JETIR.ORG ISSN: 2349-5162 | ESTD Year : 2014 | Monthly Issue
JOURNAL OF EMERGING TECHNOLOGIES AND INNOVATIVE RESEARCH (JETIR)
An International Scholarly Open Access, Peer-reviewed, Refereed Journal

RICE DISEASE RECOGNITION USING VGG16 AND TRANSFER LEARNING BASED ON DEEP LEARNING TECHNIQUES

[1]Sunil A, [2]Rashmi B R, [3]Josna O

[1]Assistant Professor, [2]Assistatant professor, [3]Assistant Professor
Department of Computer Science and Engineering,
Rajarajeswari College of Engineering, Bangalore, India

Abstract : One of the most widely grown crops in India is rice, which is afflicted by a number of diseases at different phases of cultivation. With their little understanding, farmers find it extremely difficult to appropriately identify these diseases by hand. Farmers spend a lot of time and money managing diseases, and they use a cheap, unreliable way of disease detection that results in unhealthy farming. The automatic identification of infectious microorganisms in the leaves of rice plants is made possible by the progress of technical support in agriculture. One of the deep learning algorithms that has been successfully used to solve computer vision problems such as segmentation of objects, analysis of images, and picture classification is the convolutional neural network algorithm (CNN). In our work, we use a sort of CNN model called VGG16 in conjunction with a transfer learning strategy to identify illnesses in photos of rice leaves. The suggested model's parameters were tuned for the classification task, and a respectable accuracy of 97.57% was attained.

IndexTerms- Rice leaf diseases, CNN Deep Learning, Fine-tuning, Transfer learning

I. INTRODUCTION

Plant disease identification in a timely and accurate manner is essential to resource management and sustainable agriculture. While some diseases have no outward signs, most are detected by skilled plant pathologists using optical observation. However, even highly trained pathologists can face difficulties due to disease outbreaks and climate change. Rice is a staple crop of India, a country that produces a lot of rice and where agriculture accounts for 19.9% of GDP. The financial success of rice growers can be greatly impacted by diseases. For the reason of early disease detection, an expert system of automatic data processing is therefore crucial. By efficiently processing visual input and recognising spatial correlations, deep learning—in particular, convolutional neural networks (CNNs)—offers reliable solutions for plant disease classification and other agricultural problems.

II. RELATED WORK

Many researchers have used algorithms of machine learning and deep learning to create various architectures in recent years for plant leaf disease identifications. One of the neural networks that are most commonly used in deep learning is the convolutional neural network (CNN). Amit Kumar Singh et al. classified healthy and damaged rice leaves using support vector machine (SVM), and the classification accuracy was 82% (Duan et al., 2017). Mohsen Azadbakht et al. employed machine learning techniques and hyperspectral data from wheat leaves to identify wheat leaf rot. After analysing the outcomes of four machine learning approaches, they concluded that support vector regression produced the best results in this instance (Azadbakht et al., 2019). In contrast, the performance is incredibly mediocre. CNN is used as the research method in this development because, in contrast to traditional machine vision algorithms, which call for manual feature extraction and classification, CNN only requires the input of image data into the network; the network's capacity for self-learning allows it to complete the image classification process (Xie et al., 2020).

In order to identify rice plant illnesses, Krishnamoorthy N et al. (2021) suggested an InceptionResNetV2 (Convolutional Neural Network) with transfer learning. Deep learning has been used to image identification quite quickly (Xiong et al., 2021; Naranjo-Torres et al., Krishnamoorthy N et al. 2021). To detect the disease in the millet crop, Solemane Coulibalya et al. (2019) used a VGG16 model using a transfer learning technique (Coulibaly et al., 2019). This project gathered 124 leaf photos and divided them into groups for mildew illnesses and healthy leaves. The accuracy of the VGG16 model was 95%.

For the purpose of classifying plant illnesses in their leaves, N. Nandhini et al. (2020) presented machine learning methods including SVM, K-NN, and decision trees (Nandhini and Bhavani, 2020). Task, the authors trained InceptionResNetV2 using six classes of photos, and the model produced an accuracy of 95.67%.

III. MATERIALS AND TECHNIQUES

3.1.RICE ILLNESS CLASSIFICATIONS AND DATASET OVERVIEW: The majority of the rice image dataset was gathered from Raipur's agriculture areas over the previous few months. The collection includes 4020 photos of rice leaves with illnesses, including the five most prevalent ones: brown spot, sheath blight, bacterial leaf blight, false smut, and leaf blast. 516 pictures of healthy leaves are available. While collecting the data multiple challenges were encountered, including inadequate lighting and in reality every image was having only one disease. 10% is used for validation, 10% is for testing, and 80% of the dataset is used for training. The VGG16 algorithm was benefited to implement the classification function.

3.2. IMAGE PRE-PROCESSING AND AUGMENTATION:

By encouraging significant insights, image pre-processing improves raw input data and increases model accuracy and efficiency. For uniformity, the gathered dataset photos with different dimensions and RGB coefficients (0–255) were then downsized and rescaled in this investigation.

The image's pixel values were scaled to 0–1 and downsized to 224x224x3 pixels during the pre-processing stage. The benefit of Image Data Generator class is to apply image augmentation techniques, including as rotation, random zooming, shearing, and vertical and horizontal flipping, in order to improve the size of training dataset. (Figure 4)

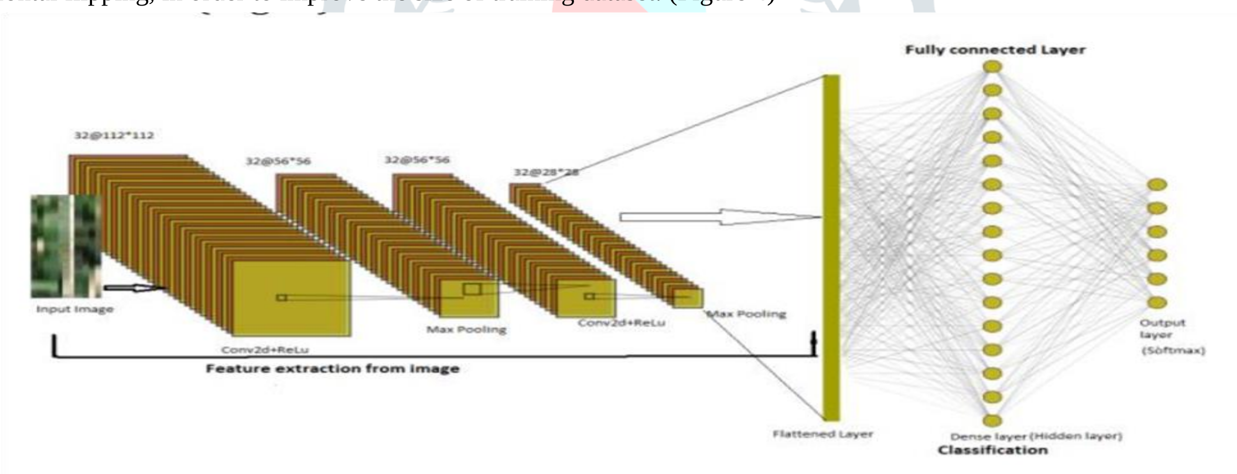

Fig. 1. Simple CNN model architecture.

IV. MODEL CONSTRUCTION

4.1 CNN without the use of transfer learning

A very basic neural network is what it is. It has only six layers: one output layer comes after two convolution layers, two downsampling layers, and one fully linked layer. Th Input photo dimensions are set to 224x224x3.In the feature extraction process, it is consisting of several convolution, activation, and pooling layers. Figure 5 displays the design that was used for the suggested system.

The foundation of a convolutional neural network is the convolutional layer ([1], 2018). Convolution layers employ stride-based 3 by 3 filters. It uses filters with a set of automatically learnable parameters (weights) to mine applicable types from the input image. ReLU is the activation function employed. ReLU, an unsaturated initiation function, improves model performance more than saturated initiation functions. Max pooling layers function by performing a downsampling operation on the input initiation maps inside a pooling window of size 3 by 3 with a stride value of 2. The maximal component from the area of the feature map enclosed by the filter is chosen by a pooling process.

The data is transformed into a single-dimensional array by the flattening layer and then sent into the fully linked layer. A set of three completely linked layers, including 112, 56, and 6 neurons each were used to classify images into various groups to which they belong. Within the third completely connected layer, the Softmax initiation function is employed. Every class's probability is returned, with the target class having the highest likelihood.

4.2. VGG16 with transfer learning

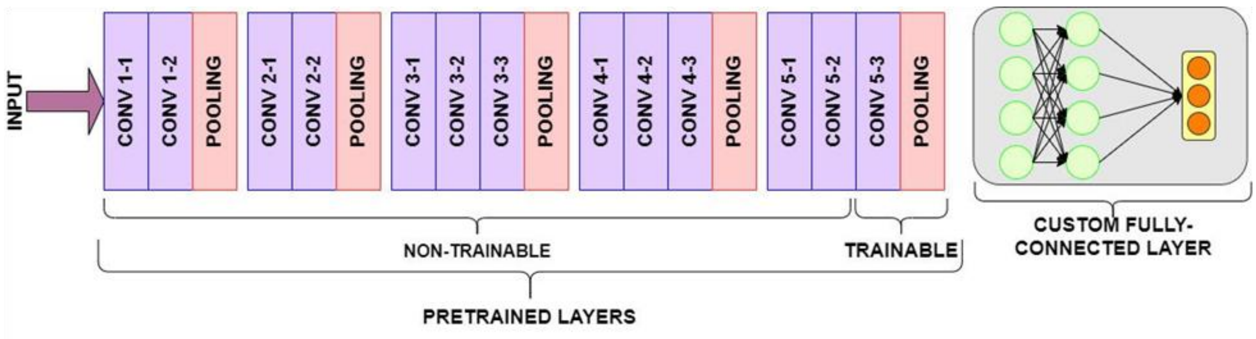

Fig. 2. VGG-16 Architecture fine–tuned with the last two layers with 128 Dense FC Layer and 6 Dense Softmax Layer as the output.

224x224x3 pixels were used as the new image size. Image Data Generator will benefit to apply image augmentation techniques, such as flipping and rotation. The categorical_crossentropy loss function and Adam optimizer benefited to construct the model, and termination of training will be done after 200 epochs. When compared to a customised CNN model, the VGG-16 based method performed better. The VGG-16 architecture and the suggested model are depicted in Figures 1 and 2, respectively.

4.3. Justification for the Chosen Model

Transfer learning, which is especially helpful when there is a shortage of labelled data available, uses the knowledge from previously trained models to increase generalisation and shorten training times. We employed the pre-trained VGG Net and adjusted it for our particular dataset for creating a powerful classification model.

V. PARAMETERS FOR EVALUATION AND EXPERIMENTAL ANALYSIS (METRICS):

We use the following metrics for performance analysis of various models;

5.1. Confusion Matrix: We can assess the model's effectiveness using the indicators including the F1 Score, Precision, Recall and Accuracy as in equations 1, 2, 3, and 4. This is done by observing the statistics of correct detections (also known as true positives), misdetections (also known as false negatives), true negatives, and false positives.

5.2. Precision

It computes the degree on which the evaluation and actual value are close and performs well with balanced datasets.

(TP+TN)/TP+FP+TN+FN) = Accuracy (1)

5.3. Precision: TP / (TP + FP) (2)

5.4. Recall = TP / (TP + FN) (3)

5.5. The F1-score is equal to 2TP/(2TP+FP+FN) (4)

This deduction will help us develop a dependable model for our objective of identifying plant leaf diseases, where the components employed in the evaluation metrics are false negative (TN), false positive (FP), true positive (TP), and false negative (FN).

VI. SETUP FOR EXPERIMENTATION

The experiment was completed using 64-bit Windows 11 PC components, a GPU runtime allotted by Google Collaboration, and 16 GB of storage on Google Drive. The Keras 2.8.3 framework and TensorFlow backend were benefited to facilitate the deep neural network training and validation processes.

VII. FINDINGS AND CONVERSATION

This section presents and discusses the outcome that the suggested methodology produced. Training and test sets for a refined pre-trained model and a basic CNN contain 11236 and 2700 instances, respectively.

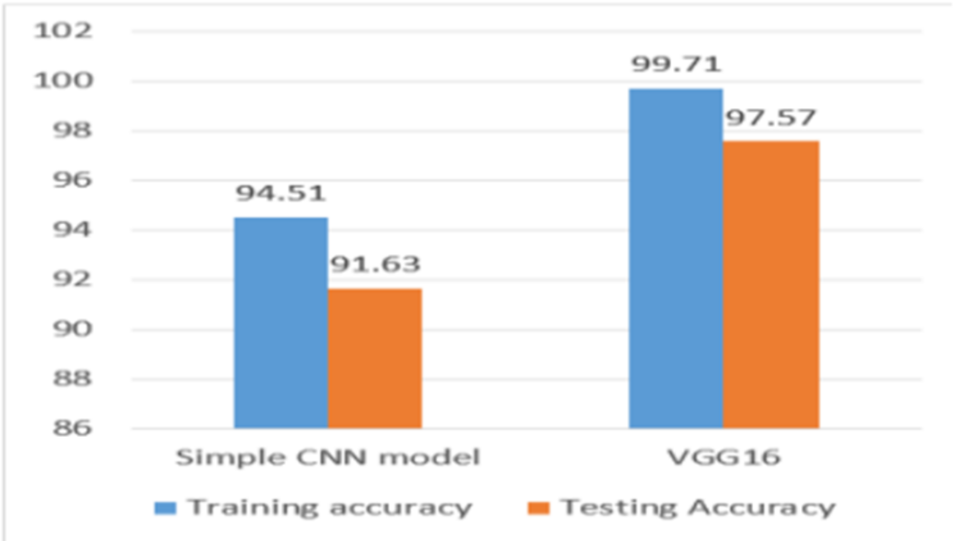

Fig. 3. Test and training accuracy of the model proposed.

The accuracy of classification of CNN models for rice leaf diseases is displayed in Fig. 1. The confusion matrix used to assess the models' performance on a grouping test is depicted in Fig. 2. It is useful to compute the F1 score, precision, accuracy and recall which are displayed in Fig. 3, and it displays the score of classification accuracy for discrete classes.

VIII. ANALYSING ERRORS

The suggested Simple CNN model incorrectly classifies some of the images depicted in Figure 2. The section that follows goes into detail on each illness type's misclassifications.

leaf Blast: Although this image is portion of the leaf Blast series, it is categorised as a Brown Spot because of its blurriness. The cause can be that the identical rice leaf has a few little brown spots on it.

Bacterial Leaf Blight: Pictures are under the Blight category still they are labelled as phoney smut. The cause could be blurry images and inadequate lighting.

Healthy: Although the images are healthy, they are categorised as false smiles, most likely due to the weak contrast and blurry image.

Brown Spot: While categorised as Blast and Sheath blight, the images are actually owned by Brown Spot. The leaf's little blast lesions could be one of the causes. Lesions in the brown spots mimic blast lesions.

False smut: Images are categorised as brown spots and healthy, but they actually belong to False Smut. The leaf's little blast lesions could be one of the causes. The brown spot lesions have weak contrast and blurry images that resemble blast lesions.

Sheath blight: Despite being associated with sheath blight, the blurry image is categorised as fake smut and Brown Spot. The rice leaf may have little brown stains on it, which could be the cause.

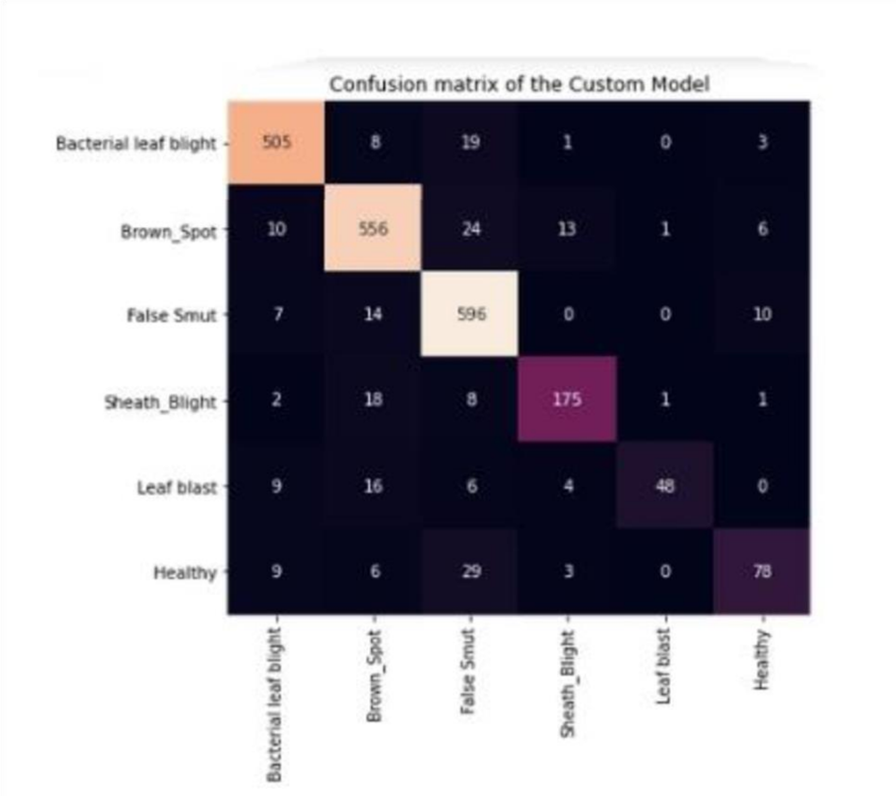

Fig. 3 Confusion matrix for Simple CNN

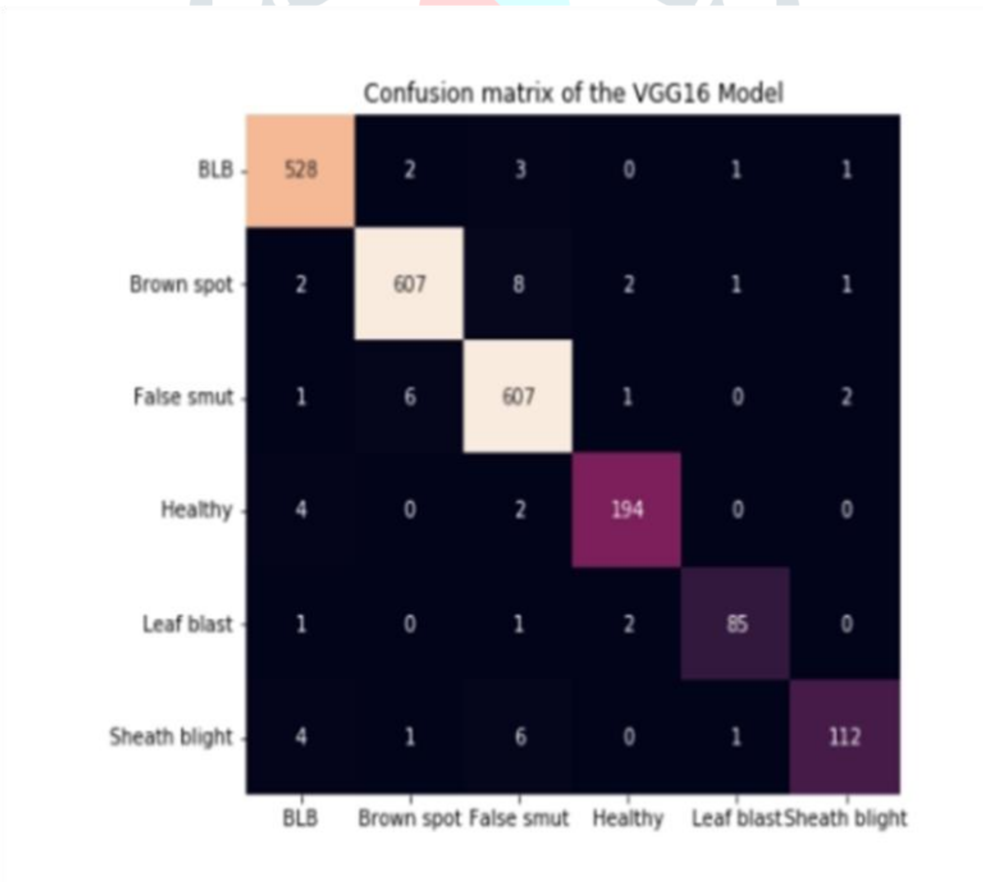

Fig. 4 Confusion matrix for VCG16

The confusion matrix observation shows that it generates much fewer false positive and false negative results, and that the diagonal values are higher.

Diseases types	Performance metrics of VCG16			
	Precision	**Recall**	**F1 score**	**Support**
BLB	0.93	0.94	0.94	536
Brown Spot	0.90	0.91	0.91	610
False Smut	0.87	0.95	0.91	627
Healthy	0.80	0.62	0.70	125
Leaf blast	0.96	0.58	0.72	83
Sheath Blight	0.97	0.90	0.93	124

Table. 1. Performance Metrics for Simple CNN

Diseases types	Performance metrics of VCG16			
	Precision	**Recall**	**F1 score**	**Support**
BLB	0.98	0.99	0.98	536
Brown Spot	0.99	0.98	0.98	621
False Smut	0.97	0.98	0.98	617
Healthy	0.97	0.97	0.97	200
Leaf blast	0.97	0.96	0.96	89
Sheath Blight	0.89	0.85	0.87	205

Table 2. Performance Metrics for VGG16

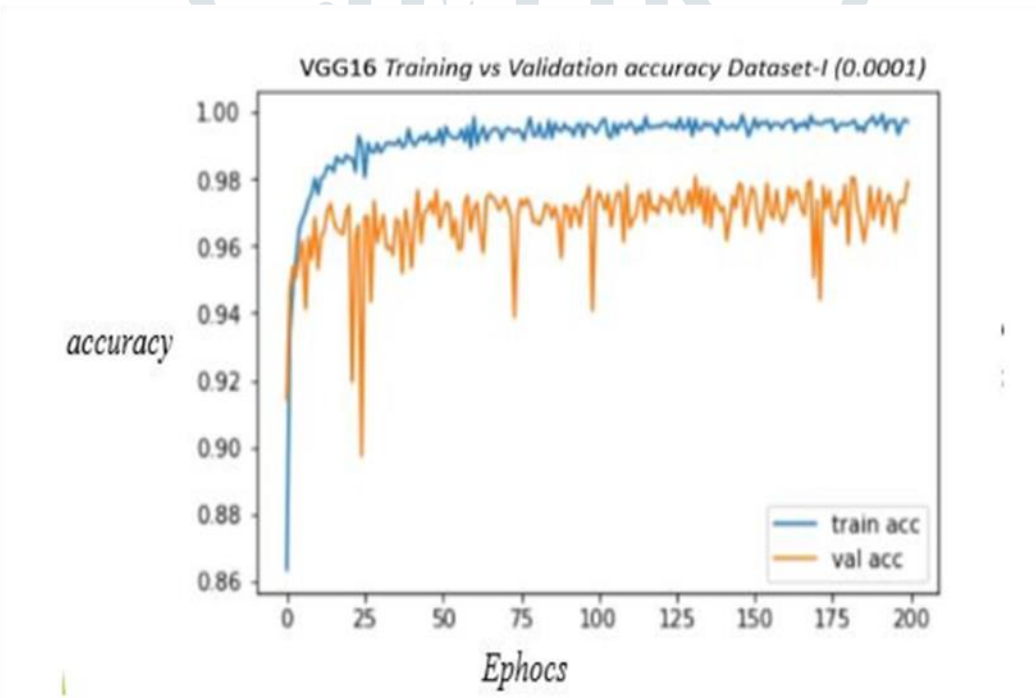

Fig. 5 Validation and Training accuracies for Simple CNN

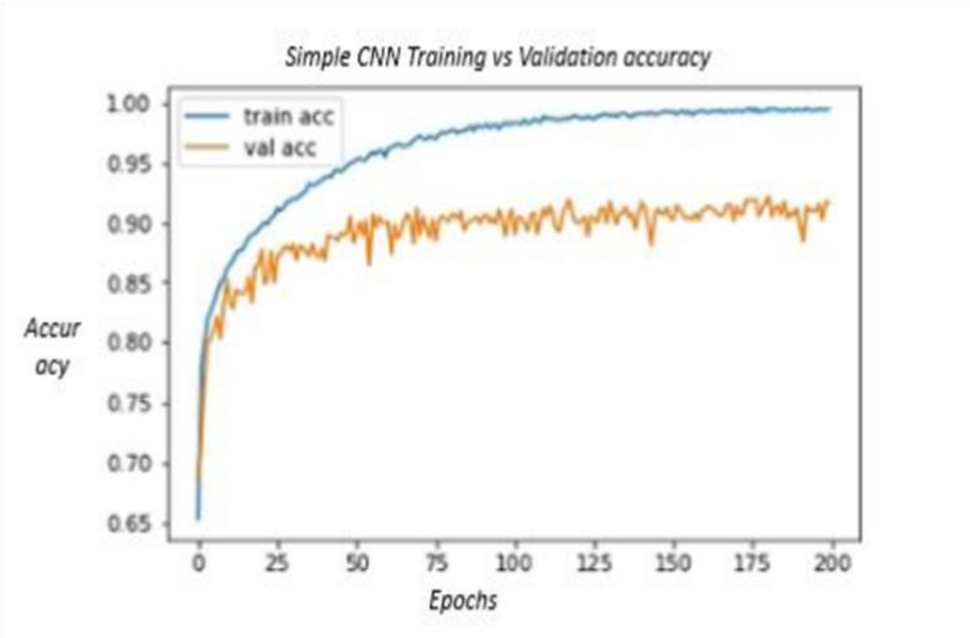

Fig. 6 Validation and Training accuracies for VGG16

Fig. 5 observation: We can see that the training and validation curves in the VGG16 model are moving in close proximity, but the curves in the simple CNN model are not moving in unison.

IX. CONCLUSION

In order to detect rice leaf illnesses, we present in this work a pre-trained deep convolutional neural network of VGG16 using a transfer learning technique. This work takes into consideration the three main rice plant attacking diseases: sheath blight, brown spot, false smut, leaf blast, and healthy class. After adjusting for various hyper parameters, the basic CNN model ran 200 epochs and reached an accuracy of 91.63%. After adjusting a few hyper parameters and utilising 200 epochs, VGG16 was able to achieve an optimised accuracy of 97.57%. In the future, convolutional neural networks will be investigated for the purpose of classifying additional diseases of plant leaf and varieties of rice diseases. Also, we like to use nature-inspired algorithms to automatically identify the best hyperparameters for enhancing the CNN. We will also use object detection techniques to detect the diseases.

REFERENCES

[1] Sankaran, S., Mishra, A., Ehsani, R., Davis, C., 2010. A review of advanced techniques for detecting plant diseases. Comput. Electron. Agric. 72, 1–13. https://doi.org/10.1016/J.COMPAG.2010.02.007.

[2] Arsenovic, M., Karanovic, M., Sladojevic, S., Anderla, A., Stefanovic, D., 2019. Solving current Limitations of Deep Learning Based Approaches for Plant Disease Detection. Symmetry (Basel). 11,939. https://doi.org/10.3390/sym11070939

[3] Duan, Y., Liu, F., Jiao, L., Zhao, P., Zhang, L., 2017. SAR image segmentation based on convolutionalwavelet neural network and markov random fifield. Pattern Recogn. 64, 255–267.

[4] Azadbakht, M., Ashourloo, D., Aghighi, H., et al., 2019. Wheat leaf rust detection at canopy scale under different LAI levels using machine learning techniques. Comput. Electron. Agric. 156, 119–128.

[5] Xie, W., Ma, G., Zhao, F., et al., 2020. PolSAR image classification via a novel semi supervised recurrent complex-valued convolution neural network. Neurocomputing.

[6] Coulibaly, S., Kamsu-Foguem, B., Kamissoko, D., Traore, D., 2019. Deep neural networks with transfer learning in millet crop images. Comput. Ind. 108, 115–120.

[7] Nandhini, N., Bhavani, R., 2020, January. Feature extraction for diseased leaf image classification using machine learning. In: 2020 International Conference on Computer Communication and Informatics (ICCCI). IEEE, pp. 1–4.

[8] Liu, B., Zhang, Y., He, D., Li, Y., 2018. Identification of apple leaf diseases based on deep convolutional neural networks. Symmetry 10 (1), 11 9. Zhang, R., Sathishkumar, V.E., Jackson Samuel, R.D., 2020. Fuzzy efficient energy smart home management system for renewable energy resources. Sustainability 12 (8), 3115.