Deep Learning Based Algorithm to Predict Plant Diseases: A Case Study with Rice Plant Disease Prediction

Project & Thesis-I
CSE-4100

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Abstract

Rice is the most staple food in Bangladesh. Because of rice plant diseases, the production of rice hampers heavily. So, rice plant disease detection is a crucial topic in the context of Bangladesh. Again, research work regarding plant disease detection is a trending topic in Bangladesh. The major goal of this work is to create an automated system for identifying the five most serious diseases affecting Bangladeshi rice plants. Additionally, it will make it simpler to identify and predict Bangladeshi rice plant diseases. This research aims to provide an easy-to-use system for the detection of diseases affecting rice plants. "Dhan Somadhan" Dataset, which includes 1106 photos of a total of five different types of rice plant diseases is used. Field backgrounds and white backgrounds have been separated in the photographs. Pre-trained models (vgg-16, Inception-V3, vgg-19, Xception) are used for feature extraction by modifying the input and output layers based on the disease classes of the dataset and Convolutional Neural Network (CNN) is used for disease classification. By flipping, zooming, and resizing the dataset, augmentation is done which provided better training and test accuracy. 71.76% test accuracy is gained using the InceptionV3 model which is the best in comparison to the performance of all other pre-trained models that were used.

Motivation

Bangladesh is an agricultural country. Rice is a major food for the people of our country. Rice cultivation provides about 48% [1] of rural development. Around 75% [1] of overall harvested area and above 80% [1] of overall irrigated zone is cultivated through rice plants. Consequently, Rice plays an important role for the peoples of Bangladesh. But the quality as well as quantity of rice production may be decreased because of Rice plant Diseases. As having disease in plants is quite natural. If a proper step is not taken in this regard then it causes serious effects on Rice plants. Therefore, it is the major task to identify Rice plant Disease in the early stages. Early detection of Rice plant diseases is very crucial for the crop protection system of our country. Most of the farmers of our country use their own experience to detect diseases, farmers use pesticides in excessive quantities which cannot help in the prevention of disease, but can have a malignant effect on plants. Thus their misclassification creates bad impact on rice cultivation. So, they need advice from rice disease specialists. In remote or rural areas, rice disease specialists are not able to give quick remedies or advice to the farmers in the right time and they also require expensive equipment and a large amount of time for manually identifying and classifying rice diseases. Moreover, traditional visual observation methods are mostly inaccurate. Besides that laboratory testing requires time and can be expensive. The research that has been done on Bangladeshi Rice plant disease is not sufficient. If the farmers can somehow afford a smartphone it will be easier for them to use image processing methods to detect rice plant diseases.

Literature Review

Paper 01: Rice Disease Identification and Classification by Integrating support vector machines with Deep Convolutional Neural Network

- Date : 2019
- Author : Md.Jahid Hasan, Shamim Mahbub, Md.Shahin Alam, Md.Abu Nasim.

Paper Description

In this paper [1], a hybrid network integrating Deep CNN with SVM for classification has been used. The transfer learning Technique has been used to improve the proposed model. Features are extracted using D-CNN and SVM classifiers are trained with the features. 1080 images of nine different diseases are used in this paper.

Strength:

The proposed model achieved 97.5 % accuracy. Complex AI systems integrating SVM and D-CNN are used.

Weakness:

Small datasets have been used for training and testing. Only 270 images have been used for testing. Combination of D-CNN and SVM only works on small dataset.

Paper 02: Rice plant Disease Detection and Classification Techniques: A Survey

- Date : 2021
- Author :Tejas Tawde, Kunal Deshmukh, Lobhas Verekar, Ajay Reddy.

Paper Description

This paper [2] focuses on distinguishing different methods based on the classifiers used in it. It gives insight into the different techniques used for the identification of Rice plant Diseases. A hardware prototype and model using CNN are proposed in it.

Strength:

The proposed model achieved 96 % accuracy. Deep Learning models are used (CNN).

Weakness:
Small datasets have been used for training and testing purposes. Latest Architectures of CNN model are not used.

Paper 03: Rice Leaf Disease Detection Using Machine Learning Techniques

- Date : 2019
- Author : Kawcher Ahmed, Tasmia Rahman, Md Irfanul Alam, Sifat Momen(NSU)

Paper Description

In this paper [3], the disease detection model was developed using CNN. Affected parts were separated using K-means clustering and SVM. For extracting the features of an image, HOG was used. A dataset of 480 images of three different images is used in this paper.

Strength:

This model achieved 96.77% accuracy.

Weakness:

Only 400+ pictures are used here as a dataset for training. Deep learning models are not used here. Only three rice plant diseases are detected here. Only traditional machine learning models are used which can work only on small datasets.

Paper 04: Rice Blast Disease Detection and Classification Using Machine Learning Algorithm

- Date : 2018
- Author : S Ramesh and D.Vydeki (VIT Chennai)

Paper Description
In this paper [4] the ANN and SVM classifications are used. K-Means Clustering is used for Image Segmentation.

Strength:

In this paper, the model achieved 99% accuracy for the blast infected images and 100% for the normal images.

Weakness:

Testing phase accuracy is found to be 90% for the infected and 86% for the healthy images. Total of 300 leaf samples are taken as a dataset. Only one leaf disease is detected here.

Paper 05: Rice Leaf Disease Recognition using Local Threshold Based Segmentation and Deep CNN

- Date : 2021
- Author: Anam Islam,Redoun Islam,S. M. Rafizul Haque,S. M. Mohidul Islam(KU)

Paper Description

In this paper [5], a segmentation-based method using deep neural networks were used. Local Threshold method is used for image segmentation. Three CNN architecture models VGG16, ResNet50, and DenseNet121 are used for classification. CNN has been trained with segmented images.

Strength:

A dataset of their own is created and used. Segmented dataset is used which gives much more accuracy than non-segmented dataset.

Weakness:

In this paper 78.84 % test accuracy is achieved. A small dataset of 786 images is used.

Paper 06: Application of machine learning in detection of blast disease in South Indian rice crops

- Date : 2019
- Author: S Ramesh and D.Vydeki (VIT Chennai)

Paper Description

In this paper [6], Rice Blast disease detection using KNN and ANN classification techniques was used. K-means Clustering is used for image segmentation. The extracted features (Color and Texture) are applied to a classifier (KNN and ANN) to determine whether it is an image of an infected crop or not.

Strength:

The ANN classifier provides 99% accuracy for normal images and 100% for blast infected images.

Weakness:

Research is based on only one type of disease (Rice Blast). A small dataset of 451 images is used. K-means Clustering segmentation method is used whereas there are other methods which give more accurate results.

Paper 07: Identification of Various Rice Plant Diseases Using Optimized Convolutional Neural Network

- Date : 2021
- Author : Md. Sazzadul Islam Prottasha , A. B. M. Kabir Hossain , Md. Zihadur Rahman , S M Salim Reza , Dilshad Ara Hossain

Paper Description

In this paper [7], a Lightweight CNN architecture based on depth-wise separable convolutions was used. A combination of depth-wise convolution followed by pointwise convolution was implemented. A baseline training method for training and testing datasets was considered.

Strength:

Relatively small parameter size of 2.4 Million. Depth-wise convolution reduce computational cost and parameter size. 12 classes of diseases are being used in the dataset. Accuracy of 96.3% is achieved in this paper.

Weaknesses:
Bias and misclassification among some diseases, namely brown spot, leaf smut and leaf scald due to similar characteristics.

Paper 08: Rice Plant Disease Classification Using Transfer Learning Of Deep Convolutional Neural Network

- Date : 2019
- Author : Vimal K. Shrivastava , Monoj K. Pradhan, Sonajharia Minz , Mahesh P. Thakur

Paper Description

In this paper [8], deep convolutional Neural Network (CNN) as feature extractor & Support Vector Machine (SVM) as a classifier was used. Alex-Net deep CNN pre-trained on large ImageNet dataset was used for feature extraction.

Strength:

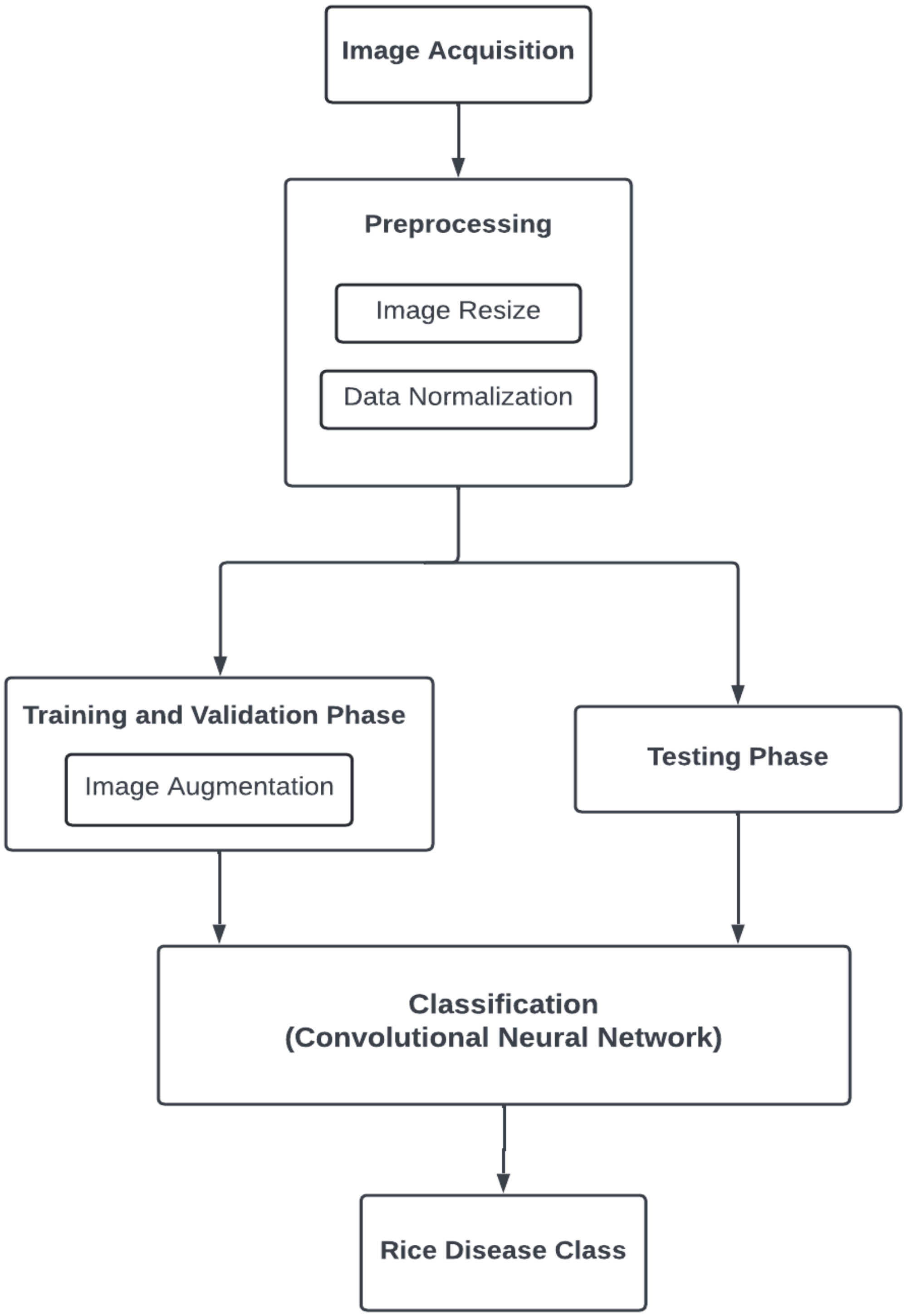
In this paper 91.37% accuracy is achieved. Alex-Net model pre-trained on the large ImageNet dataset of 1.2M Images & 1000 classes.

Weakness:
Small dataset consisting of 619 images is used in this paper. Research based on only 3 types of rice diseases. In this paper unavailability of standard labeled rice disease images is also noticed.

<u>Uniqueness in our work</u>

- ❑ Worked on local Bangladeshi Dataset called Dhan-Shomadhan
- ❑ Used Transfer learning approach
- ❑ Used both deep learning and machine learning approach for comparison analysis
- ❑ Fine tuning of the pre trained models
- ❑ Different augmentation techniques to increase the dataset and get better training accuracy
- ❑ Merging local dataset with other countries dataset for getting superior result

Workflow Diagram



Proposed Approach and its solution :

- The name of the dataset is 'Dhan-Somadhan' which consists of images of Rice Plants with 5 different diseases.

- **Preprocessing**
  After selecting an appropriate dataset for the work, changes and modifications were made based on the needs of our objectives. The dataset of 5 different rice plant diseases were divided into 3 sets of data. The training set, the testing set and the Validation set. Feature scaling or Normalization was done for the data to decrease the load of the training and testing process. To improve the training process the dataset was significantly augmented (horizontal and vertical flipping, Zooming, Resizing) to bring well needed variation in the training data to avoid overfitting.

- **Algorithms**
  The focus was primarily on the Deep Learning Algorithm CNN (Convolutional Neural Network) for feature extraction and image classification. Pre-trained models such as Inception V3, VGG-16, Xception were used for better training and testing accuracy. This enabled the models to use the relatively standard sized dataset with models of large parameters. Since the thesis work includes comparative study, we will also use a few machine learning models such as KNN, SVM for comparison analysis.

- **Comparison with different models**
  A comparative analysis was done of the data split variants of different types and the accuracy was determined for each of them. The analysis shows a quantitative analysis of the "Dhan Shamadhan" Dataset, the relationship between training and testing accuracies, Training and validation loss, and an overall comparison between the pre-trained models to get a better understanding of the results that were achieved.

- **Fine tuning for better accuracy**
  Since pre-trained models were used for enabling transfer learning, dropout layers were used to avoid any particular neuron from training which may result in an accuracy that is overfitting. Furthermore, such types of models have multiple layers that are not useful to relatively standard-size datasets. This is why certain layers were frozen in the pre-trained models. Dropout layers were also used to stop overfitting.

- **Visualization of different model accuracy**
  Two types of graphs have been used to visualize the accuracy and loss for both training and validation.

Methodology/Algorithms

The primary focus was on the Deep Learning Algorithm CNN (Convolutional Neural Network) for feature extraction and image classification. Pre-trained models were used such as Inception V3, VGG-16, Xception, and VGG-19 for better training and testing accuracy. This enabled the usage of the relatively standard-sized dataset with models of large parameters.

Taking the images on the dataset, they were resized based on the needs of the pre-trained models to give the best possible accuracy for the training and testing processes. The dataset was tested with different values for epoch, and batch size to improve the training and testing of the dataset. The data was split into four different split variations (80:20, 65:10:15, 70:10:20, 70:20:10) to test the accuracies for each of them separately. Fine-tuning was done and the hyper parameters were similarly changed to check for the best accuracy possible.

These resized images were put on the input layer. The layers were frozen in the middle to make sure the weights and biases are not updated while the training process repeated with every iteration. Dropout layers were added in some cases to avoid making the training process computationally heavy. A modified softmax activation function was added to the output layer to make sure the output classes are giving the 5 different rice disease classes present on the dataset.

Tools,devices/platform

- Python as a programming language
- Google colab
- Tensorflow (Open source platform)

Dataset

- Dhan-Shomadhan: A dataset of 5 different harmful diseases of rice leaf called Brown Spot, Leaf Scaled, Rice Blast, Rice Turngo, and Sheath Blight.
- Dhan-Shomadhans dataset contains 1106 pictures in two different background variations named field background picture and white background picture.
- Dhan-Shomadhans dataset can be used for rice leaf diseases classification, disease detection using Computer Vision and Pattern Recognition for different rice leaf diseases. [9]

(a)

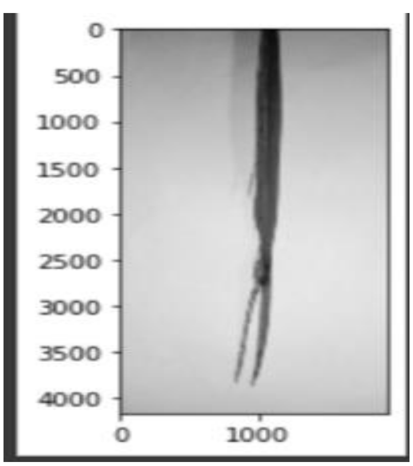
(b)

(c).

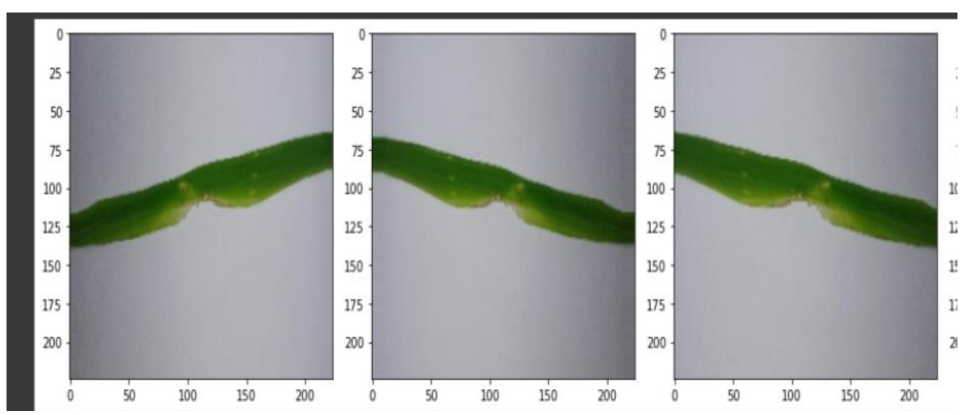
(d)

(e)

Fig: Collected images of Rice plant diseases a) Brown Spot, b) Leaf Scaled, c) Rice Blast, d) Rice Tungro, e) Sheath Blight



(a)



(b)

Fig: (a) Actual image sample, (b) Augmented Images sample

Result Comparison

Before Augmentation

TABLE I: Performance comparisons

Model Name	Train Accuracy	Test Accuracy	Optimizer	Split Ratio (%)
Vgg19	.9805	.5613	Adam	80-20
Xception	.5746	.5031	Adagrad	70-10-20
Vgg16	1.00	.4965	Adagrad	65-10-15
InceptionV3	.4757	.4539	Rmsprop	70-20-10

After Augmentation

TABLE II: Performance comparisons (80:20)

Model Name	Train Accuracy		Test Accuracy	
Optimizers	**Adam**	**Adagrad**	**Adam**	**Adagrad**
Vgg16	**.8420**	**.5570**	**.6065**	**.5355**
Xception	**.8762**	**.8713**	**.6387**	**.6581**
Vgg19	**.7182**	**.5847**	**.6387**	**.5290**

TABLE III: Performance comparisons (80:20)

Model Name	Precision		Recall		F-Score	
Optimizers	Adam	Adagrad	Adam	Adagrad	Adam	Adagrad
Vgg16	.6791	.8333	.5871	.2581	.5585	.4596
Xception	.6364	.6812	.6323	.6065	.6205	.6181
Vgg19	.6364	.7209	.6323	.2000	.6205	.4584

TABLE IV Performance comparisons (70:10:20)

Model Name	Train Accuracy		Test Accuracy	
Optimizers	Adam	Adagrad	Adam	Adagrad
Vgg16	.8545	.5280	.5849	.4906
Xception	.9627	.8638	.6638	.6289
InceptionV3	.8601	.8825	.5723	.6289

TABLE V: Performance comparisons (70:10:20)

Model Name	Precision		Recall		F-Score	
Optimizer	Adam	Adagrad	Adam	Adagrad	Adam	Adagrad
Vgg16	.6875	.7143	.5535	0.2516	.5043	0.3600
Xception	.6613	.6940	.6575	.5849	.6592	.6083
Inception V3	.8633	.9175	.8601	.8507	.8449	.8752

TABLE VI: Performance comparisons (65:10:15)

Model Name	Train Accuracy			Test Accuracy		
Optimizer	Adam	SGD	Adagrad	Adam	SGD	Adagrad
Vgg16	0.8046	0.5609	0.5448	0.5532	0.5106	0.4965
Xception	0.8299	0.7908 (RMSprop)	0.8667	0.5319	0.5461 (RMSprop)	0.5745
InceptionV3	0.8529	0.7287	0.9563	0.5248	0.4967	0.5887

TABLE VII: Performance comparisons (65:10:15)

Model Name	Precision			Recall			F-Score		
Optimizer	Adam	SGD	Adagrad	Adam	SGD	Adagrad	Adam	SGD	Adagrad
Vgg16	0.6875	0.5194	0.6800	0.4681	0.4752	0.2411	0.5297	0.4564	0.4015
Xception	0.5319	0.5500	0.5745	0.5319	0.5461	0.5035	0.5346	0.5408	0.5722
Inception V3	0.5214	0.4967	0.5538	0.5177	0.4967	0.5106	0.5180	0.4725	0.5136

TABLE VIII: Performance comparisons (70:20:10)

Model Name	Train Accuracy		Test Accuracy	
Optimizer	Adam	Rms-Prop	Adam	Rms-Prop
Vgg16	0.6723	0.5169	0.6053	0.5461
InceptionV3	0.7697	0.6854	0.7105	0.6579

TABLE IX: Performance comparisons (70:20:10)

Model Name	Precision		Recall		F-Score	
Optimizer	Adam	Rms Prop	Adam	Rms Prop	Adam	Rms Prop
Vgg16	0.7746	0.5909	0.5599	0.5132	0.6499	0.5493
Inception V3	0.7152	0.6579	0.7105	0.6579	0.7131	0.6679

Result Discussion:

Table 1 shows the accuracy for 4 different pre-trained models without augmentation. It is observed that the models vgg16 and vgg19 are displaying overfitting tendencies due to a lack of variation in the training data. Due to this, the testing accuracies are severely hampered. The pre-trained models, Xception & Inception V3 also display underfitting tendencies.
Taking 4 different splitting ratios, the accuracies have been calculated. The training and testing accuracy along with precision, recall & f-score for each split variation has been shown in the **tables 2 to table 9.**

In **Table 2** (splitting ratio **80:20**) the optimizers Adam and Adagrad have been used. The models which have been used are Vgg16, Xception, and VGG-19. It is observed that Xception (Adagrad) gave a test accuracy of 65.81% which is the highest for this split ratio. On the other hand, VGG-19 for the Adam optimizer overfit less.

In **Table 4** (splitting ratio **70:10:20**) optimizers Adam and Adagrad have been used. The models which have been used are Vgg16, Xception and InceptionV3. Xception for the Adam optimizer showed a testing accuracy of 66.38% which is the highest for this split ratio. InceptionV3 has 62.89% accuracy which shows less overfitting tendency.

In **Table 6** (splitting ratio **65:10:15**) we used optimizer Adam, SGD, RMS prop, and Adagrad. The models which have been used are vgg16, Xception, and Inception v3. It is observed Inception v3 Adagrad gave 58% test accuracy which is the highest for this split ratio. Vgg16 for Adam optimizer shows the least overfitting.

In **Table 8** (splitting ratio **70:20:10**) optimizer Adam and RMS prop have been used. The models used are vgg16 and inception V3.
The Best testing accuracy of **71.05%** has been observed for Inception V3 with the Adam optimizer (split ratio **70:20:10**).

In **Tables 3, 5, and 9** the precision, recall, and f scores have been recorded. These metrics give a better idea in comparison to just the accuracies. It also helps to identify false negatives in the predictions.

Comparative Result Analysis

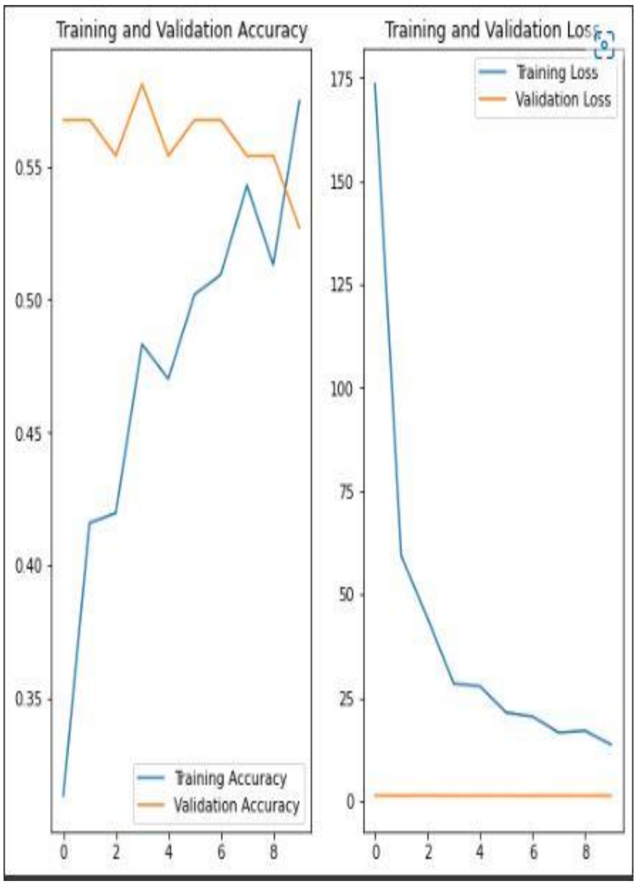


Fig 1: Before Augmentation xception (70:10:20) for Adagrad

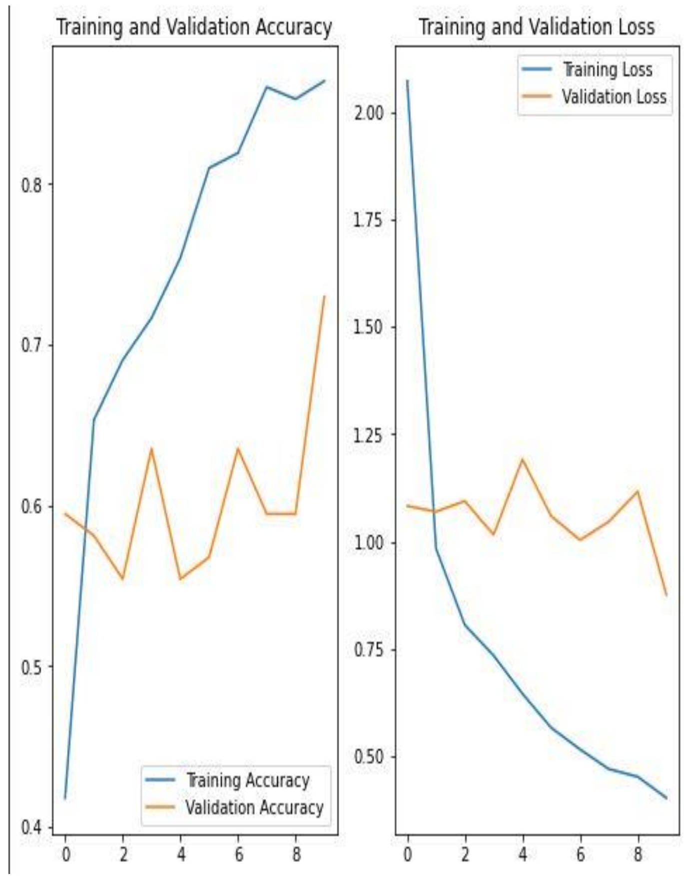


Fig 2: After Augmentation xception (70:10:20) for Adagrad

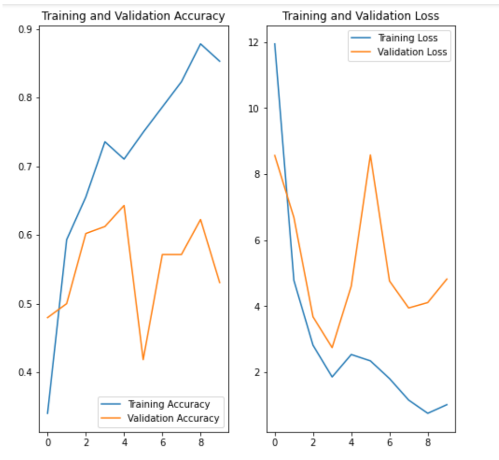


Fig 3: Inception Curve (65-10-15) for Adam

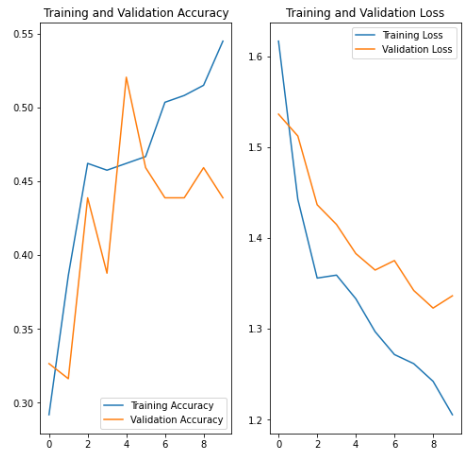
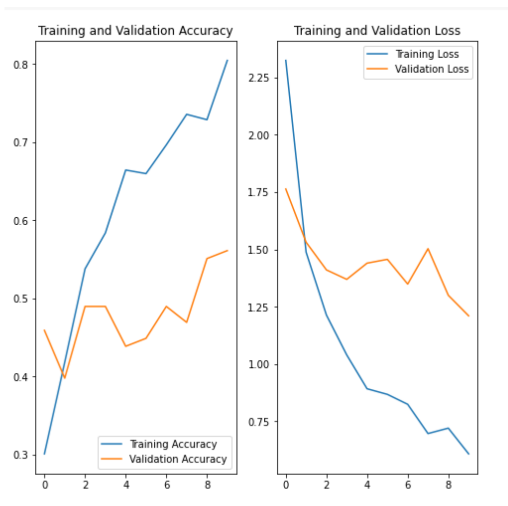


Fig 4: VGG16 Curve (65-10-15) for Adagrad



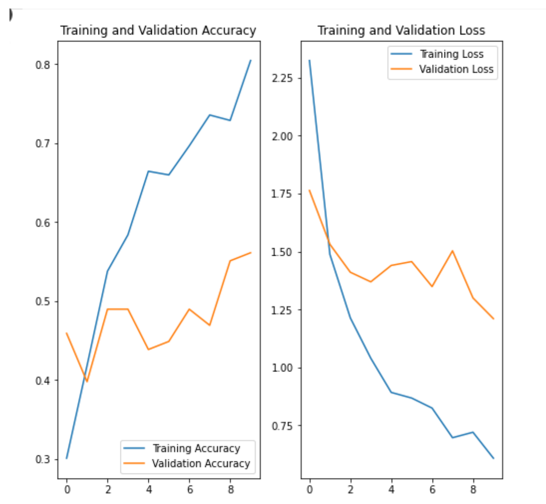


Fig 5: Inception Curve (65-10-15) for SGD

Fig 6: VGG16 Curve (65-10-15) for Adam

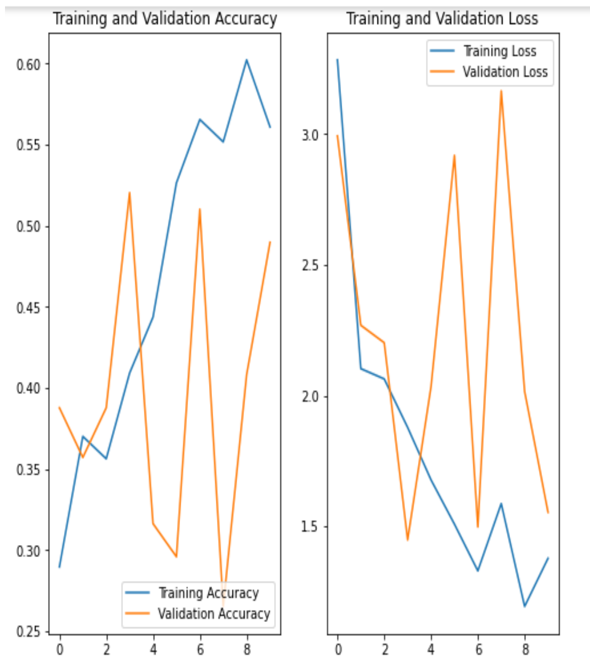


Fig 7: VGG16 Curve (65-10-15) for RMSprop

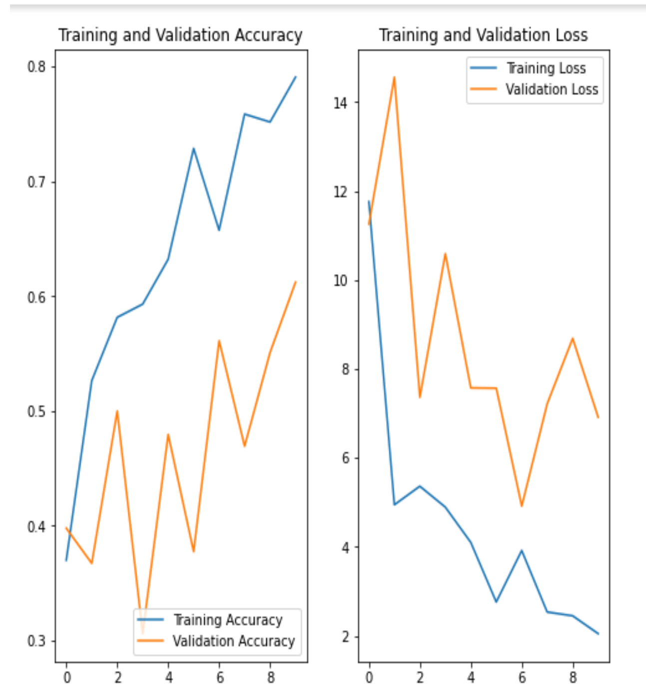


Fig 8: Xception Curve (65-10-15) for RMSprop

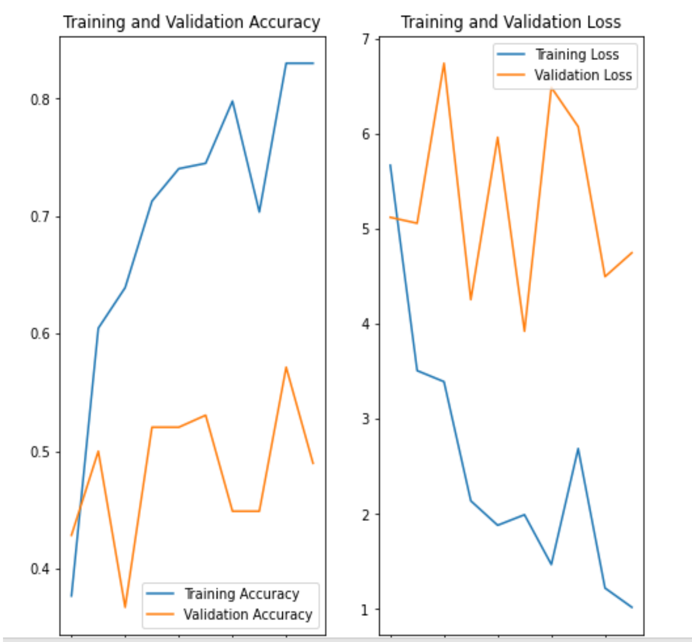


Fig 9: Xception Curve (65-10-15) for Adam

Fig 10: Xception Curve (65-10-15) for Adagrad

Fig 11: VGG16 curve (70:20:10) Rms Prop

Fig 12: Inception V3 (70:20:10) Adam

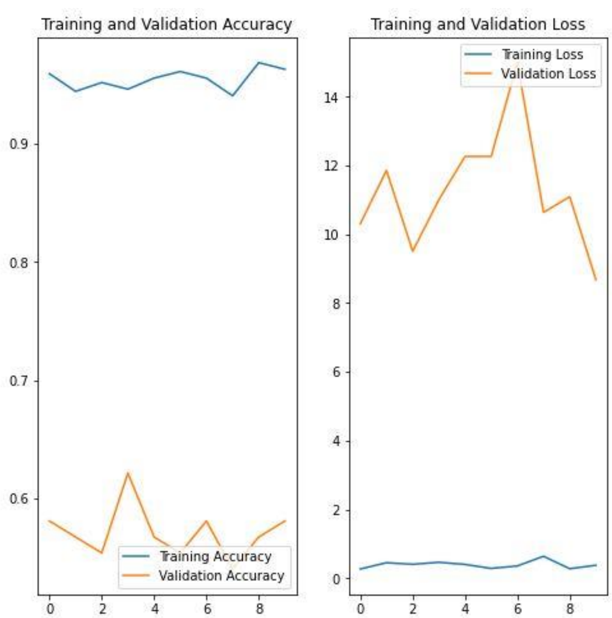


Fig 13: Xception(70-10-20) for Adam

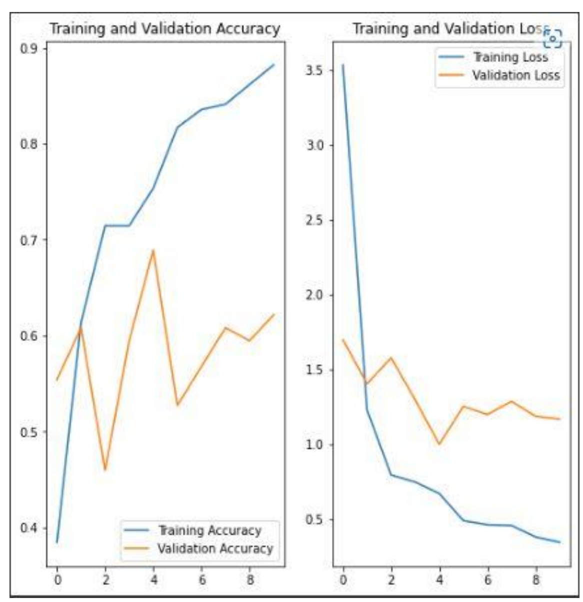


Fig 14: InceptionV3(70-10-20) for Adagrad

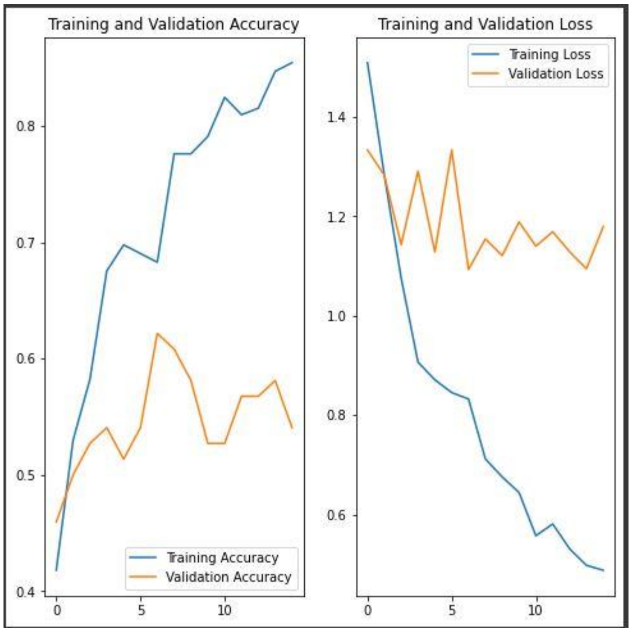


Fig 15: VGG-16 (70-10-20) for Adam

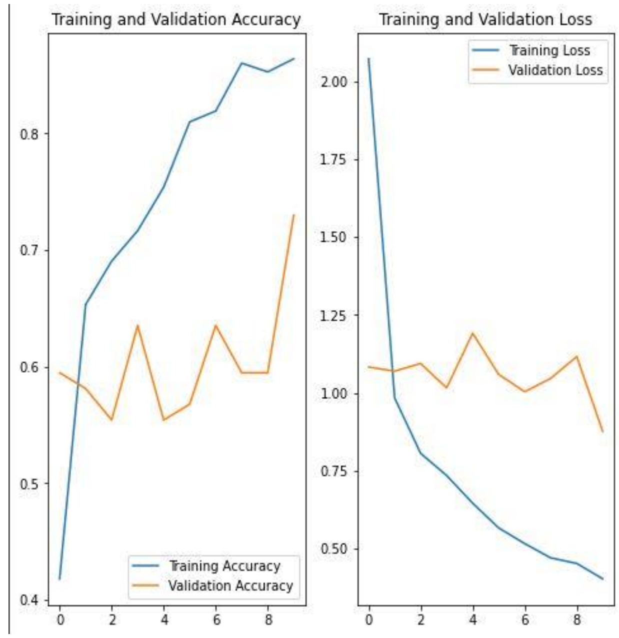


Fig 16: Xception (70-10-20) for Adagrad

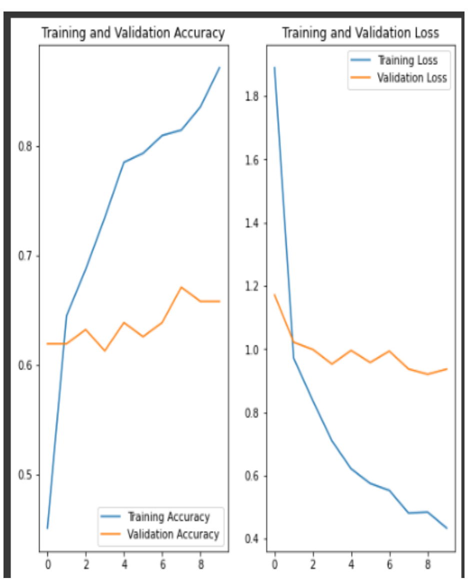


Figure 17: Xception-Adagrad(80-20)

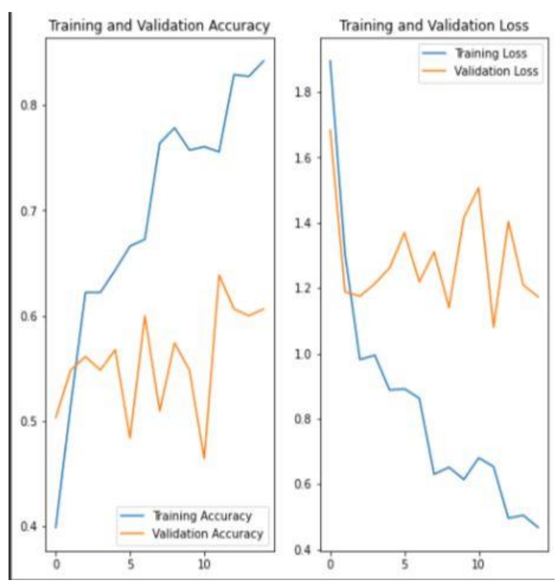


Figure 18: Vgg16-Adam(80-20)

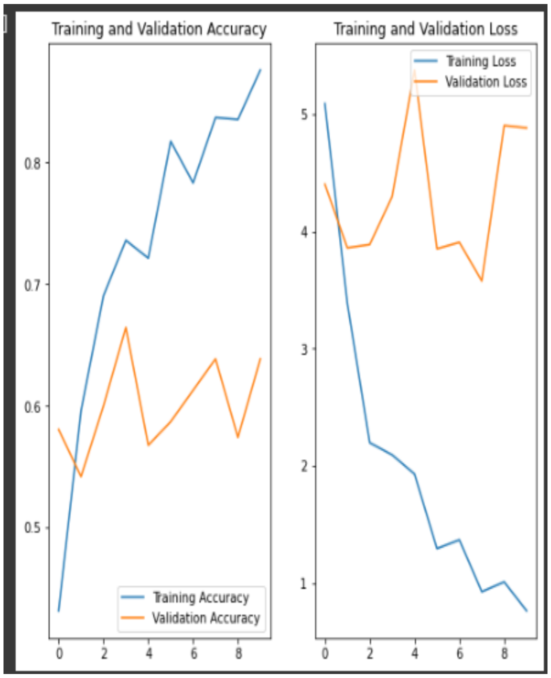


Figure 19: Xception-Adam(80-20)

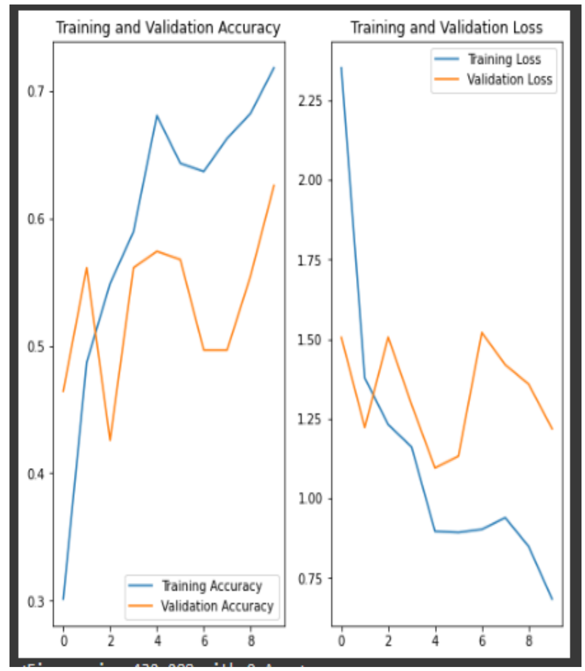


Figure 20: Vgg19-Adam(80-20)

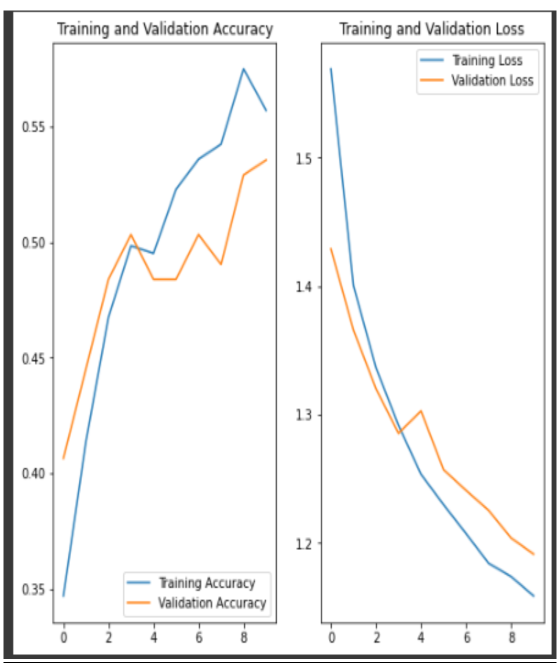


Figure 21: vgg-16-Adagrad(80-20)

There are 21 figures with two types of graphs. The first one is a graph of epochs vs accuracy where epochs are on the x-axis and accuracy is on the y-axis (Training & Validation). The second one is an epoch vs loss graph, where epoch is on the x-axis and loss is on the y-axis (Training and Validation).

Overfitting generally occurs when the training accuracy is very large and validation accuracy is lower compared to the training accuracy. Usually, the training and validation losses are meant to decrease proportionally with each epoch.

In **figure-13**, there is high training accuracy and yet very low validation accuracy. The proportion between the training and validation loss is also very dissimilar, which denotes a condition of overfitting. (Xception for Adam (**70:10:20**) for 10 epochs)

Underfitting generally occurs when training and validation accuracy are small and loss is very high as well.

In the case of **figure-1**, there is low training and validation accuracy which displays the characteristics of an underfitting situation. (Xception for Adagrad (**70:10:20**) for 10 epochs).

Figure 12 shows the **best** relationship between the training and validation accuracy. The loss equally decreases for training and validation. This means there is neither overfitting nor underfitting in this case. (Inception V3 for Adam (**70:20:10**) for 5 epochs).

Future work

- Only white background images were used but in future field background images will also be considered
- For better accuracy custom ensemble techniques will be used.
- Several Machine Learning Algorithms will be used for comparison purposes.
- To balance the dataset more, oversampling or under sampling techniques will be implemented.
- To avoid overfitting, custom Resnet/VGG-16 model and dropout layers will be added over the enriched dataset.
- Datasets from other countries will be taken and they will be merged with the local dataset to enhance the training and testing result.

Conclusion

Identification & classification of rice disease is quite impossible for farmers by naked-eye. It needs a large quantity of time and human effort besides professional knowledge. Hence, an effective approach has been taken in order to computerize the procedure of classifying and identifying disease from rice plants image. In this thesis, the proposed method was aimed to develop an automated system to classify images of rice plant disease through the execution of an AI and computer vision techniques. Transfer learning approach to classify rice plant diseases have been implemented. Inception V3, Vgg-16, Vgg-19, Xception etc models were intended for the instinctive extraction of features. CNN classifier has been adopted for the image classification of rice diseases. An image dataset of most common rice diseases of Bangladesh have been used. Inception V3 model achieved the highest accuracy among all other pre-trained models that are used. There are scopes for further research to get better results.

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