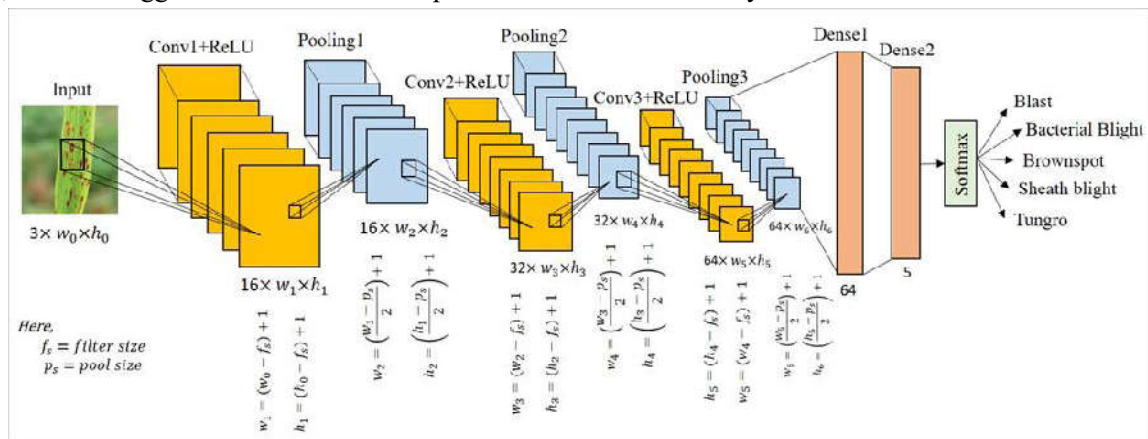


Fig.2. Augmented images of rice leaf diseases: (a) original Brownspot image (b) rotated Brown spot image (c) zoomed Brown spot image (d) shifted Brown spot image (e) flipped Brown spot image and (f) scaled Brown spot image collected from the International Rice Research Institute (IRRI) and Bangladesh Rice Research Institute (BRRI). A sample of each class of rice leaf disease is shown in Fig. 1. In all our experiments conducted in this paper, different sizes of images are used to evaluate the performances of recognizing rice leaf diseases. The sizes of the rice leaf disease images are 128×128 , 256×256 and 512×512 . To tackle the challenge of identifying the best features in different backgrounds.

SYSTEM DESIGN

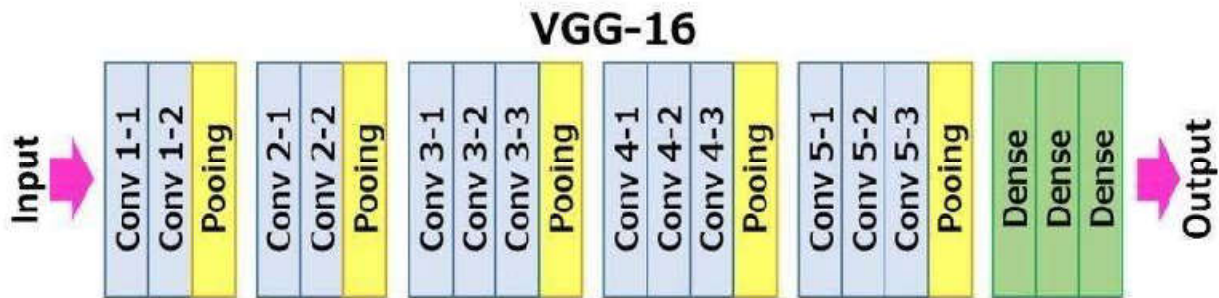
CNN BASED-MODEL

Fewer amount of training data is a major bottleneck for developing an effective deep learning models including CNN-based models for rice leaf disease recognition . To ensure the robustness of the neural network based model, we need bigger amount of data to expand the functional diversity of the model.



VGG-16

A convolutional neural network is also known as a ConvNet, which is a kind of artificial neural network. A convolutional neural network has an input layer, an output layer, and various hidden layers. VGG16 is a type of CNN (Convolutional Neural Network) that is considered to be one of the best computer vision models to date. The creators of this model evaluated the networks and increased the depth using an architecture with very small (3 × 3) convolution filters, which showed a significant improvement on the prior-art configurations. They pushed the depth to 16–19 weight layers making it approx -138 trainable parameters.



The 16 in VGG16 refers to 16 layers that have weights. In VGG16 there are thirteen convolutional layers, five Max Pooling layers, and three Dense layers which sum up to 21 layers but it has only sixteen weight layers i.e., learnable parameters layer.

VGG16 takes input tensor size as 224, 244 with 3 RGB channel

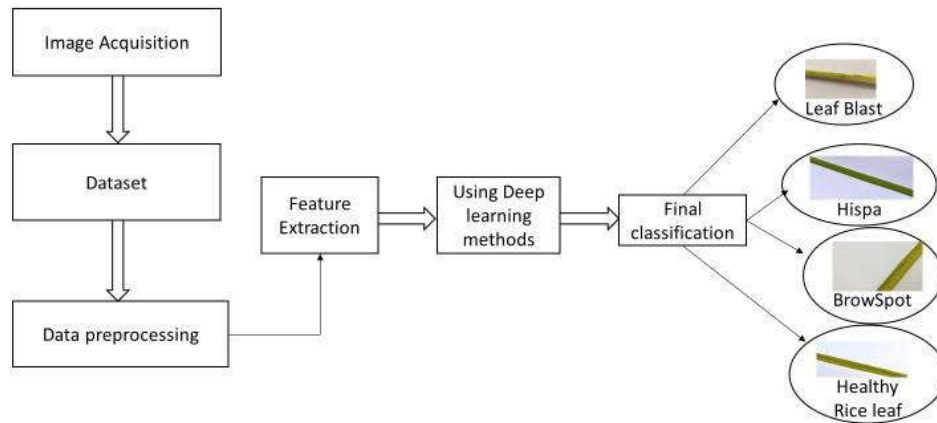
Most unique thing about VGG16 is that instead of having a large number of hyper-parameters they focused on having convolution layers of 3x3 filter with stride 1 and always used the same padding and maxpool layer of 2x2 filter of stride 2.

IMPLEMENTATION

PROCESS

Data collection: : Gather a dataset of labeled images that include various types of healthy rice leaves as well as leaves affected by different diseases. The dataset should cover a wide range of disease symptoms and severity levels.

Data preprocessing: Preprocess the images to ensure consistency and improve the training process. Common preprocessing steps include resizing the images to a consistent size, normalizing pixel values, and augmenting the dataset with techniques like rotation, flipping, or adding noise to increase its diversity.



VGG-16:

A convolutional neural network is also known as a ConvNet, which is a kind of artificial neural network. A convolutional neural network has an input layer, an output layer, and various hidden layers. VGG16 is a type of CNN (Convolutional Neural Network) that is considered to be one of the best computer vision models to date. The creators of this model evaluated the networks and increased the depth using an architecture with very small (3×3) convolution filters, which showed a significant improvement on the prior-art configurations. They pushed the depth to 16–19 weight layers making it approx -138 trainable parameters.

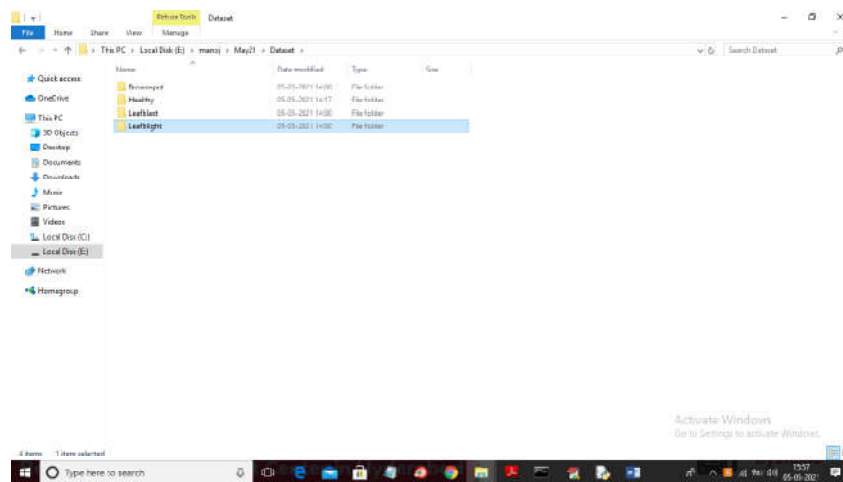
Predicting on new data : Once the model is trained and evaluated, it can be used to predict the diseases of new, unseen rice leaf images. Preprocess the new images in the same way as the training images, then feed them through the trained CNN model to obtain predictions.

Compiling the CNN

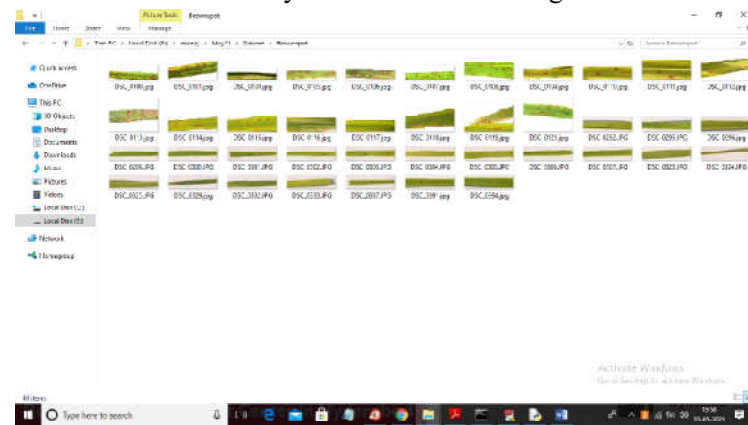
Now we are going to compile the CNN, which means that we are going to connect it to an optimizer, a loss function, and some metrics. As we are doing once again a binary classification, so we are going to compile our CNN exactly the same way as we compiled our ANN model because indeed, we are going to choose once again adam optimizer to perform stochastic gradient descent to update the weights in order to reduce the loss error between the predictions and target. Then we will choose the same loss, i.e., the binary_crossentropy loss because we are doing exactly the same task binary classification. And then same for the metrics, we will choose accuracy metrics because it is the most relevant way to measure the performance of the classification model, which is exactly our case of CNN.

RESULTS

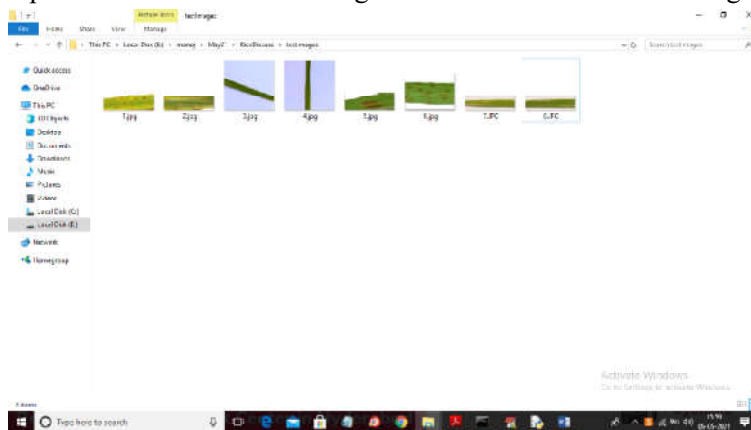
Below is the dataset screen shots used to train VGG16 model.



To train VGG 16 we are using rice dataset which contains 4 different types of images or disease and you can go inside any folder to view its images



In above screen you can see images from 'Brownsport' disease. After training model we can use below test images to predict diseases and test images are available inside 'test images' folder.



Above test images can be uploaded to application to predict their disease status.

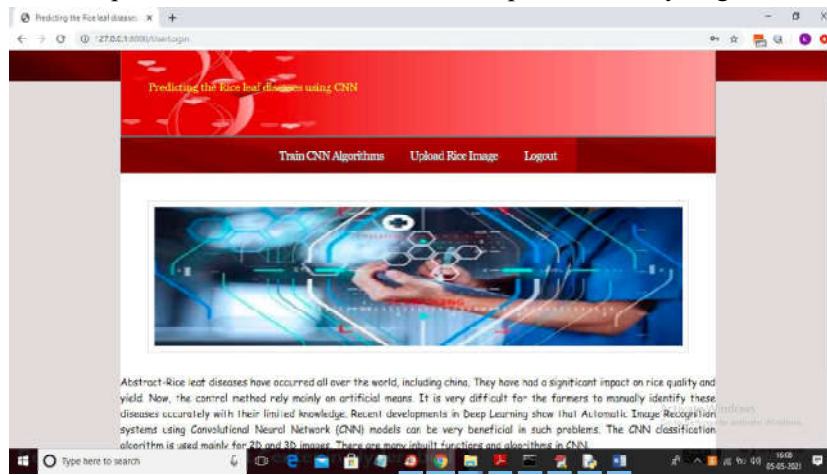
To implement this project we have designed following modules

- 1)Login: This is an online application and user need to login by using username as 'admin' and password as 'admin'.
- 2)Train CNN Algorithms: After login user can use this model to train normal CNN and VGG16 CNN with above rice disease dataset and after training model we will calculate both models accuracy on test data.

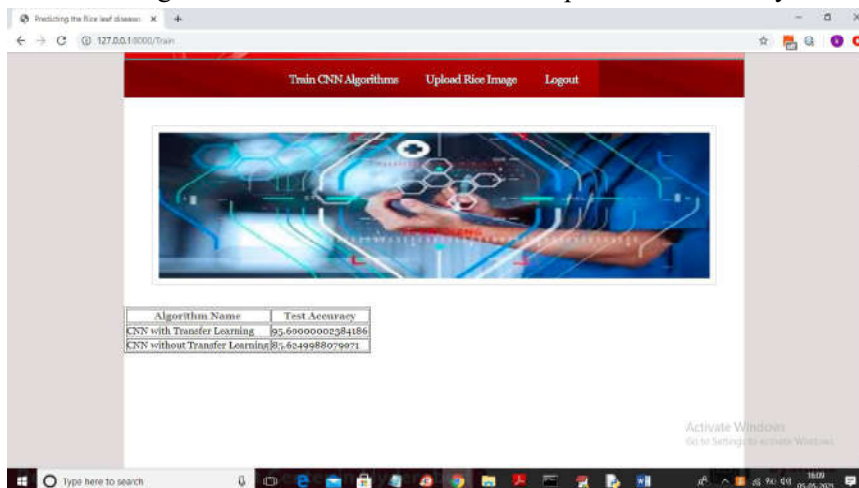
3) Upload Rice Image: using this module we will allow user to upload rice leaf images and the application will predict condition of leaf as healthy or effected with disease.

To run project install python 3.7 and tensorflow package 1.14.0 and then install Django==2.1.7

After installation run below command from 'RiceDisease' folder Python manage.py runserver Then open browser and enter URL as http://127.0.0.1:8000/index.html and press enter key to get below screen



In above screen click on 'Train CNN Algorithms' link to train both VGG16 and normal CNN without transfer learning on rice dataset and then calculate prediction accuracy.



In above screen CNN with transfer learning VGG16 got 95% accuracy and without transfer learning got 85% accuracy so VGG16 is giving better result. In below console you can see layer details of VGG 16 and Normal CNN.

```

backends.py:422: The name tf.global_variables is deprecated. Please use tf.compat.v1.global_variables instead.

Model: "sequential_1"
-----
Layer (type)                Output Shape              Param #
-----
conv2d_1 (Conv2D)           (None, 62, 62, 32)       896
max_pooling2d_1 (MaxPooling2D) (None, 31, 31, 32)       0
conv2d_2 (Conv2D)           (None, 29, 29, 32)       9248
max_pooling2d_2 (MaxPooling2D) (None, 14, 14, 32)       0
Flatten_1 (Flatten)         (None, 6272)              0
dense_1 (Dense)             (None, 256)               1625984
dense_2 (Dense)             (None, 4)                 1028
-----
Total params: 1,617,060
Trainable params: 1,617,060
Non-trainable params: 0

None
CNN without transfer learning Training Accuracy = 85.6349988075071
Model: "model_1"
    
```

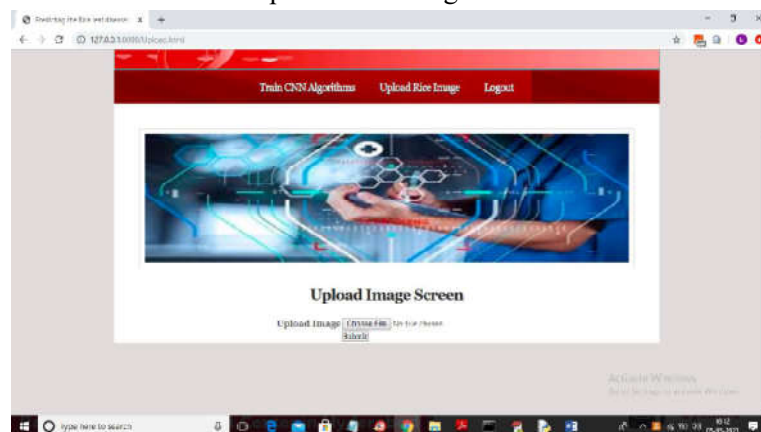
In above screen normal CNN created 4 layers and got 85% accuracy and in below screen you can see VGG16 layers.

```

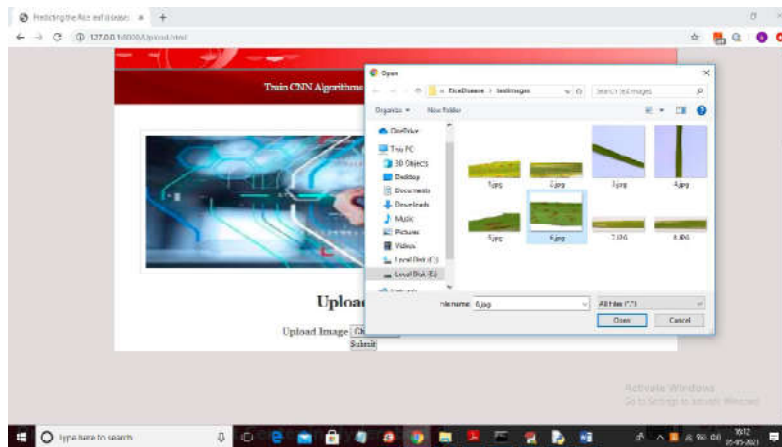
block1_pool (MaxPooling2D)   (None, 32, 32, 64)       0
block2_conv1 (Conv2D)        (None, 32, 32, 128)      73856
block2_conv2 (Conv2D)        (None, 32, 32, 128)     147584
block3_pool (MaxPooling2D)   (None, 16, 16, 128)     0
conv2d_1 (Conv2D)           (None, 14, 14, 64)       73792
max_pooling2d_1 (MaxPooling2D) (None, 7, 7, 64)        0
Flatten_1 (Flatten)         (None, 3136)              0
dense_1 (Dense)             (None, 256)               803072
dropout_1 (Dropout)         (None, 256)                0
dense_2 (Dense)             (None, 4)                 1028
-----
Total params: 1,138,052
Trainable params: 877,892
Non-trainable params: 260,160

None
VGG-CNN with transfer learning Training Accuracy = 95.60800082384186
[05/May/2021 16:09:22] "GET /Train HTTP/1.1" 200 1191
    
```

In above screen VGG16 contains so many layers and its accuracy is 95% and now in below screen click on ‘Upload Rice Image’ link.



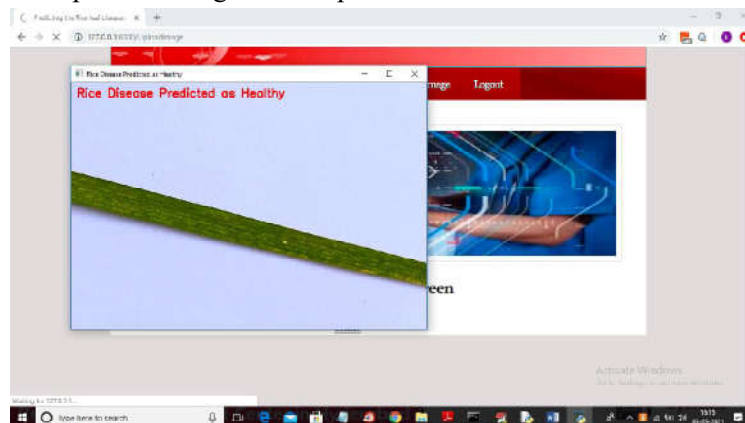
Now in above screen click on ‘Choose File’ button to upload leaf test image from ‘testImages’ folder.



In above screen selecting and uploading '6.jpg' file and then click on 'Open' button then click on 'Submit' button to get below result.



In above screen in uploaded image disease predicted as 'Leaf Blast' and now test other image.



In above screen leaf predicted as healthy and similarly you can upload other images and test them.

CONCLUSION

In Conclusion, we have proposed a custom CNN-based model that can classify five common rice leaf diseases commonly found in Bangladesh. Our model is trained to recognize the rice leaf diseases in different image backgrounds and capture conditions. Our model achieves 97.82% accuracy on independent test images. Moreover, our model is effective with respect to memory storage due to

its reduced number of network parameters. Despite having better accuracy, we aim to improve the reliability and robustness of our model on different datasets from other regions. We will work on classifying rice leaf disease images when complex backgrounds are present and have varied illumination condition. Also, as classification accuracy is an incomplete description of most real-world tasks, we will concentrate on interpretable CNN-based models to present features in understandable terms for which diseases will be classified. By implementing CNN algorithms we got 95.67 accuracy in the leaf disease detection. Due to the specialty of Black rot and Leaf blight with small and dense diseased spots, a variety of backbone networks, such as AlexNet, VGGNet, and ResNet, were experimented with and analyzed, and ResNet has been found to be the most suitable backbone network. Hence, data augmentation technology is used to simulate real-life interference, which plays an important role in the model training stage. As more images are generated via data augmentation, the model can learn as many different patterns as possible during the training, avoiding the overfitting problem and achieving better detection performance in practice.

FUTURE SCOPE

In this paper, we have proposed a custom CNN-based model that can classify five common rice leaf diseases commonly found in Bangladesh. Our model is trained to recognize the rice leaf diseases in different image backgrounds and capture conditions. Our model achieves 97.82% accuracy on independent test images. Moreover, our model is effective with respect to memory storage due to its reduced number of network parameters. Despite having better accuracy, we aim to improve the reliability and robustness of our model on different datasets from other regions. We will work on classifying rice leaf disease images when complex backgrounds are present and have varied illumination condition. Also, as classification accuracy is an incomplete description of most real-world tasks [4,8], we will concentrate on interpretable CNN-based models to present features in understandable terms for which diseases will be classified

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