Proceedings of the International Conference on Artificial Intelligence and Smart Systems (ICAIS-2021)
IEEE Xplore Part Number: CFP21OAB-ART; ISBN: 978-1-7281-9537-7

Application of Pre-Trained Deep Convolutional Neural Networks for Rice Plant Disease Classification

2021 International Conference on Artificial Intelligence and Smart Systems (ICAIS) | 978-1-7281-9537-7/20/$31.00 ©2021 IEEE | DOI: 10.1109/ICAIS50930.2021.9395813

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Abstract— **Rice is a primary food and encounters an essential role in providing food security worldwide. However, several diseases affect this crop that significantly reduces its production and quality. Therefore, early detection of diseases is much needed task to prevent spreading of diseases. Hence, it is desirable to develop an automatic system which will help agronomist, pathologist and even the farmers to diagnose the rice diseases more efficiently and take preventive measures in time. In the present era of advanced artificial intelligence, various learning techniques have been explored for rice plant disease classification. Among various machine learning techniques, deep learning has been widely applied in various domains of computer vision and image analysis recently. It has successfully delivered promising results with large potential. However, training the deep learning model from the scratch requires huge labeled data and collection of huge labeled data is expensive, laborious and time taking process. Transfer learning of pre-trained deep learning model is a technique to overcome such problems. This paper has explored the performance of various pre-trained deep CNN models such as: (i) AlexNet; (ii) Vgg16; (iii) ResNet152V2; (iv) InceptionV3; (V) InceptionResNetV2; (vi) Xception; (vii) MobileNet; (viii) DenseNet169; (ix) NasNetMobile; and (x) NasNetLarge for image based rice plant disease classification. The dataset used in this paper consist of 1216 rice plant diseased images and these have been collected from the real agricultural field having seven classes: (i) rice blast; (ii) bacterial leaf blight; (iii) brown spot; (iv) sheath blight; (v) sheath rot; (vi) false smut; (vii) healthy leaves. The Vgg16 model resulted highest classification accuracy of 93.11%. The outcome of the model can be used as an advisory and as an early detection tool in the real agriculture domain.**

Keywords— ***Deep Learning, Convolution Neural Networks, Pre-trained models, Transfer Learning, Classification, Rice Plant Diseases.***

I. INTRODUCTION

Agriculture is India's principal source of income. 70 percent of Indian population and about 58 percent of India's rural population depend on agriculture [1]. Among the other crops, rice is the most essential. It provides energy and protein to more than half of the world's population [2]. It has been approximated that the population of the world will rise around 8.5 billion in 2030, 9.7 billion in 2050 and 10.9 billion in 2100, respectively [3]. The demand and consumption of rice increases with the increase in the population. To meet out this challenge, it is estimated and expected that rice production is to be increased by 40% in 2030 [2]. A sustainable increase in rice production is requirement which will provide global food security. This increase in the rice production would be possible by adaptation of high yield varieties and protection of diseases and insects in agriculture field. Fungus, bacteria and virus are the main culprits for the rice plant diseases. The outbreak of these diseases results in reduction of rice production. It destroys about 10 to 15% of rice production in Asia [4]. Table 1 presents some important rice plant diseases and their effect on yield production in Indian context.

Early diagnosis of these diseases is very important as it improves the production quantity and quality, reduces the use of pesticides, thereby increasing the country's economic growth. But the traditional methods such as manual observation or optical observation has high degree of complexity. Due to this complexity, even the experienced agronomist or pathologist often fails in successful diagnosis of the diseases which makes these traditional methods subjective, erroneous and time consuming. Therefore, it is desirable to develop an automatic system which will help agronomist, pathologist and even the farmers to diagnose the rice diseases more efficiently and take preventive measures in time.

Table 1: Important rice plant diseases and their effect on yield production in Indian context.

Rice Plant Diseased Class	Scientific Name	Intensity of Damage	Yield Loss	Remarks
Rice blast	*Pyricularia*	Low to	70-	More destructive

	oryzae (*Magnaporthe oryzae*)	high	80%	in terms of yield loss.
Bacterial leaf blight	*Xanthomonas oryzae pv. oryzae*	Low to high	Up to 80%	Adverse effect on seed quality along with yield loss.
Brown spot	*Bipolaris oryzae*	Low to high	26-52%	Water scarcity, fertility imbalance.
Sheath blight	*Rhizoctonia solani*	Low to high	50%	Reduction of total seed weight due to less filled grain resulting signification yield losses
Sheath rot	*Sarocladium oryzae*	Low to high	2.7-89.8%	Rotting and discoloration of sheath leading to chaffy and sterility.
False smut	*Ustilaginoidea virens*	Low to medium	0.2-49%	More severe during heavy rainfall seasons.

In literature, several Computer Aided Diagnosis (CAD) systems have been presented on agricultural domain [5][6]. These CAD systems may be generally grouped into traditional machine learning and deep learning based systems. In traditional machine learning approaches, hand-crafted features are extracted whereas in deep learning models features are extracted automatically from the data [7]. Under the traditional machine learning based CAD systems, several features were extracted from rice plant diseased images such as color [8-11], texture [8] [11-12], shape [10] [12] and morphological features [11]. These features were given as input to classifiers such as multilayer perceptron [8], support vector machine [12], probabilistic neural network [9], k-nearest neighbor [10], minimum distance classifier [10] and back propagation neural network [11]. Apart from these literatures, there are few literatures which have first segmented the diseased region using techniques such as global thresholding [13] and K-means clustering [14] and then features were extracted from segmented image and fed to KNN and SVM classifiers respectively.

Under the second category of CAD systems which is based on deep learning, a handful number of literature available on rice plant disease detection and classification. Lu et al., 2017 explored deep convolutional neural network (CNN) on 500 images having 10 common diseases with layers of three convolution, three stochastic pooling and one softmax [15]. Rahman et al., 2018 has proposed stacked CNN model on 1500 images having nine classes (five diseases, three pests, one healthy leave) [16]. Liang et al., 2019 explored the identification of rice blast disease using deep CNN model on 2906 positive samples and 2902 negative samples [17]. Alfarisy et al., 2018 explored CaffeNet deep CNN model for identification of 13 classes of pests and diseases of rice plants using 4511 images [18]. Vanitha, 2019 has presented a comparative study of three deep CNN models: VGG16, ResNet50 and InceptionV3 along with data augmentation technique for classification of diseased, healthy and dead leaves of rice plants [19]. Shrivastava et al., 2019 explored Alexnet CNN model with transfer learning technique for classification of four classes of 619 rice plant diseased images [20].

Deep learning [7] is an active research area in machine learning field. It has achieved significant success in various domains such as classification [20][21], natural language processing [22], audio processing [23] and computer vision [24-25], etc. Among different profound deep learning models, convolutional neural network (CNN) has emerged as successful image classification technique. However, efficient training of deep CNN model requires large labeled dataset and high computation power. The solution to this problem is transfer learning where knowledge of pre-trained deep CNN model on large dataset is transferred to task in hand.

This paper has applied the concept of transfer learning to rice disease classification task and presented an exhaustive comparative performance analysis of 10 pre-trained deep CNN models. The pre-trained models used here are: (i) AlexNet; (ii) VGG16; (iii) ResNet152V2; (iv) InceptionV3; (v) InceptionResNetV2; (vi) Xception; (vii) MobileNet; (viii) DenseNet169; (ix) NasNetMobile; (x) NasNetLarge. Following are our contributions in this paper:

(i) Collection of large dataset of 1216 images having six diseased and one healthy class of rice plant from the real agriculture field.

(ii) Development of rice plant disease classification model based on transfer learning technique.

(iii) Exhaustive comparison of performance of 10 pre-trained deep CNN models based on transfer learning on classification of rice plant diseases.

In the remainder of the paper, section 2 gives a description of rice plant dataset, transfer learning and pre-trained deep CNN models. Section 3 explains the experimental setup and results. Section 4 comprises the discussion and lastly, the paper is concluded by section 5.

II. Material and Methods

A. Dataset Collection and Preparation

Rice plant disease dataset with 1216 images have been used in this experiment. This data set was created with images capturing by two smartphone mobiles (Gionee and LYF mobile phones having 5.0 megapixel) and a digital camera (Canon PowerShot SX530HS with 16.0 megapixel). Adobe Photoshop CS5 (64 Bit) software tool has been used to pre-process the images to remove the other information by making background black for the purpose of reducing the complexity and computational cost. All these images were acquired on various weather conditions from the agricultural field of Indira Gandhi Agricultural University that is situated in Raipur, Chhattisgarh state, India. The dataset contains seven classes: (a) Rice Blast (RB); (b) Bacterial Leaf Blight (BLB); (c) Brown Spot (BS); (d) Sheath Blight (SB); (e) Sheath Rot (SR); (f) False Smut (FS) and (g) Healthy Leaves (HL). Table 2 depicts the details of dataset along with few sample images. Moreover, we have provided a brief description about each class below:

- *Rice Blast (RB):* Rice Blast is caused by *Magnaporthe Oryzae*. This disease was first recorded in 1913 in India by Padmanabhan [26]. This is one of the most destructive diseases in the world [27]. In India, more than 266000 tons of rice was lost between 1960-61 [28]. Further, a yield loss of 70-80% was reported in 2019 by Baskaran [29]. The lesion of this type appears on the grains, panicles, nodes, leaves. The spots on leaf are elliptical with less or more pointed. The center is grayish or white and the outer margin is generally brown or reddish-brown. The spot usually starts with small water-soaked whitish grayish or bluish dots.

- *Bacterial Leaf Blight (BLB):* It is described by *Xanthomonas Oryzae*. It is a common disease occurring in all the states of India [30]. Yield loss occurs between 6-60% in some state [31]. Further, the yield loss is reported up to 80% in India [29]. The symptoms of it appear as tiny water-soaked spots at the margin of fully developed leaves. Further it turns dry, yellow and whitish as it grows. The lesions may start from one or other edge of the leaves. Further, the entire leave turns white and later become grayish.

- *Brown Spot (BS):* It is described by *Helminthosporiurn Oryzae*. It is coined by Breda De Haan et al. in 1900 [32]. It is reported a yield loss of 26-52% in India due to this disease [29]. The reduction of yield is due to reduction of grains in panicle and its weight as well. A severe damage was recorded in Bengal famine in 1942 (Ou, 1985). The loss was around 50-90% [33] [34]. The symptoms of this disease appear as spots on leaves, glumes, panicle branches and other parts of the plant. The color of the spot is brown with gray and whitish when they are developed fully and they are small circular with dark brown or purplish brown in color in their younger stage or in undeveloped stage. The spots are oval in shape. Sometime the length of the spot may reach 1 cm or more.

- *Sheath Blight (SB):* It is caused by *Rhizoctonia Solani* [35]. It is reported a yield loss of upto 50% in India [29]. The symptoms of this disease is ellipsoid or ovoid, irregular diseased regions with reddish-brown color at the borders and straw color at the center [36]. It is also greenish gray with a grayish-white and brown margin in the center [27]. It appears in the lower part in beginning and then spread in rest part of the leaves.

- *Sheath Rot (SR):* It was described by sawed from Taiwanin 1992 [37]. This was described by *Acrocylindrium Oryzae*. The is a common disease in Indian sub-continent [38-39][40] and also in USA [41]. A damage of 85% was reported in Taiwan [27]. It is reported a loss of 2.7-89.8% in India [29]. The symptoms of this disease takes place on the upper most leaf sheaths enclosing young panicles. The spot appears as oblong and sometime irregular. It has brown margins with gray centers. Sometimes, it appears grayish brown. The young panicles either remains within the sheath or partial emerge.

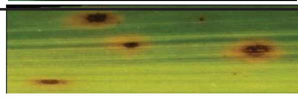
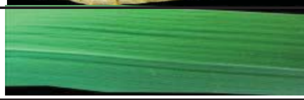
- *False Smut (FS):* It is fungal disease and described by *Ustiloginoidea Virens*. It was first coined by Cooke [42]. A severe infection had occurred in the Philippines during damp weather and there was epidemic in Burma in 1935 [43]. It is reported a reduction of 0.2-49% in India. It appears in most of the rice growing areas (CMI Distribution Map 347) [27]. The symptoms appear on the grains of the panicle. They are greenish spore balls in color. The diameter may be 1 cm or more enclosing complete floral parts. It is flat, smooth and yellow covered by membrane in their initial stage. The membrane bursts as they grow further. Its color converts to orange and later yellowish-green.

- *Healthy Leaves (HL):* Healthy leaves are uninfected from any kind of diseases. The leaves have normally uniform color distributions and infected leaves have non-uniform color distribution. The healthy leaves of rice plant have been used here so that our model could also detect the uninfected images.

B. Transfer Learning

Deep CNN model has been applied widely and successfully for image classification task in various domains such as hyperspectral remote sensing [44-45], agriculture [15] etc. However, training of deep CNN model from scratch requires huge, labeled dataset, high computational hardware resources (GPUs) and high computation time [46]. The collection of a large labeled dataset is challenging task in the field like agriculture due to local weather condition, indiscrimination of plant diseases, uncontrolled experimental field and rare-availability of experts.

Table 2: Sample images of dataset from each class.

Class Name	# Images	Sample Image
RB	122	
BLB	265	
BS	153	
SB	159	
SR	113	
FS	213	
HL	191	

Further, there may be a problem of overfitting [47] due to less training dataset, where the classification performance on test dataset will be degraded. One solution to overcome such challenges is transfer learning, where pre-trained model on large dataset is used and acquired knowledge is applied for training on new dataset. In this way, it avoids the training of entire model from scratch resulting in requirement of less hardware resources and low computation time while achieving adequate classification accuracy on small labeled dataset. Fig. 1 depicts the block diagrams of transfer learning technique. Here, Conv block represents convolutional layer and FC denote fully connected layer. The figure 2 shows general deep CNN pre-trained models on large dataset. This is the general deep CNN block diagram with transfer learning technique. Depending on the specific deep CNN model, number of convolutional, pooling and fully connected layers may vary. While training, all the layers of this model are frozen (non-trainable layers) except last layer (trainable layer). Due to this, only the weights of last layer are updated while training. Hence, it reduces the computational cost while achieving adequate performance.

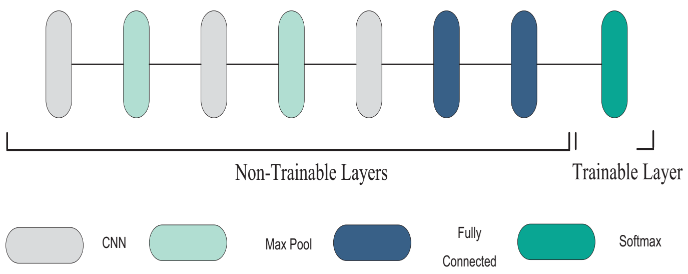
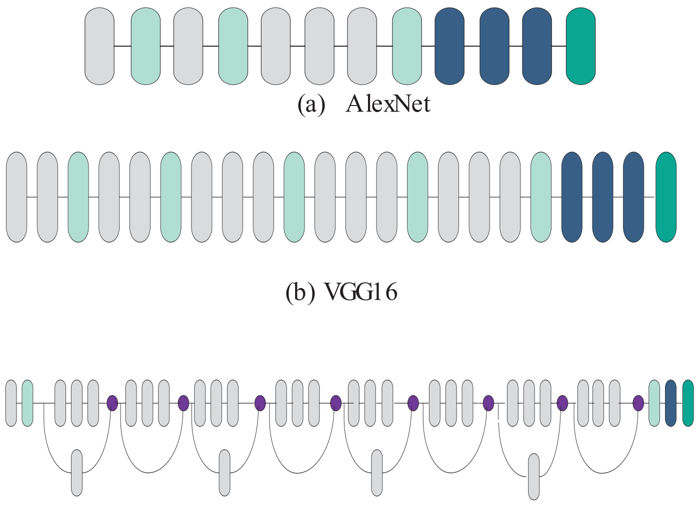


Fig. 1. Block diagram of transfer learning process.

III. Pre-trained Deep CNN Models

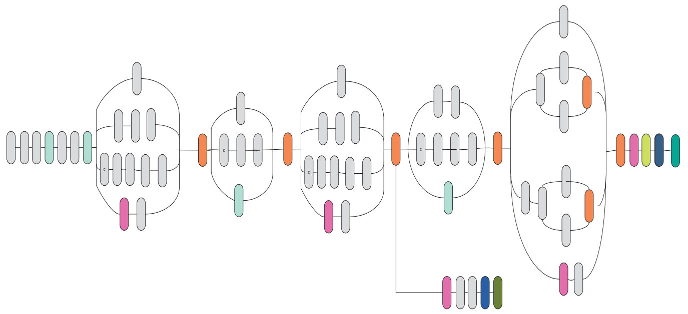
In this paper, we have explored 10 pre-trained deep CNN models namely :(i) AlexNet; (ii) VGG16; (iii) ResNet152V2; (iv) InceptionV3;(v) InceptionResNetV2; (vi) Xception; (vii) MobileNet; (viii) DenseNet169; (ix) NasNetMobile and (x) NasNetLarge. The block diagrams of these pre-trained deepCNN models were presented in Fig. 2. In addition, details of all 10 pre-trained models were provided in Table 3. AlexNet [24] was proposed by Krizhevsky et al. 2012. It comprises of 5 convolution, 3 max-pooling, 3 fully connected and output layer with softmax activation function. Moreover, it explores regularization technique known as dropout to reduce the overfitting. It comprises of 650000 neurons and 60 million parameters. VGG16 [48] is proposed by Simonyan et al. 2014. It is a sequential convolutional neural network using 3x3 filters with increasing depth of 16 layers. Max-pooling was performed on 2x2 pixel window with stride of 2. After each max pool layer, the number of convolution filters gets doubled. It has three FC layers. The first two FC layers consist of 4096 neurons while the third one consists of 1000 neurons. ResNet was introduced by [49]. It employs residual learning framework which has skip connections from previous layer. Each residual unit is composed of convolution and pooling layers. InceptionV3 works in blocks and each block consists of parallel existence of convolution filters and pooling layer. It handles the computing resources in a better way. InceptionResNetV2 is the combination of Inception architecture and residual connections. This model has three ensemble residual and one InceptionV3 connection. Xception model is the result of depth wise separable convolution implying a complete separation of spatial convolution and cross channel convolution. MobileNet is built from depth wise separable convolutions and followed Inception models to reduce complications in initial few layers. DenseNet [50] was proposed by Huang et al. 2017. It is densely connected CNN architecture where each layer is interconnected to each other in feedforward manner, *i.e.*, the output of all preceding layers is the input of each layer. It introduces $L(L+1)/2$ direct connections instead of L layers in other models. NasNet [51] was proposed by Zoph et al. 2018. It introduced a new regularization technique known as scheduled drop path which improves the performance. Moreover, it is a scalable CNN architecture that consists of basic building blocks known as normal cell and reduction cell. We have also shown the block diagram of normal and reduction cell for NasNet model in Fig. 2. There are two variants of NasNet Viz. NasNetmobile and NasnetLarge. NasNetmobile is optimized small model suitable for embedded vision task compared to NasNetlarge and hence, only the basic architecture of NasNet has been shown in Fig. 2(i).



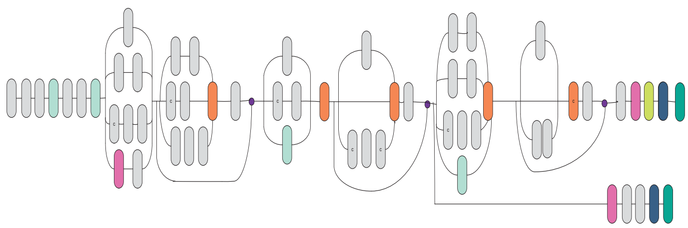
(a) AlexNet

(b) VGG16

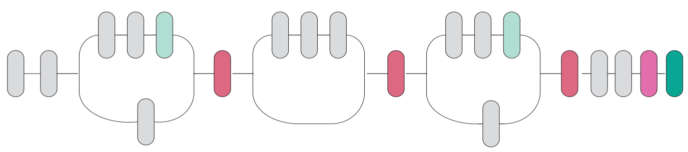
(c) ResNet152V2



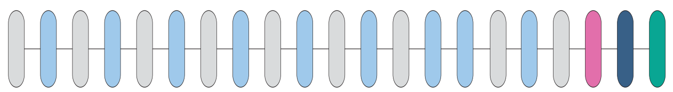
(d) InceptionV3



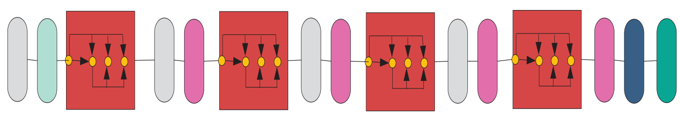
(e) InceptionResNetV2



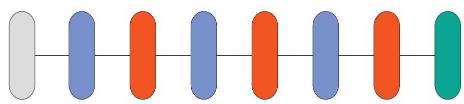
(f) Xception



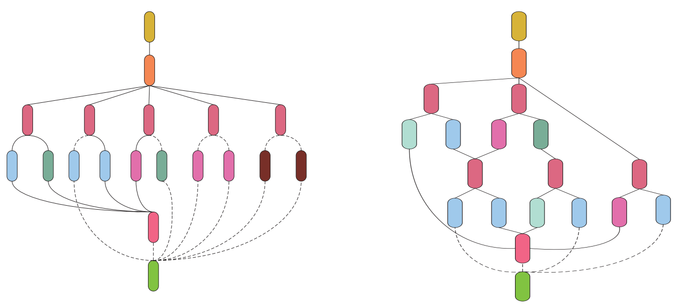
(g) MobileNet



(h) DenseNet169



(i) NasNet



Normal Cell Reduction Cell

Fig. 2. Block diagrams of pre-trained deep CNN models used in this paper.

Table 3: Details of pre-trained deep CNN models.

Deep CNN Model	Input Shape	#Convolution Layers	#Pooling Layers	# Fully Connected Layers	Non-Trainable Parameter	Trainable Parameter
AlexNet	227×227×3	5	3	3	58,281,344	4097000
Vgg16	224×224×3	13	5	3	134,260,544	40,970
ResNet152V2	224×224×3	151	4	1	58,331,648	20,490
InceptionV3	299×299×3	83	12	1	21,802,784	20,490
InceptionResNetV2	299×299×3	240	6	1	54,336,736	15,370
Xception	299×299×3	37	4	1	20,861,480	20,490
MobileNet	224×224×3	14	1	1	4,253,864	10,010
DenseNet169	224×224×3	152	5	1	12,642,880	16,650
NasNetMobile	224×224×3	183	57	1	4,269,716	10,570
NasNetLarge	331×331×3	227	76	1	84,916,818	40,330

IV. Experiments and Results

A. *Experimental Setup*

In this section, we have provided all the experimental setup for training 10 deep CNN models for rice plant disease classification. It can be observed from Table 3 that the input shape varies for each model. Therefore, we have reshaped our rice plant images to the desired shape as per the connected layer with seven neurons. This is done because all the 10 pre-trained deep CNN models dealt here were trained on ImageNet dataset which is having 1000 classes and hence last layer consists of 1000 neurons. Whereas, the rice plant dataset used in this study is having seven classes and hence last fully connected layer should have seven neurons. Further, all the layers were frozen while training except last layer based on the concept of transfer learning as shown in Fig. 1, *i.e.*, the weights obtained from training of ImageNet dataset were remained intact while training for rice plant dataset and only the weights of last layer will be updated. Consequently, the number of trainable parameters were drastically reduced as shown in Table 3. Then, we have randomly partitioned the rice plant disease dataset into 70%, 20% and 10% training, test and validation set, respectively. Each model has been trained for 100 epochs with a mini-batch size of 8 and learning rate of 0.01. The experiment was performed with Adam (Adaptive

Moment Estimation) optimizer. Moreover, we have run our model for five trials (*T*) to reduce the variability obtained in classification accuracy due to random partitioning of train, validation and test dataset. Finally, the overall accuracy (OA) has been calculated by averaging the accuracy of five trials. In addition, we have shown standard deviation (STD) of accuracy in five trials which demonstrate the robustness of the model. All experiments have been performed in Python 3.6 with Keras framework having Tensorflow backend. Simulation were carried out in Google Colab that provides Intel(R) Xeon(R) CPU @ 2.30GHz, 13GB RAM and NVIDIA Tesla K80 GPU.

B. Experimental Results

The classification accuracy obtained using 10 pre-trained deep CNN models on test set of rice plant dataset has been shown in Table 4. We have shown the classification accuracy for each trial along with OA and STD of five trials. It can be observed that the highest OA of 93.11% with STD of 3.02% has been obtained by applying VGG16 model. Further, Fig. 3 depicts the graphical view of performance comparison of 10 pre-trained deep CNN models on rice plant dataset. For more detailed analysis, we have calculated following parameters: Class-wise Accuracy, Precision, Sensitivity, Specificity and F1 Score using VGG16 model as it has produced highest OA (Table 5). It can be observed that the performance of VGG16 model for SR, FS and HL classes were mostly accurate whereas RB and BLB classes were difficult to classify. Moreover, the performance graph with respect to loss vs. epoch and accuracy vs epoch has been depicted in Fig. 4 and receiving operating characteristic (ROC) curve has been shown in Fig. 5 for seven classes of rice plant disease dataset using VGG16 model. As the curves for all seven classes are closer to top-left corner, it demonstrates promising performance of VGG16 model.

Table 4: Classification results obtained using 10 pre-trained deep CNN models on rice plant dataset.

Deep CNN model	T1	T2	T3	T4	T5	OA ± STD
AlexNet	72.13	72.54	79.92	79.51	73.36	75.49 ± 3.88
Vgg16	96.31	87.70	94.26	95.08	92.21	93.11 ± 3.02
ResNet152V2	75.82	84.43	85.25	87.30	85.25	83.61 ± 4.48
InceptionV3	75.82	75.00	72.13	78.69	77.46	75.82 ± 2.51
InceptionResNetV2	77.46	85.25	77.87	81.15	85.25	81.40 ± 3.80
Xception	78.28	88.11	84.84	79.10	81.15	82.30 ± 4.12
MobileNet	71.31	71.31	70.49	67.62	63.52	68.85 ± 3.34
DenseNet169	77.05	80.74	73.77	73.77	83.61	77.79 ± 4.34
NasNetMobile	73.36	73.77	78.68	68.85	79.10	74.75 ± 4.24
NasNetLarge	84.84	84.43	84.43	86.07	89.75	85.90 ± 2.25

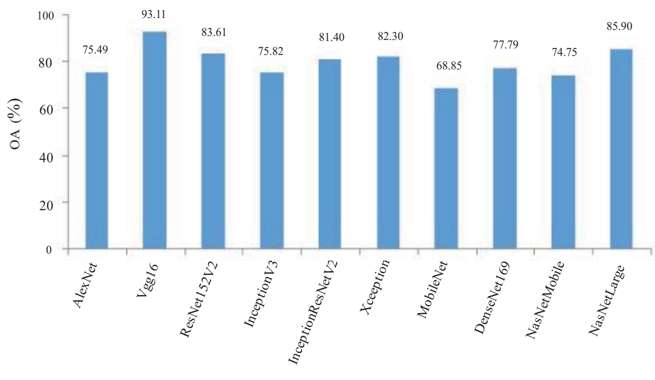
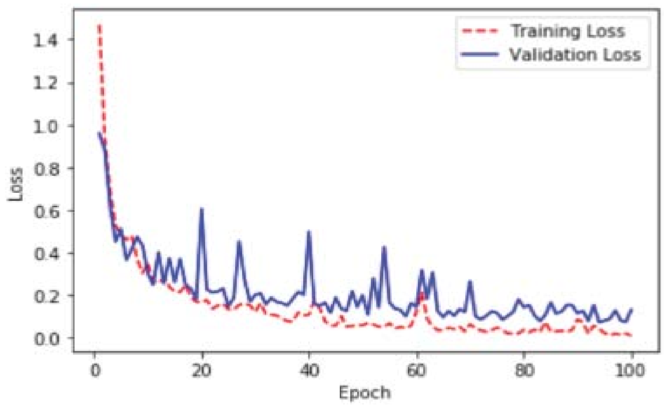


Fig.3. Performance comparison of 10 pre-trained deep CNN models on rice plant disease dataset.

Table 5: Other performance parameters obtained using VGG16 model for rice plant dataset.

Classes	Class Accuracy (%)	Precision (%)	Sensitivity (%)	Specificity (%)	F1-Score
RB	83.33	81.61	84.01	98.11	0.83
BLB	82.35	91.10	89.38	97.48	0.90
BS	92.59	98.18	92.25	99.72	0.95
SB	88.00	86.66	91.27	98.04	0.89
SR	95.65	100	93.22	100	0.96
FS	100	97.74	100	99.50	0.99
HL	97.67	95.25	96.98	99.02	0.96



(a)

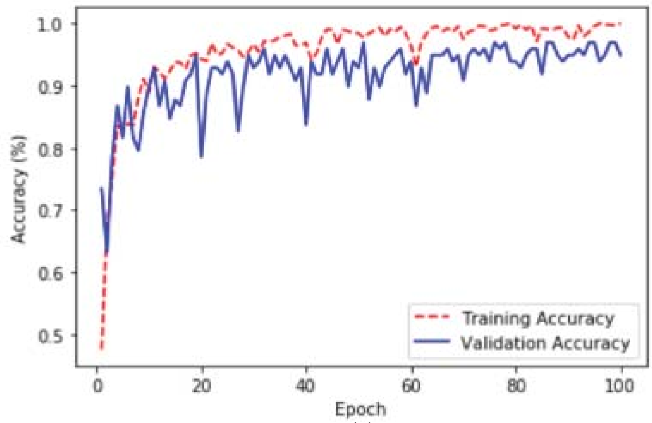


Fig. 4. Performance of VGG16 model while training: (a) Loss vs. Epoch; (b) Accuracy vs. Epoch.

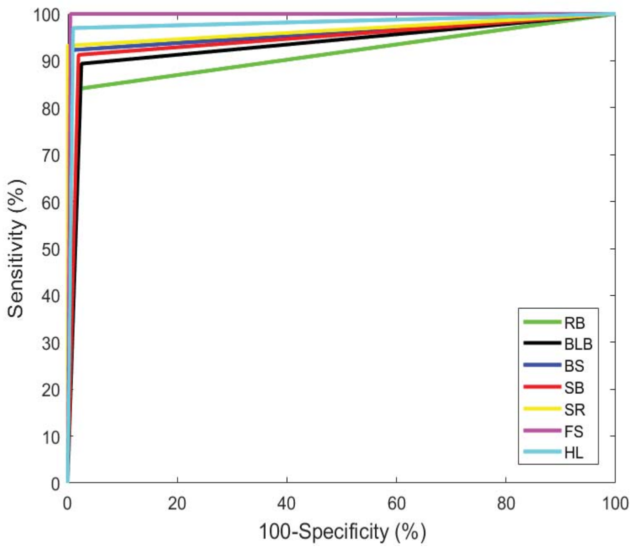


Fig. 5. ROC curve for seven classes of rice plant disease dataset using VGG16 model.

V. CONCLUSION

The paper presents an image-based rice plant disease classification using transfer learning of deep CNN models. We employed 10 pre-trained deep CNN models namely: AlexNet, VGG16, ResNet152V2, InceptionV3, InceptionResNetV2, Xception, MobileNet, DenseNet169, NasNetMobile and NasNetLarge. Our results showed that the VGG16 model obtained the highest classification accuracy of 93.11% among the 10 models. The rationale behind better performance of VGG16 might be its greater number of parameters which helps to fit the new data. On the other hand, the depth of most of other models is deeper than VGG16 that requires more epochs to fine-tune. Overall, the presented transfer learning approach shows the encouraging results and demonstrates its ability of classifying rice plant diseases. In future, we intend to work on data augmentation technique to generate large dataset and train the deep CNN model from scratch for classification of rice plant diseases.

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