Rice Plant Infection Recognition using Deep Neural Network Systems

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Abstract

In this work, identification of diseases present in the plant of rice is carried out using methods of Deep Neural Network. So as to achieve image accession, a dataset having 2212 leaf images with different diseases is used. In this work, the entire dataset is divided into two classes in which class 1 contains the healthy leaves and the other class contains infected leaves. The identification is done using VGG-19, LeNet5, and MobileNet-V2predefined Convolutional Neural Network (CNN) models that own a fixed number of Convolutional layers and also the layers that are connected completely also known as fully connected layers. The architecture is designed as per the details for the LeNet5 model while for the other two methods that is MobileNet-V2 and VGG-19, the architecture is directly imported from some predefined libraries which are ready to use, and further, they are used according to the author's requirement. Once the experiment was completed successfully, it was observed that the accuracy achieved of VGG-19, LeNet5, and MobileNet-V2 was 77.09 %, 76.63 %, and 76.92 %respectively.

Keywords: Rice disease detection, deep learning models, VGG-19, MobileNet-V2, LeNet5.

1. Introduction

Agriculture has become an important factor for making a full day meal for 20% to 30% of the entire population. In the present scenario, agriculture cultivation has become an important source of income [1] and 65 % of the entire population find themselves completely dependent on the farming sector in India [2]. In comparison with other countries like USA, UK, Russia and so on, India has more percent of the population that is dependent on farming. However, there are several problems like plant diseases, waterlogging, water scarcity, disease infection, natural disasters, poor quality of soil, that are being faced by the Indian farmers. These diseases have led to the downfall of the production rate of rice and are surely a major problem [3]. Among these, there are several numbers of diseases that have made a major impact on the production of rice and thus Recognition and identification of rice disease (RRD) at appropriate times has become an essential and important research area in the field of agriculture [4].

Some of the well-known diseases found in rice are Bacterial Leaf Blight (BLB), Rice Tungro Disease (RTD), Brown Spot (BS), Leaf Smut (LS), etc [5]. These diseases cannot be seen by naked eyes when it comes to recognition on large scale. Manual Detection is sometimes possible, but the consumption of time is very much [6]. In order to overcome the manual workforce that at some point becomes unproductive, we use Image Processing Techniques [7]. The important constituent that one needs to think about seriously is that not all diseases are of a similar type, nor all of them have the same functionality. Color, Size, Quantity, Quality, and Nature diverge within the diseases. Some diseases might look brown in color, whereas some might have a yellow color existence [8]. In order to fix this up for the difficulties for recognition of different diseases at the same time, segmentation is used and is considered to be an important aspect of the image processing technique as it breaks a single image into a wide range of categories [9].

Thus, it becomes major research for the researchers to figure out the recognition of the rice plant diseases at the earliest in order to

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keep the production go in a proper flow. Some of the related works on this particular problem have been talked about in studies [10-15]. In the study [10] proposed a new and completely different approach or the method for the recognition of rice plant disease. Under this work, identification and the observation of the malady (disease) present in the plant of the rice became possible by applying image processing techniques. By considering the desired percentage of RGB value (three tinctures of light which result in the creation of new different colors when mixed together) of the infected part that resulted in the classification and figuring out of disease's presence in the plant of rice. A similar type of problem has been accomplished in the study [11] using deep learning methods. In this, a different approach for bringing out the recognition of the diseases that are present in rice plants and the pest video detection is considered. A custom backbone video detection architecture based on deep learning was proposed by them in order to detect plant diseases and pests in the video in which the video was converted into a still frame at first and further detection was sent to still image detector that made the detection easy and reliable. At last, they converted the frames into the video. This is how the classification was carried out.

By using different image processing methods in the study [12] achieved the recognition of diseases present in the plant of rice. On the basis of images of the rice plant that was infected, they identified the disease and did the further categorization of diseases present in the plant of rice. Within this approach, they had used different techniques for the classifications. K-Means Clustering related to intermediate feeding for the sectionalizing of a particular area or infected disease portion was proposed by them for the detection. Green pixels were removed from a particular infected portion for the enhancement of the output of K-Means clustering and further all the features were extracted into different categories by taking the help of SVM that is Support Vector Machine, thus multiclass classification was achieved.

In order to automatically recognize the diseases, present in the rice plant, using image processing technique an approach was developed in the study [13] using the K means clustering on an infected leaf, two random centers or pixels were chosen. Other imaging techniques like hyperspectral and thermal imaging were used. These techniques were completely dependent on the specification of the images that included quality features and other specifications.

Considering the processing of image techniques, so as to achieve disease kind been affected by Paddy leaves, an approach was developed by D. Nidhis et al. [14] In this approach, the intensity of infection was calculated by considering a particular diseased area and then by calculating the actual percent of the area that was infected. On the basis of the intensities and adaptation of diseases, the recognition of the rice plant diseases was carried out.

S.Ramesh and D.Vydeki [15] developed an approach for the recognition of infection that was present in the rice plant using an optimized deep learning models along with a Jaya algorithm. As the figures were directly taken from the farm, so the RGB figures were transfigured into HSV figures in order to remove the background. Different concepts like clustering, deep network with Jaya optimization, and feedback loops were used in order to achieve high accuracy. A similar kind of study was also found in the study reported in [21].

After the analysis of the previously proclaimed work, it is understood that rice plant disease identification using plant leaf is an interesting topic and also helpful for society to increase the production of rice. It is also observed that the maximum number of studies are based on image segmentation which is totally image dependent and time-consuming process. Therefore, the authors are trying to propose a rice disease identification method using a fully automated deep neural network method. Through this work, the main focus of the authors is the recognition of rice plant diseases with Neural Network Methodology using deep learning techniques like VGG19, MobileNetV2, LeNet-V5.

2. Material and Methodology

2.1. Dataset preparation

For this work, the combination of two different datasets having 120 and 2092 samples of rice leaf images respectively is taken. The first dataset contains 120 samples of three different disease classes BS, BL, and LS. The total number of these three different samples in this dataset is 40, 40, and 40 respectively. In the second dataset, a total set of 2092 images are used for four different diseases. Among four different types of images, one set represents a healthy set, and the other three sets represent the infected class. Each infected class contains 523 samples of rice leaf images and the healthy class contains 523 images. After the combination of both datasets total of 2212 images are used. Among 2212 samples, 523 samples are used for the healthy class and 1689 samples are used for the infected class type. The abstract details of dataset bifurcation and their preparations have been listed in Table 1.

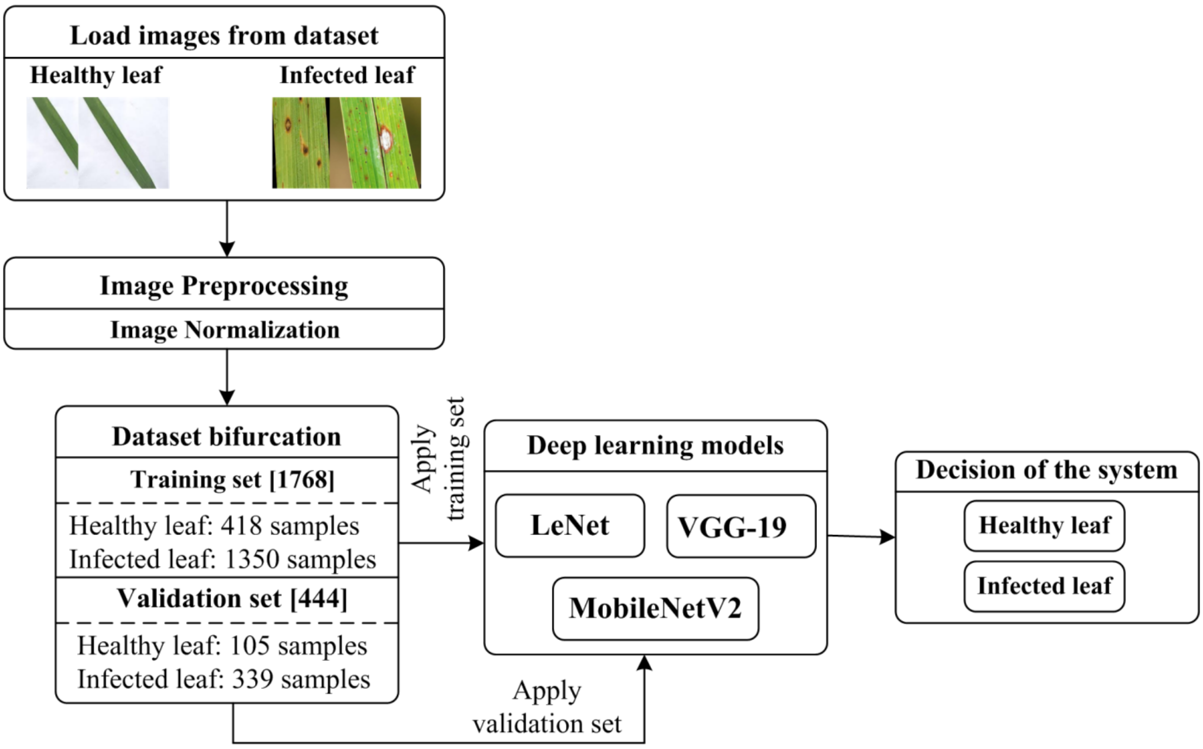

Figure 1: Work-Structural chart for the experiment

2.2. Proposed work

The experimental structural chart of the work that is brought out for "detection of disease present in rice plant using deep neural network methodology" has been depicted in figure 1. The experimental structural chart mainly comprises the sections of dataset bifurcation, image preprocessing, deep learning section of validation and training respectively, and also the section of the diagnosis of a system. The abstract description of every individual section is discussed in the forthcoming section of the manuscript.

2.2.1. Preprocessing Section

Image preprocessing is an essential part of the experiment carried out for the work. In this, image normalization is performed to ensure that all the pixel values of the selected image lie in the same range and also to ensure that the comprehensive processing of the system produces effectively on its outcome. The formula used to achieve the value of the resultant pixel for the key in a pixel has been defined accordingly as per the Eq. 1.

$$Y_i = \frac{X_i - least(X)}{maximal(X) - least(X)} \quad (1)$$

Here, the scale of the intensity differs between 0 to 255.

2.2.2. Dataset Bifurcation Section

Under this segment, the entire dataset is divided into two different sets out of which, one is a set of training whereas, other is the set of validation and in a ratio of 80:20. The training set comprises 1768 samples and the testing set consists of 444 samples. Among 1768 samples of the training set, 418 samples belong to the healthy class image and 1350 samples belong to the infected class. In the same manner, the validation set comprises 105 samples of healthy class images and 339 samples of infected classes. The abstract details of dataset bifurcation and its preparation is discussed in Table 1. Both sets are further inputted to subsequent module of the proposed work.

Table 1
Abstract details of the dataset bifurcation and its preparation.

Considered class	No. of samples per class		Data bifurcation		Total samples
			Training set	Validation set	
Healthy image class	Healthy image:	523	418	105	523
Infected image class	Brown Spot:	563	450	113	
	Hispa:	523	418	105	
	Leaf Blast:	523	418	105	1689
	Bacterial Leaf:	40	32	8	
	Leaf Smut:	40	32	8	
Total		2212	1768	444	2212

2.2.3. Deep learning models

Under this work, three different models of deep neural networks that is LeNet-V5, MobileNet-V2, and VGG-19 are used for discerning of diseases present in the rice plants.

In this work LeNet-V5, VGG-19, and MobileNet-V2 particular models compare the old model (LeNet) with newly proposed models namely MobileNet and VGG-19. On making a comparison within the models that is MobileNet and VGG-19 found that MobileNet is a model that is considered as a lightweight network, that uses a depth-wise separable Convolutional deepening network, and thus reduces parameters and computational complexity. The main objective to use these different models at the same time is to bring out the working comparison among the different models. A slight modification was done in the LeNet model, using ReLU as its activation function.

The size of the image that is considered best for this experiment is 224 × 224 which is designated to layer that is responsible for input and further sent between the layers that are hidden of Convolutional Neural Network (CNN) that is constructed [20]. The filters that are taken into the consideration in order to allow the performance of the Convolutional operation with complete success on the specific given set of images are 32, 48 and the size is 5 × 5, 5 × 5. Padding is set to the valid for distinct convolutional layers which are cnvn1 and cnvn2 respectively of the two layers that are hidden. The weight or the immensity of the first convolutional (cnvn1) filter is [5, 5, 3, 32] while for the second convolutional (cnvn2) filter, it is [5, 5, 32, 48). The formula because of which the production of the desired dimension of turnout attribute or turnout assigned map that was generated is discussed in Eq. 2.

$$w_2 = \left(\frac{w_1 - f + 2_p}{s} + 1\right), \quad h_2 = \left(\frac{h_1 - f + 2_p}{s} + 1\right) \tag{2}$$

Here, $w_1 \times h_1 \times d_1$ is the size of the input image whereas$w_1$represents the width, $h_1$resembles image height and d_1 is the complete quantity of the color band in the image. Further, the remaining entities like the size of the filter is denoted by f and p is the maximum number of padding whereas s denotes the stride value. The description for each model is given here.

LeNet5: An architecture as shown in Figure 2 with multiple layers that focuses on the classification of handwritten numeric digits or character numbers [19] is the LeNet 5 architecture and was proposed in 2015 by LeCun. LeNet5 consists of a layer responsible for input, and a layer responsible for output, two separate convolutional, two pooling layers, andtwo entirely connected layers. LeNet5 has been the most used concept for recognition of character digits.

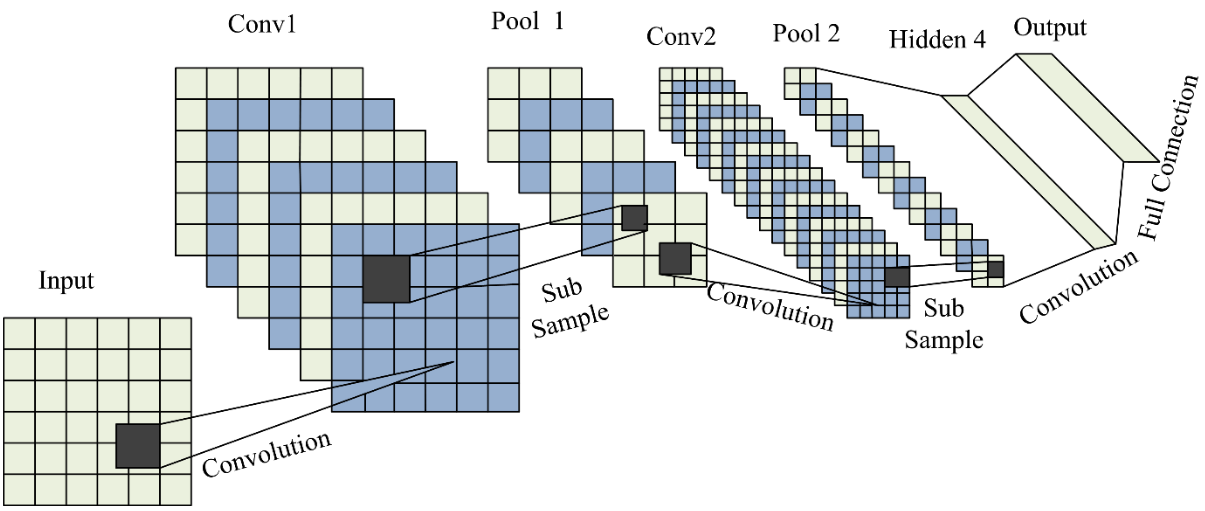

Figure 2: The LeNet Architecture [19]

VGG-19: Architecture with two different layer versions – 16 layers (VGG16) and 19 layers (VGG19) was proposed by Simonyan and Zesserman [16]. In the field of localization and classification tracks, Visual Geometry Group (VGG) had secured first and second positions respectively. Five blocks of convolutional layers in the starting accompanied by 3 fully connected layers is what completes the structure of VGG19. On comparing both the versions of the architecture that is VGG16 and VGG19, VGG19 was found to be deeper and more expensive as compared to VGG16 [17]. The architecture of the VGG model is given in Figure 3.

MobileNet-V2: As the name itself has the mobile word in it, thus MobileNet is a CNN architecture that primarily focuses on the classification of Mobile Versions and the image. In-depth convolutions under which the inputs are filtered even without creating new features and point-to-point convolutions, because of which the generating of the new features as per two core cables that are present inside the Architecture of the MobileNet [18]. Softmax and ReLU are the two different non-linear functions used for activation in this work. The MobileNet model architecture is shown in Figure 4.

Softmax: A softmax function also referred to as a normalized exponential justification or softargmax function is the function that is very useful. Its main use is to convert the output of the ending layer of the proposed model into a probability distribution that is essential. We use the softmax function so that our output layers can communicate with each other and are aware of the result.

Softmax function (σ) is represented with the help of the following formula given in Eq. 3.

$$\Sigma(oi)= \frac{\boldsymbol{e_i^0}}{\sum_{\boldsymbol{j=1}}^{\boldsymbol{n}} \boldsymbol{e_j^0}} \tag{3}$$

Where, index I is in the range of 0 to n-1, whereas o is the output vector of the desired network.

$o=(o_0,o_1,\dots,o_{n-1})$.

ReLU: ReLU or Rectified linear unit is an activation function that has become very effective and popular over the years when it was supposed to be in the CNN model. It acts as a functional method that is used to break linearity and thus increases non-linearity as it is seen that images are distinctly non-linear. Thus, the formula used for the ReLU function is discussed in Eq. 4.

$$f(x) = \text{maximum } (X, 0)$$

$$\text{Here, } X = \sum_{i=1}^{m} W_i X_i \tag{4}$$

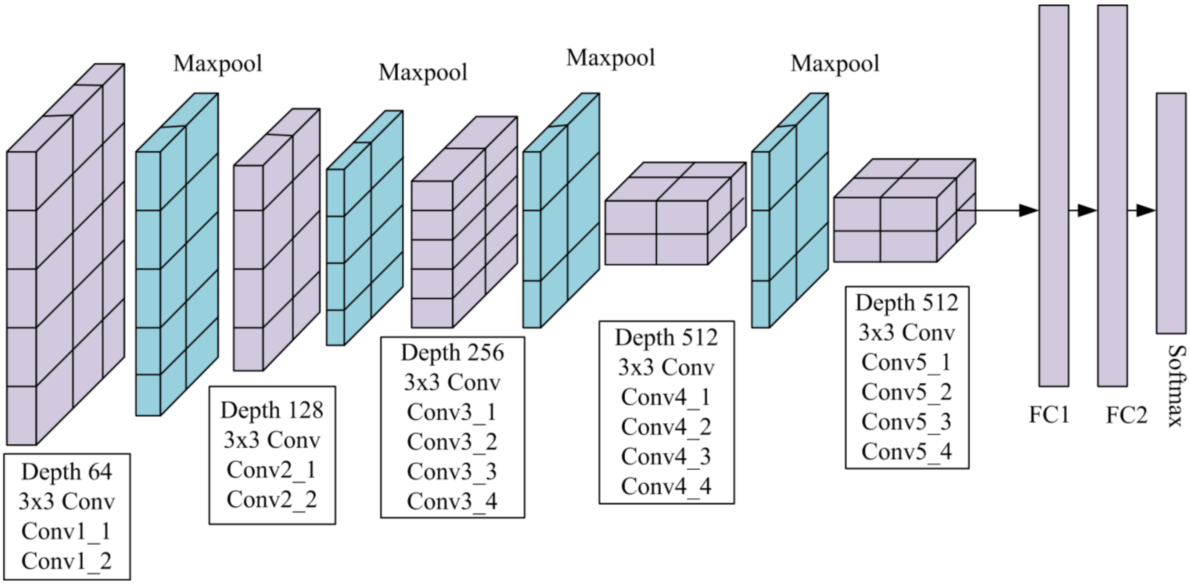

Figure 3: VGG Architecture [16]

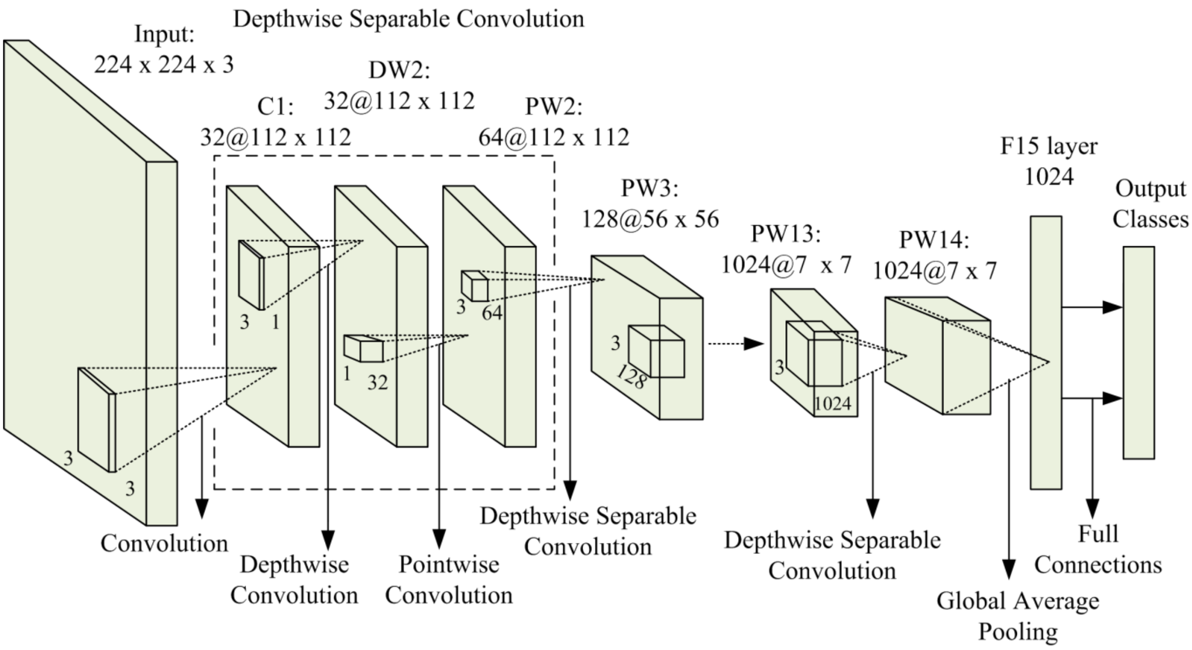

Figure 4: The MobileNet-V2 Architecture [18]

3. Experiment and Results

3.1. Environmental setup

The inclusive investigational work has been carried out on a system having specifications of processor Intel® Core™ i5-7200U CPU@ 2.50 GHz, physical memory of 16 GB, 2 GB Intel HD Graphic 620+4 GB NVIDIA GeForce 940MX graphic and 2TB hard drive. All the images and ROIs are stored in the above-said system. Python having spyder is considered and extensive experiments have been carried out in the same environment.

3.2. Results

A considerable experiment has been brought forward for this work using deep learning models i.e.VGG-19, MobileNet, and LeNet. The outcome of the extensive experiments using various deep learning models (VGG-19, MobileNet, and LeNet) for 0.5 dropouts and 50 epochs is represented in Table 2.

Table 2
Achieved results of extensive experiments carried out for the work.

Model Name	Training Phase			Validation Phase		
	Number of cases	**Accuracy (%)**	**Loss**	**Number of cases**	**Accuracy (%)**	**Loss**
LeNet5	1768	76.63	0.4709	444	73.44	0.5153
Mobile Net-V2	1768	76.92	3.5190	444	73.43	4.0505
VGG19	1768	77.09	3.4925	444	73.43	4.0505

3.2.1. Result Analysis

The result analysis of the extensive experiments has been carried out in the form of a confusion matrix. TNR or True negative rate and the TPR or True positive rate is computed by using confusion matrix accuracy (ACC)and according to the equation given as Eq. 5, Eq. 6, and Eq. 7. The obtained results are given in Table 3.

$$ACC(\%) = \frac{\sum(TP+TN)}{\sum(TN+FP+TP+FN)} \times 100 \quad (5)$$

$$TPR(\%) = \frac{\sum TP}{\sum(TP+FN)} \times 100 \quad (6)$$

$$TNR(\%) = \frac{\sum TN}{\sum(TN+FP)} \times 100 \quad (7)$$

Table 3.

Obtained results from extensive experiments carried out through this work.

Model Name	**Confusion Matrix**			**Accuracy (%)**	**Sensitivity (%)**	**Specificity (%)**
		Healthy	**Infected**			
LeNet5	Healthy	73	32	73.4	57.0	89.8
	Infected	55	284			
Mobile Net-V2	Healthy	63	42	73.4	49.2	86.7
	Infected	65	274			
VGG19	Healthy	78	27	73.4	46.1	90.1
	Infected	91	248			

From Table 3, it has been observed that the maximum identification rate is 73.4 % for all cases. But the sensitivity and specificity of the experiment using the LeNet5 model are 57.0 % and 89.8 %, respectively. Similarly, 49.2 % of sensitivity and 86.7 % of specificity are obtained by using the Mobile Net-V2 deep learning neural network model. The model VGG-19 yields 46.1 % of sensitivity and 90.1 % of specificity for the experiment carried out using 444 samples.

Now through the paper, the question might arise that how accuracy is same for all the models. Thus, accuracy is almost the same for all the models as the authors had taken the weight of the last epoch instead of the best weights according to the accuracy. If the best weights would have been taken into the consideration, the scenario would have been completely different and thus can be referred from Figure 5, but the reason for not taking the best weight according to accuracy was just to avoid overfitting of the model.

Figure 5 shows the learning curves for both the phases that is of the training phase and of the validation phase, respectively. It also contains training accuracy and training loss. Apart from this, it also contains validation accuracy and the validation loss.

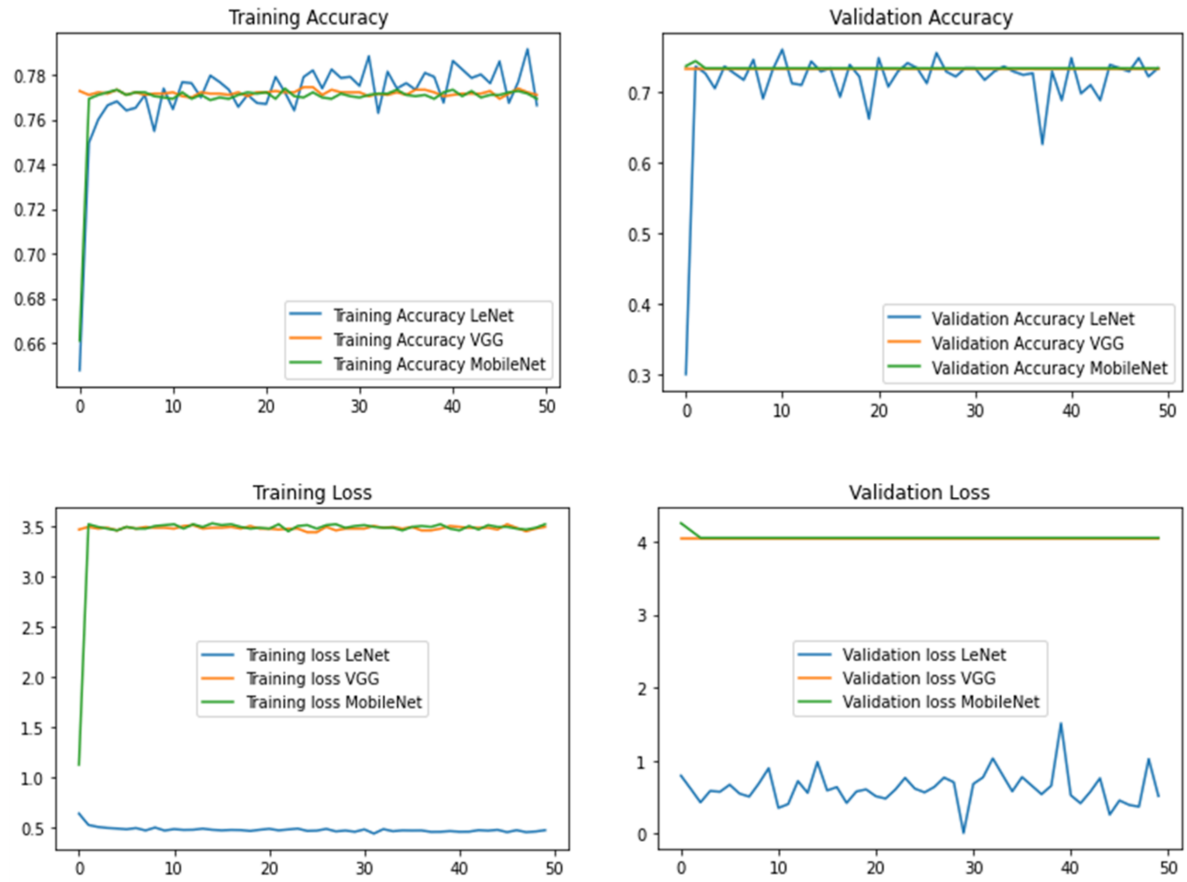

Figure 5: The learning curve representing training phase and the validation phase

3.2.2. Comparative Analysis

The present work is compared with the previously published work [22]. In study [22], the authors used to find the optimal wavelet band for the detection of disordered rice seed. In this study various classifiers are used and found that the SVM performs outstandingly for this type of problem. In study [21], R-CNN fusion is implemented for the rapid detection of the rice disease and obtained an accuracy of 97.2 %. In study [21], a total of 3010 images were used therefore the obtained model yields very good accuracy. In the present study, only a limited number of images is used so the proposed model performs a little bit lower than the study [21]. It also noticed that the proposed system is easy to implement and fast with respect to study [21]. Therefore, the proposed model can be also suitable for the problem like detection of rice disease using images.

4. Conclusion

Under this experiment, different and advanced CNN models such as LeNet5, MobileNetV2, and VGG19 are used and all of them were performed on the same dataset and observed that how they work when performed on the same dataset. Through this work, we concluded that MobileNet and VGG19 perform almost similar on the same dataset as the accuracy and validation loss are almost the same whereas LeNet performs a bit differently from both the CNN models. Though the epoch were same for each model so less variation is found but when taking a smaller number of epochs, it was figured out that LeNet resulted better in comparison with MobileNetV2 & VGG19. Refer to the accuracy graph for reference. Thus, it is concluded that for a smaller number of epochs, LeNet works better than the other models.

This work can be further extended to get better objectives by applying some image pre-processing techniques before training the model to get better accuracy. Increasing the value of RGB images remains an important factor that needs to be kept in mind. One also can use GoogleNet to train the model and see what results it produces. Google Net is an advance version of models and it is expected to get better results when using GoogleNet.

References

[1] T. Xuan. “Rice production, agricultural research, and the environment”. Routledge, In Vietnam's rural transformation (2018) pp. 185-200.

[2] I.V. Malhan and S.Rao. “Agricultural knowledge transfer in India: A study of prevailing communication channels”. Library Philosophy and Practice, 200. (2007)

[3] R. Islam, R. Islam. "An image processing technique to calculate percentage of disease affected pixels of paddy leaf." International Journal of Computer Applications Vol. 123.(2015) 28-34.

[4] M. Yusof,N.F.Rosli,M.Othman,R.Mohamed, MHA Abdullah. “MDCocoa. M-agriculture expert system for diagnosing cocoa plant diseases”. Proc. International Conference on Soft Computing and Data Mining (2018). 363–71.

[5] H.B. Prajapati, J.P. Shah,V.K.Dabhi. “Detection and classification of rice plant diseases”. IntellDecis Technol ;11(3)(2017):357–73.

[6] S,PMohanty, D.P. Hughes, M. Salathe. “Using deep learning for image-based plant disease detection”. Front Plant Sci ;7 (1419):(2016).1–10.

[7] R. Deshmukh, "Detection of paddy leafdiseases", International Conference on Advances in Science and Technology, vol. 2, pp. 8-10, 2015.

[8] J.GBarbedo, L.V Koenigkan,T.TSantos. “Identifying multiple plant diseases using digital image processing”. BiosystEng ;147:(2016)104–16.

[9] S. Sladojevic, M. Arsenovic, A. Anderla,D.Culibrk, D. Stefanovic.“Deep neural networks-based recognition of plant diseases by leaf image classification”. ComputIntellNeurosci(2016):1–11.

[10] T. Islam, M. Sah, S. Baral, R.R. Choudhury. “A faster technique on rice disease detection using image processing of affected area in agro-field”. In: In: Proc. Second International Conference on Inventive Communication and Computational Technologies (2018) p. 62–6.

[11] D. Li, R. Wang, C. Xie, L. Liu, J. Zhang, R. Li, F. Wang, andW. Liu. “A recognition method for rice plant diseases and pests video detection based on deep convolutional neural network”. Sensors, 20(3), 578.(2020)

[12] H.B. Prajapati, J.P. Shah,V.K.Dabhi. “Detection and classification of rice plant diseases”. Intell Decision Technology;11(3)(2017):357–373.

[13] P.K. Sethy, N.K. Barpanda, A.K. RathandS.K. Behera. “Image Processing Techniques for Diagnosing Rice Plant Disease: A Survey”. Procedia Computer Science, 167, (2020). 516-530.

[14] A.D. Nidhis,C.N.VPardhu, K.C Reddy and K. Deepa. “Cluster based paddy leaf disease detection, classification and diagnosis in crop health monitoring unit”. Comput Aided IntervenDiagnost Clinic Med Images; 31: (2019). 281–91.

[15] S. Ramesh, andD. Vydeki. “Recognition and classification of paddy leaf diseases using Optimized Deep Neural network with Jaya algorithm”. Information processing in agriculture, 7(2), (2020). 249-260.

[16] K. Simonyan, and A. Zisserman. “Very deep convolutional networks for large-scale image recognition”. arXiv preprint arXiv: (2014). 1409.1556.

[17] E.E.D. Hemdan, M.A. Shouman and M.E. Karar. “Covidx-net: A framework of deep learning classifiers to diagnose covid-19 in x-ray images”. arXiv preprint arXiv:2003.11055. (2020)

[18] W. Sae-Lim, W. Wettayaprasit and P. Aiyarak, “Convolutional Neural Networks Using MobileNet for Skin Lesion Classification”. In 2019 16th

International Joint Conference on Computer Science and Software Engineering (JCSSE) (2019). (pp. 242-247). IEEE.

[19] T. Guo, J. Dong, H. Li andY. Gao. “Simple convolutional neural network on image classification”. In 2017 IEEE 2nd International Conference on Big Data Analysis (ICBDA) (2017) (pp. 721-724). IEEE.

[20] C. Bhatt, I. Kumar, V. Vijayakumar, K.U. Singh, A. Kumar. “The state of the art of deep learning models in medical science and their challenges”. Multimedia Syst. https://doi.org/10.1007/s00530-020-00694-1.(2020).

[21] G. Zhou, W. Zhang, A. Chen, M. He, X. Ma. “Rapid Detection of Rice Disease Based on FCM-KM and Faster R-CNN Fusion”. IEEE Access, Vol. 7, (2019) 143190-143206.

[22] I. Baek, M.S Kim, B.K. Cho, C. Mo, J. Y. Barnaby, A.M. McClung, andM. Oh. “Selection of optimal hyperspectral wavebands for detection of discolored, diseased rice seeds”. Applied Sciences, Vol. 9, No.