Optimized Deep Learning Techniques for Disease Detection in Rice Crop using Merged Datasets

Muhammad Junaid[1], Sohail Jabbar[2], Muhammad Munwar Iqbal[1], Saqib Majeed[3], Mubarak Albathan[2,*], Qaisar Abbas[2,*], Ayyaz Hussain[4]

Qaabbas@imamu.edu.sa , mmalbathan@imamu.edu.sa

[1] Department of Computer Science, University of Engineering and Technology, Taxila, Pakistan
[2] Department of Computer Science, Imam Mohammad Ibn Saud Islamic University (IMSIU), Riyadh 11432, Saudi Arabia
[3] University institute of Information Technology, PMAS-Arid Agriculture University, Rawalpindi
[4] Department of Computer Science, Quaid-i-Azam University, Islamabad, 44000, Pakistan

Summary
Rice is an important food crop for most of the population in the world and it is largely cultivated in Pakistan. It not only fulfills food demand in the country but also contributes to the wealth of Pakistan. But its production can be affected by climate change. The irregularities in the climate can cause several diseases such as brown spots, bacterial blight, tungro and leaf blasts, etc. Detection of these diseases is necessary for suitable treatment. These diseases can be effectively detected using deep learning such as Convolution Neural networks. Due to the small dataset, transfer learning models such as vgg16 model can effectively detect the diseases. In this paper, vgg16, inception and xception models are used. Vgg16, inception and xception models have achieved 99.22%, 88.48% and 93.92% validation accuracies when the epoch value is set to 10. Evaluation of models has also been done using accuracy, recall, precision, and confusion matrix.

Keywords:
:Rice; Disease; Detection; deep learning; CNN; brown spots; bacterial blight; tungro; Vgg16; in-ception; Xception.

1. Introduction

The Rice is an essential staple diet for most of the population in the world [1]. So, its production has a great impact on human lives. Generally, the production of crops is greatly reduced due to pests and crop diseases [2]. The Rice crop is also vulnerable to various viral, bacterial, and fungal diseases that decrease rice production [3]. It is im-portant to diagnose rice diseases at the early stages. Proper checking for pest existence on crops is necessary for providing a timely solution. Negligence can result in the re-duction of food production as well as the deterioration of its quality. The scarcity of food can cause an increase in poverty, uncertainty about food, and even an upsurge in the death rate. Due to this economy of any nation can be disrupted specifically in agroe-conomic countries where 70% population depends on agricultural sector goods for their living. Pests can cause occasional occurrences of diseases resulting in famine and scar-city of food. Major diseases that affect the rice plant leaves are brown spots, tungro, leaf blasts, bacterial blight, etc.

Figure 1. A visual sample of rice leaf diseases.

Brown spot is a fungal disease. It develops in areas where humidity is between 86% to 100% and temperature is between 16oC to 36oC. It is commonly present in the soil that is nutrient deficient or contains toxic substances, it can be reduced by improving the fertility of the soil. Bacterial blight causes the leaves to appear as dry and yellow. It occurs in environments where humidity is more than 70% and temperature is between 25oC to 34oC. It occurs commonly due to heavy rains that cause harmful bacteria to spread in plants. Leaf blast occurs due to fungus that affects those parts which are grounded above. It occurs due to low moisture soil and heavy rains that cause cold during the daytime. Appropriate fertilizers and fungicides can be used to control the blast in rice plants. Rice tungro is caused due to combination of two types of viruses that are transmitted due to leafhoppers. It can cause discoloration in leaves and can cause stunted growth. Infection of tungro can occur at any growth stage. It is one of the main destructive rice diseases that can cause even 100% yield loss. Tungro disease is not curable however preventive measures can be taken to control the disease.

Manuscript received March 5, 2023
Manuscript revised March 20, 2023
https://doi.org/10.22937/IJCSNS.2023.23.3.6

2. Background

Traditional approaches like naked are not viable in the identification of rice dis-eases [4]. It requires a significant amount of time and effort. Furthermore, there is a high degree of complexity related to plant classification as the disease characteristics vary due to the variety of plants. For providing help and convenience to the farmers and obtaining high accuracy of plant disease detection, various methods have been used including machine learning approaches like Support Vector Machine (SVM) [5-7]and Neural Networks [8]. However, Feature selection techniques are important for achieving high accuracy in these systems. Obtaining a large dataset for these problems is also a challenging task. In the case of a small dataset, we use a transfer learning approach where an already trained model on the ImageNet dataset is used for prediction. In the transfer learning approach, feature extraction is done by removing the last layers or by getting the last layers fine-tuned.

After training of deep learning model, we can predict the disease after capturing the image of the disease and then passing it to the trained model. Image can be taken simply by using a mobile phone and no expensive equipment is needed. After prediction, the model will return the label of the disease to which the image belongs. Three models have been used in this paper namely Vgg16, Inception and Extreme inception model. These models use transfer learning approach and are already trained on the ImageNet dataset. The fully connected layers in transfer learning models are finetuned to train our dataset. Vgg16 has achieved 99.40% train accuracy and 99.22% validation accuracy. The weighted average of Precision, recall, and F1 score of Vgg16 is 0.99 for each. Inception v3 model has achieved 99.04% train accuracy and 88.48% validation accuracy. Inception v3 has a precision value of 0.90 and the value of recall and F1 score is 0.88. The extreme inception model or Xception model has achieved 98.64% train accuracy and 93.95% validation accuracy. The precision, recall, and F1 score for the Xception model is 0.94. Eventually, we also evaluated models using a confusion matrix.

The main points of this study are as follows:

- First, we conducted a thorough analysis of previous studies on rice leaf disease detection to understand the state-of-the-art in this field.
- Second, we developed a new methodology for detecting rice leaf diseases with high accuracy, which outperforms previous work in this area. Our methodology relies on a merged dataset and optimal adjustment of parameter values, such as input size, batch size, optimizer, loss, epochs, and learning rate. This approach is key to achieving high accuracy in detecting rice leaf diseases.
- Third, we verified the effectiveness of our methodology using evaluation metrics such as precision, recall, and F1 score. Our results demonstrate the superiority of our approach compared to previous work, and further reinforce the importance of parameter optimization and dataset selection for effective disease detection.

Overall, our study highlights the potential of our methodology to improve the accuracy of rice leaf disease detection and contribute to better crop management practices.

3. Related Work

Bhattacharya et al. [9] used CNN for the classification of various diseases of rice like leaf bast, bacterial blight, and brown spots. The disease identification process was comprised of two steps. The first step was to differentiate between healthy and infected leaves. In the second step, the type of the disease was identified. 94% accuracy and 78.44% accuracy were obtained respectively for each step. S. Ghosal et al. [10]proposed a Classification methodology with a Transfer Learning approach. In this paper, they have prepared their dataset. Vgg16 model is used for classification and the accuracy of the model is 92.46%.

M. E. Pothen et al. [11]proposed an Image Processing based classification method-ology. In this paper rice diseases such as Leaf smut, Brown spots, and Bacterial blight are classified by use of Otsu's method. Local Binary Patterns (LBP)" and "Histogram of Oriented Gradients (HOG) have been used to extract the features. After this, Support Vector Machine (SVM) is used for the classification of these extracted features. Krish-namoorthy et al. [12] used a deep learning methodology. In this paper transfer learning algorithm, InceptionResNetV2 is used. 95.67% accuracy is achieved while training for classification purposes.

P. Mekha et al. [13] proposed Random Forest based classification algorithm. In this paper rice diseases like brown Spot and Leaf Blight are classified using machine learning algorithms like Random Forest, Naïve Bayes, decision trees, and gradient boosting al-gorithms. Performance is evaluated using accuracy, recall, and precision. The random forest has done better and achieved 69.44% accuracy. Upadhyay et al. [14] proposed a new methodology using a deep neural network. In this paper, they have classified dis-eases like leaf blasts, leaf smut, and brown spot. Binarization of image is performed for removing backgrounds using Otsu's global thresholding technique. CNN model is used for training on 4000 images belonging to each disease. CNN-based classification has been used.

S. M. Shahidur et al. [15] have provided a Machine learning-based system with IoT and edge intelligence. Rice diseases are detected in this paper Artificial intelli-gence-based detection system. Edge computing concepts are applied using a raspberry pi device. Rice diseases such as Hispa, Brown Spot, and Leaf Blast were considered. Images were preprocessed and used for extraction of features for the model training. Machine learning algorithms were applied, and Random Forest has achieved 97.50% accuracy. Jiang et al. [16] proposed a transfer learning technique based on multi-task. Three rice disease types and two types of wheat diseases were addressed in this paper. 40 images of each disease were collected and enhanced them. VGG16 model was ap-plied, and 97.22% accuracy was obtained on rice diseases and 98.75% accuracy was ob-tained on wheat diseases. VGG16 model performed better than resnet50 and dense-net121.

Sethy et al. [17] used the support vector machine for the identification of rice dis-eases. In the paper, 5932 images regarding rice diseases such as tungro, bacterial blight, leaf blasts, and brown spots were used. The paper shows deep features along with SVM have performed better than Transfer learning models. Performance evaluation metrics like accuracy, training time, precision, false positive rate (FPR), recall, and F1 Score were used. SVM with resnet50 deep features has performed well and shows a 0.9838 value of the f1 score. Jiang et al. [18] proposed a methodology for enhancing classification and computational performance for the identification of rice diseases. Diseases of rice in-cluding brown spot, leaf blast, and leaf blight were addressed. K-means segmentation was used for separating the background of the image. After this, novel intensity-based color feature extraction (NIBCFE), bit pattern features (BPF), and gray-level cooccur-rence matrix (GLCM) methods were used for extracting color, texture, and shape fea-tures. Then classification of images is done using a new SVM-based probabilistic neural network (NSVMBPNN). Performance of the support vector machine, naïve Bayes, and probabilistic neural network were compared. The result was obtained using fivefold cross-validation having accuracies of 99.20%, 95.20%, 98.40%, and 97.60%, for healthy leaves, bacterial blight, rice leaf blast, and the brown spot respectively.

Verma et al. [19] proposed a review paper on CNN, SVM, and VGG16 Classifiers based on Artificial Intelligence for wheat and rice crops diseases detection. In the paper review of classifiers such as SVM, CNN and VGG16 was done for the identification and classification of crop illness. Patil et al. [20] proposed a data fusion-based diagnosis of rice disease. Features were extracted from images using CNN. Internet of Things is used to collect meteorological information for real-time diagnosis of images. So, the combi-nation of CNN and IoT has been used in the diagnosis of rice diseases. Dataset was comprised of 3200 images belonging to various categories. Initially, data was collected from sensors and then followed by images for extracting visual features. Then the dense layer gave single output. 95.31% accuracy was obtained for the data fusion rice model..

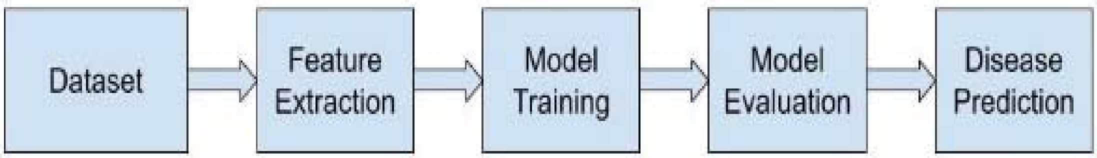


Figure 2. A systematic flow diagram of Rice disease recognition system.

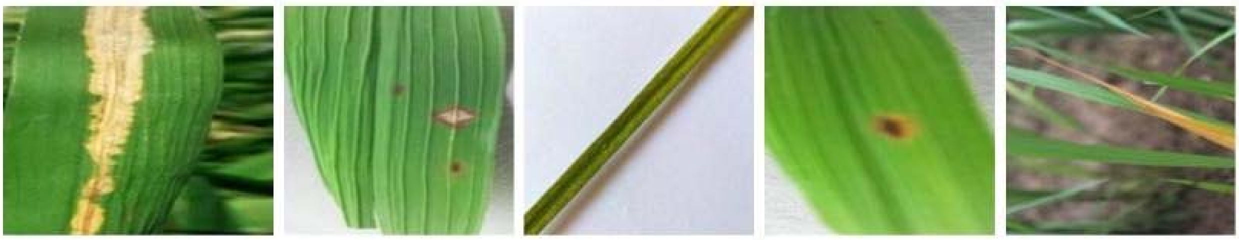


Figure 3. A sample of rice diseases dataset utilized in this paper.

4. Methodology

4.1 Data Acquisition

Rice leaf images are collected [10], [21] and then the images of these datasets are merged for experimentation. These datasets are open-source and are publicly available for re-search purposes. The dataset contains sixty-five hundred and forty images of five dis-eases. Dataset is partitioned into two subcategories i.e., train and test. Train and test classes are subdivided into five groups according to the number of diseases. Each category in the train set contains nine hundred images and the test set contains four hundred and eight images. Each image in the dataset contains a target size of (224×224) for vgg16 model and (299×299) for inception and Xception model and batch size is equal to 10. The model is trained by using 70% train and 30% test images. The sample dataset is illustrated in Fig 3. In figure 3, images belonging to each category are mentioned.

4.2 Proposed Methodology

Deep learning is subset of machine learning and inspired by human brain structure. Deep learning uses multi layered algorithm structure known as neural network. These neural network structures identify patterns and classifies the input information. These structures use feature extraction for collecting insights from data. Neural network con-sists of fundamental processing nodes known as neurons. These neurons take input from previous layers and weights to produce output. Weights are chosen randomly at first and then adjusted optimally. Optimizers are used for adjusting weights of models. We have used Adam optimizer as illustrated in below equation.

$$m_t = \beta_1 m_{t-1} + (1-\beta_1)[\frac{\delta L}{\delta w_t}] v_t = \beta_2 v_{t-1} + (1-\beta_2)[\frac{\delta L}{\delta w_t}]^2 \quad (1)$$

In equation (1), ϵ = a small +ve constant to avoid 'division by 0' error when (vt -> 0). (10-8), β1 & β2 = decay rates of average of gradients (β1 = 0.9 & β2 = 0.999), α = Step size parameter / learning rate (0.001). Here m1 and v1 are initialized to 0 because they can be biased toward zero as both β1 & β2 ≈ 1. This problem is fixed by optimizer by computation of bias corrected vt and mt. Weights are adjusted while training based on loss function. Loss function compares the actual output with predicted output. The aim while training is to minimize the loss value. We have used categorical cross entropy loss function in this research as explained below.

$$CE = -\frac{1}{N}\sum_{i=1}^{N}\sum_{c=1}^{C} 1_{y_i \in C_c} \log p_{mod\,el}[y_i \in C_c] \quad (2)$$

In equation (2), i = observations up to number N, c = categories up to number C, p = Probability predicted by model. The term $y_i€C_c$ represents that the i^{th} observation belongs to C^{th} category. $P_{model}[y_i€C_c]$ represents the probability predicted by model for i^{th} observation for c^{th} category. Minimum loss shows that the model is well trained, and the accuracy is high. Accuracy shows the correct predictions from total input samples. Accuracy has been used as evaluation metrics while training of model as illustrated below.

4.3 Classification Models

We have used three classification models for rice leaf disease classification i.e., Vgg16, inception model and Xception model.

At Oxford University, VGG16 has been presented by A. Zisserman and K. Simo-nyan in the paper "Very Deep Convolutional Networks for Large-Scale Image Recog-nition". This model is based on a convolutional neural network. When the model was trained from the ImageNet dataset, 92.7% testing accuracy has been achieved. The im-ages included in ImageNet are more than 14 million that belong to 1000 classes. It is submitted to ILSVRC-2014 and is one of the popular models. Alex Net has been im-proved by the replacement of large kernel-size filters one after another with multiple 3×3 filters of kernel size. During several weeks, the VGG16 model was trained, and NVIDIA GPUs were used for processing.

Conv1 layer takes input in 224 x 224 size. After passing from convolutional layers, a receptive field filter of 3×3 is used. Input channels are linearly transformed using a convolution filter of 1×1 during configuration. A stride of 1 is used in convolution for maintaining spatial resolution. Five layers that use max-pooling operation perform the spatial pooling. On a 2×2-pixel matrix, Max-pooling is performed with a stride value of 2.

The fully Connected three convolutional layers were used. 4096 channels were used in the first two layers and in the third layer classification was performed that comprises of 1000 channels. Soft-max layer is the last layer. The configuration is same in all fully connected layers of the network.

Rectified linear unit (ReLU) is used in all hidden layers of vgg16 model and it is illustrated below.

$$y = max(0, x) \rightarrow \frac{\delta f}{\delta x} = 1 if x > 0\ else\ 0 \quad (3)$$

In equation (3), x= Summation of weighted input and bias value. ReLU function is monotonic. It gives 0 in case of negative values and 1 in case of positive values. So, output range of ReLU is zero to infinite. The local Response Normalization (LRN) is not contained by any network, the ILSVRC dataset does not enhance performance using such normalization, but results in enlarged computation time and memory consumption.

The inception model is an image classification model that is already trained on the ImageNet dataset. It is also known as the Google Net model. It accepts images of input size equal to 299x299x3. While training, the model has achieved more than 78% accuracy in 170 epochs. It uses RMSprop as an optimal optimizer as illustrated below:

$$V_t = \rho V_{t-1} + (1-\rho) * g_t^2$$

$$\triangle w_t = -\frac{\eta}{\sqrt{v_t + \epsilon}} * g_t \quad (4)$$

$$w_t + 1 = w_t + \triangle w_t$$

In equation (4), ή=Initial learning rate, vt = Exponential average of squares of gradients, gt = Gradient at time t along w^{jl}. Firstly, computation of average of gradient squares is done. The gradient gt represents projection. Then the exponential average is multiplied with hyperparameter nu. Then multiplication of current gradient is done with (1-nu). This model was trained on 1000 object categories. So, the model has two parts i.e., feature extraction and classification using SoftMax.

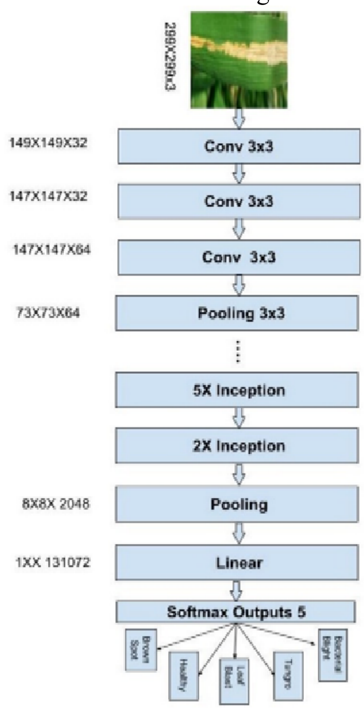


Figure 4. Inception v3 Architecture.

Xception is a CNN model proposed by Francois Chollet. It was trained on 1000 objects. It receives images of input size 299x299x3. Xception stands for extreme inception, and it has 36 convolution layers for feature extraction. It is an extension of the inception model having separable convolutions in depth. Xception model consists of depth wise separable convolution and batch normalization. Batch normalization is used for normalizing the inputs from each layer. Batch normalization normalizes the inputs by calculation of mean(μ), standard deviation(σ), normalization of layers input(h_{norm}) and by scale and shift(hi) operations.

$$\mu = \frac{1}{m}\sum h_i$$

$$\sigma = \sqrt{\frac{1}{m}\sum (h_i - \mu)^2} \quad (5)$$

$$h_{(norm)} = \frac{(h_i - \mu)}{\sigma + \varepsilon}$$

$$h_i = \gamma h_{(norm)} + \beta$$

In (5), firstly batch input is obtained from the layer h for calculation of mean. Standard deviation is calculated using mean. Then for normalization, subtraction of mean is done from each input and then dividing by the summation of smoothing term (€) and standard deviation. At last, for calculation of sale and shift, two learnable parameters gamma and beta are used.

Xception has achieved 79% top1 accuracy and 94% top 5 accuracies. The number of parameters in Xception model is same as inception v3 model.

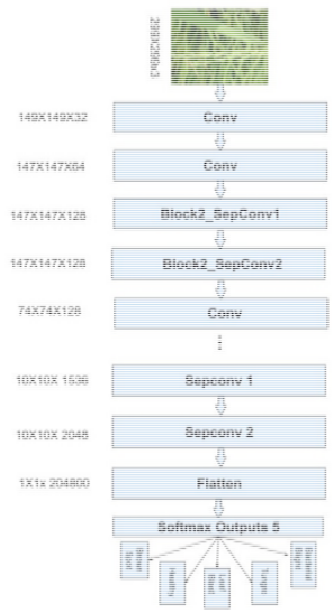


Figure 5. Xception v3 Architecture.

The dataset of ImageNet has more than million images of high-resolution which are labeled with more than 22,000 categories. The images were labeled by human labelers and collected from the web. In 2010, a ILSVRC competition was held. In ILSVRC, ImageNet with approximately 1000 categories were used. So, the train images were almost 1.2 million. Therefore, the resolution of images was changed to 256×256. The central 256×256 part is cropped, and rectangular image is rescaled in resulting image.

The dataset plays a great role in achieving the high accuracy of deep learning models. Dataset can be split down into two parts i.e., train set and test set. We have split the dataset as 70% for training and 30% for testing. Optimizer plays a pivotal role in the learning process of deep convolution neural networks. Adam has been utilized as an optimizer here and the batch size is 32. The epoch value is set to 10 and the loss function used is categorical cross entropy during the learning process of the model.

5. Experimental Results and Discussion

Implementation of rice leaf diseases is done using vgg16 to detect whether the rice leaf image is healthy or infected with bacterial blight, leaf blast, tungro, or a bacterial blight. Dataset is classified as 70% is used for training and 30% for testing.

For achieving optimal accuracy, Adam optimizer is used. Categorical cross-entropy has been used as a loss function. Batch size is set to 32. Number of epochs used are 10. Learning rate of 0.001 has been used and input size of 224x224x3 is used in Vgg16 and 299x299x3 is used in inception and Xception model.

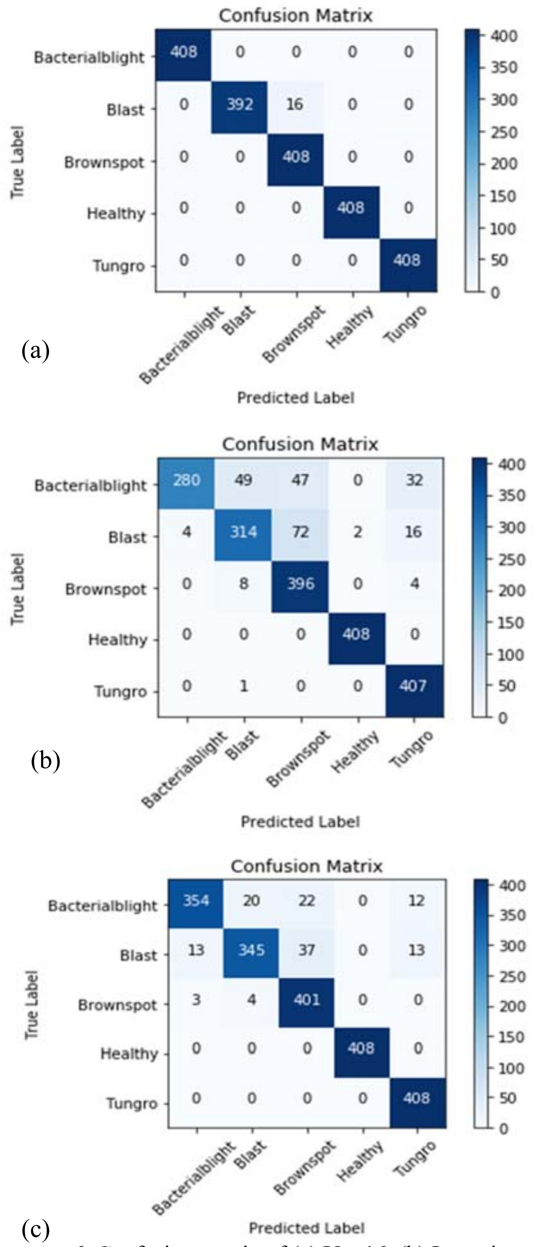
For evaluating the performance of the model, evaluation is done using metrics like precision, accuracy, recall, and F1 have been done. The accuracy that has been obtained on the training images is train accuracy. Similarly, the accuracy that has been obtained on the test dataset is validation accuracy. The proportion of positive values that are truly identified is known as Recall or sensitivity. Precision is the ratio between correctly identified values to all the positively classified samples. F1-Score is considered as the Harmonic Mean of sensitivity/recall and Precision. Values of metrics like accuracy, precision, and recall are mentioned in table 1. These values are taken as a weighted average.

Table 1: Experimental Results

Model	Precision	Recall	F1 Score
Vgg16	0.99	0.99	0.99
Inception	0.90	0.88	0.88
Xception	0.94	0.94	0.94

The confusion matrix shows the more accurate value of accuracy that has been achieved while testing. The below figure shows the confusion matrix of vgg16 trained on the rice disease dataset, here columns depict predicted classes of data and rows represent actual labels of data. Fig 6 represents the confusion matrix of the vgg16, Inception v3 and Xception models respectively after the training.

Accuracy is used to represent all the data instances that are correctly identified over total data samples. Loss function is used for comparing true output and the predicted output. The accuracy graph shows the variation between training accuracy and validation accuracy. Similarly, the loss graph shows the difference between training loss and validation loss. Accuracy and loss values obtained from training as well as validation of vgg16, inception and Xception models are depicted in table 2.



(a) (b) (c)

Figure 6. Confusion matrix of (a) Vgg16, (b) Inception v3, (c) Xception model.

Accuracy value as well as loss value changes with respect to epoch number. To make sure that the model after training did not overfit on the given data, the accuracy graph and loss graphs for the model training and the validation of the trained model are mentioned in figure 8. The first three graphs represent the accuracy of vgg16, inception and Xception models and the second three graphs represent the loss of vgg16, inception and Xception models. Accuracies of vgg16, inception and Xception models are 0.992, 0.8848 and 0.9393 respectively. The loss values of vgg16, inception and Xception models are 0.0209, 0.3921 and 0.1608 respectively.

Table 2: Evaluation metrics values

Models	Train Accuracy	Validation Accuracy	Train Loss	Validation Loss
Vgg16	0.9940	0.9922	0.0220	0.0209
Inception	0.9904	0.8848	0.0298	0.3921
Xception	0.9864	0.9392	0.0425	0.1608

Table 3: Comparison with existing state-of-the-work

Reference	Accuracy	F1 Score	Precision
Bhattacharya et al. [9]	94%	-	-
S. Ghosal et al. [10]	92.46%	-	-
Krishnamoorthy et al. [12]	95.67%	-	-
P. Mekha et al. [13]	69.44%	-	80.00
S. M. Shahidur et al. [15]	97.50%	0.98	0.98
Jiang et al. [16]	97.22%	-	-
Sethy et al. [17]	-	0.9838	-
Patil et al. [20]	95.31%	0.95	0.95
Proposed vgg16 model	0.9922	0.99	0.99
Proposed Inception model	0.8848	0.88	0.90
Proposed Xception model	0.9392	0.94	0.94

Vgg16, inception and Xception models are compared in Figure 9. A graphical representation of all the metrics for evaluation purposes i.e. train and validation accuracy, loss, precision, f1 score, and recall corresponding to the models are illustrated in figure 9. Evaluation metrics are represented vertically, and the models are represented horizontally. Vgg16 has 0.9922 accuracy and loss is 0.0209. Accuracy of Inception model is 0.8848 and loss is 0.3921. Accuracy of Xception model is 0.9392 and loss is 0.1608. Precision, recall and F1 score of vgg16 is 0.99. Inception v3 has 0.90 precision and 0.88 F1 score and loss. Xception model has 0.94 precision, recall and F1 score as represented in figure 7.

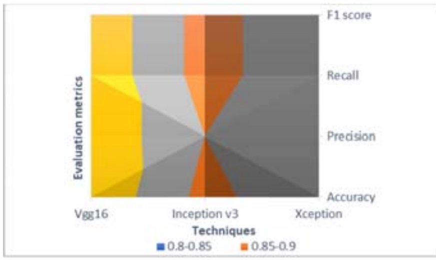


Figure 7. Comparison of models

Results of all the models used in this paper as well as the results of existing work have been compared in table 3. The metrics used for comparison are validation accuracy and weighted average of F1 score, Precision, and recall. It is clear from comparison that vgg16 has performed better not only from inception and Xception models but also from the mentioned previous papers of rice leaf disease classification when trained on the dataset.

The proposed vgg16 model has performed better among all the techniques. Because the dataset we have used has 6500 images and the model is trained very well on the dataset. As we can observe from the train and validation accuracies, there is neither overfitting nor underfitting of the model. Evaluation metrics like precision, recall, F1 score, and confusion matrix have also verified the results obtained during training and validation of the model. The models initially did not give better accuracy due to some parameter values like input size, batch size, optimizer, loss function, etc. But when these parameters are set to input size=224, batch size =32, Adam optimizer instead of RMSprop, categorical cross entropy as loss function, and epochs=10. The model gave us optimal results. Similarly, for Xception and inception models by setting input size =299 and learning rate=0.001, results were improved.

After applying the optimal weights based on transfer learning, the same well-known CNN models were used to run the trials again. Table 2 presents the outcomes. GoogleNet performed the worst with an average accuracy of 89.63% when using the non-normalized dataset, while VGG19 had the greatest average accuracy of 96.01%. VGG16 had the greatest average accuracy for the normalized augmentation, at 94.76%, while GoogleNet had the lowest, at 86.9%. VGG19 had the greatest average accuracy of 96.08% while utilizing the non-normalized augmented dataset, whereas AlexNet had the lowest average accuracy of 85.71%. The training and validation accuracy results for the various model settings employed in this paper's proposed VGG-19-based transfer learning model are shown in Figure 6. As may be observed, training and validation accuracy begin with levels between 80 and 85%.

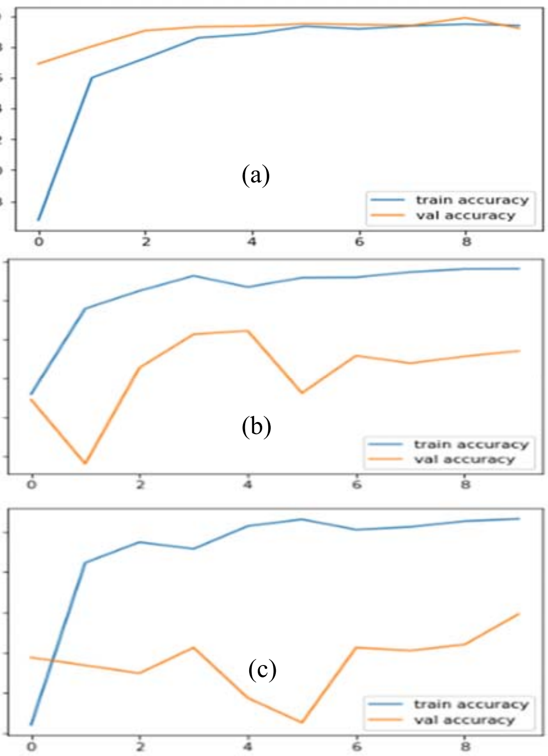


Figure 8. Accuracy (a)Vgg16, (b) Inception v3 and (c) Xception models

for the freeze-augmented, freeze-normalized, and freeze-augmented non-normalized with non-freeze normalized, non-freeze non-normalized, and non-freeze non-normalized enhanced data, the range then rises to between 90 and 95%. The consistency between the training and validation accuracy trends in every example demonstrates that the over-fitting issue was taken into consideration. This shows that the model is operating as intended for fresh data with the same accuracy as the data that it was trained for. The validation accuracy is following the trend of the training accuracy. The validation loss and training loss for the various model sets utilizing the VGG-19-based transfer learning technique are shown in Figure 6 for each model setup.

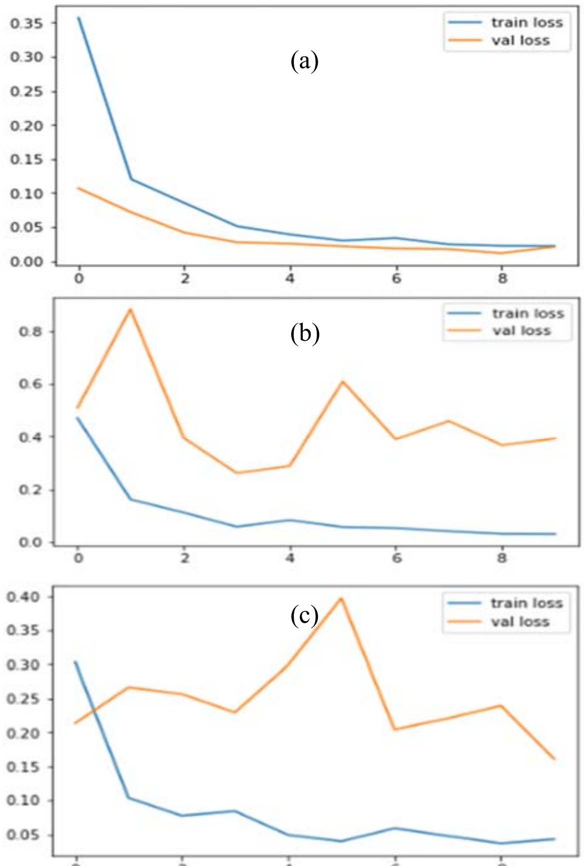


Figure 9. Loss graph (a)Vgg16, (b) Inception v3 and (c) Xception models

It is evident that the loss curves exhibit the same pattern of continual decline and eventual stability at a point where there is little distinction between training and validation losses. This demonstrates that the suggested strategy fits the data well and is neither overfitting nor underfitting. A successful fit technique may be identified by the steady decline in loss accuracies towards zero and subsequent stabilization with a minor difference between the training and validation trends. Figure 7 compares the confusion matrices for the different models utilizing vgg16-based transfer learning for classifying and diagnosing rice diseases. The confusion matrix reveals that all classes have good classification accuracy, but model Xception has greater misclassification across all classes. The second highest misclassification in all models may be seen in individual TL models. All classes, however, generally exhibit good classification accuracy.

Importantly, the best model was chosen for the application's development based on its quick prediction time, capacity to handle a sizable image dataset, and relatively compact size, which is appropriate for the majority farmers. When taken as a whole, this study offered a novel concept for rural communities and field-level consultants to use to detect agricultural diseases using typical web-based application, suggesting both theoretical and practical value for disease categorization. In the future, we will work on smartphone-based application [21-24] to detect signs of crop micronutrient insufficiency that are frequently overlooked.

6. Conclusion

In this paper, the classification of rice leaf diseases has been done using transfer learning models. Three transfer learning models i.e., Vgg16, Inception, and Xception have been used for the detection of rice diseases. Five diseases were considered for classification namely brown spots, bacterial blight, leaf blast, tungro and healthy. The dataset was obtained from two sources and merged for obtaining optimal accuracy. After merging, the dataset contains 6540 images, 4500 training images, and 2040 validation images. Dataset is split into 70% training images and 30% validation images. Accuracy obtained for vgg16, inception and Xception model is 99.22%, 88.48% and 93.92% respectively. Evaluation metrics such as precision, recall, F1 score, and confusion matrix have been calculated. The evaluation metrics have verified the results obtained while training and verification of models. The weighted average of precision for Vgg16, inception and Xception is 0.99, 0.90, and 0.94 respectively. The weighted average of recall for Vgg16, inception and Xception is 0.99, 0.88, and 0.94 respectively. The weighted average of F1 score for Vgg16, inception and Xception is 0.99, 0.88, and 0.94 respectively. We have obtained high accuracy of 99.22% for vgg16.

Acknowledgments

The authors extend their appreciation to the Deanship of Scientific Research at Imam Mohammad Ibn Saud Islamic University (IMSIU) for funding and supporting this work through Research Partnership Program no. RP-21-07-11.

References

[1] Zhang, N., M. Wang, and N. Wang, Precision agriculture—a worldwide overview. Computers and electronics in agriculture, 2002. 36(2-3): p. 113-132.
[2] Oerke, E.-C., Crop losses to pests. The Journal of Agricultural Science, 2006. 144(1): p. 31-43.
[3] Araby, A.A., et al. Smart iot monitoring system for agriculture with predictive analysis. in 2019 8th International Conference on Modern Circuits and Systems Technologies (MOCAST). 2019. IEEE.
[4] Arnal Barbedo, J.G., Digital image processing techniques for detecting, quantifying and classifying plant diseases. SpringerPlus, 2013. 2(1): p. 1-12.
[5] Es-saady, Y., et al. Automatic recognition of plant leaves diseases based on serial combination of two SVM classifiers. in 2016 International Conference on Electrical and Information Technologies (ICEIT). 2016. IEEE.
[6] Gupta, T., Plant leaf disease analysis using image processing technique with modified SVM-CS classifier. Int. J. Eng. Manag. Technol, 2017. 5: p. 11-17.
[7] Padol, P.B. and A.A. Yadav. SVM classifier based grape leaf disease detection. in 2016 Conference on advances in signal processing (CASP). 2016. IEEE.
[8] Liu, L. and G. Zhou. Extraction of the rice leaf disease image based on BP neural network. in 2009 International Conference on Computational Intelligence and Software Engineering. 2009. IEEE.
[9] Bhattacharya, S., A. Mukherjee, and S. Phadikar, A deep learning approach for the classification of rice leaf diseases, in Intelligence enabled research. 2020, Springer. p. 61-69.
[10] Ghosal, S. and K. Sarkar. Rice leaf diseases classification using CNN with transfer learning. in 2020 IEEE Calcutta Conference (CALCON). 2020. IEEE.
[11] Pothen, M.E. and M.L. Pai. Detection of rice leaf diseases using image processing. in 2020 Fourth International Conference on Computing Methodologies and Communication (ICCMC). 2020. IEEE.
[12] Krishnamoorthy, N., et al., Rice leaf diseases prediction using deep neural networks with transfer learning. Environmental Research, 2021. 198: p. 111275.
[13] Mekha, P. and N. Teeyasuksaet. Image classification of rice leaf diseases using random forest algorithm. in 2021 Joint International Conference on Digital Arts, Media and Technology with ECTI Northern Section Conference on Electrical, Elec-tronics, Computer and Telecommunication Engineering. 2021. IEEE.
[14] Upadhyay, S.K. and A. Kumar, A novel approach for rice plant diseases classification with deep convolutional neural network. International Journal of Information Technology, 2022. 14(1): p. 185-199.
[15] Rumy, S.S.H., et al. An IoT based System with Edge Intelligence for Rice Leaf Disease Detection using Machine

Learning. in 2021 IEEE International IOT, Electronics and Mechatronics Conference (IEMTRONICS). 2021. IEEE.

[16] Jiang, Z., et al., Recognition of rice leaf diseases and wheat leaf diseases based on multi-task deep transfer learning. Com-puters and Electronics in Agriculture, 2021. 186: p. 106184.

[17] Sethy, P.K., et al., Deep feature-based rice leaf disease identification using support vector machine. Computers and Elec-tronics in Agriculture, 2020. 175: p. 105527.

[18] Archana, K., et al., A novel method to improve computational and classification performance of rice plant disease identifi-cation. The Journal of Supercomputing, 2022. 78(6): p. 8925-8945.

[19] Verma, A., SVM, CNN and VGG16 Classifiers of Artificial Intelligence Used for the Detection of Diseases of Rice Crop: A Review. Sentimental Analysis and Deep Learning, 2022: p. 917-931.

[20] Patil, R.R. and S. Kumar, Rice-Fusion: A Multimodality Data Fusion Framework for Rice Disease Diagnosis. IEEE Access, 2022. 10: p. 5207-5222.

[21] Zakzouk, S., et al. Rice Leaf Diseases Detector Based on AlexNet. in 2021 9th International Japan-Africa Conference on Electronics, Communications, and Computations (JAC-ECC). 2021. IEEE.

[22] Latif, Ghazanfar, Sherif E. Abdelhamid, Roxane Elias Mallouhy, Jaafar Alghazo, and Zafar Abbas Kazimi. "Deep Learning Utilization in Agriculture: Detection of Rice Plant Diseases Using an Improved CNN Model." Plants 11, no. 17 (2022): 2230.

[23] Haider, Kashan, Maaz Ahmed, Ankit Pal, Sur Singh Rawat, Vimal Gupta, Rabindra Nath Shaw, and Ankush Ghosh. "A Comprehensive Study of Plant Disease Detection Using Deep Learning Methods." In Advanced Communication and Intelligent Systems: First International Conference, ICACIS 2022, Virtual Event, October 20-21, 2022, Revised Selected Papers, pp. 441-458. Cham: Springer Nature Switzerland, 2023.

[24] Nayak, Anshuman, Somsubhra Chakraborty, and Dillip Kumar Swain. "Application of smartphone-image processing and transfer learning for rice disease and nutrient deficiency detection." Smart Agricultural Technology 4 (2023): 100195.