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ORIGINAL ARTICLE

Rice Disease Classification using Deep Learning

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ABSTRACT

Rice is one of the essential foods for most of the world's population, and its cultivation is done in large areas of Pakistan. It satisfies the food demand and plays a vital role in the economy of Pakistan. But rice leaf diseases can affect its production. Rice leaf diseases can be categorized into various diseases like brown spots, bacterial blight, tungro and leaf blasts. Early detection of rice leaf diseases is critical for effective management and prevention of crop losses. Effective treatment of these diseases can be done after their detection. Detection of such diseases can be performed using a deep learning approach. Due to the small dataset allowing transfer learning models, enhanced Xception models are used to detect diseases effectively. The Xception model has achieved 93.92% test accuracy when the epoch value is set to 10. Model evaluation has also been done using accuracy, recall, precision, and confusion matrix. Deep learning approaches for the detection of rice leaf diseases in Pakistan can have a positive impact on rice production and the country's economy.

Keywords: Rice Disease Detection; Deep Learning; CNN; Brown Spots; Bacterial Blight, Xception Model.

Author`s Contribution

[1,2,3]Data analysis, interpretation and manuscript writing, Active participation in data collection, Conception, synthesis, planning of research. Interpretation and discussion

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Article info.
Received: May 12, 2022
Accepted: October 26, 2022
Published: December 30,2022

Cite this article: *Junaid M, Iqbal MM, Hameed N, Saeed S. Rice Disease Classification Using Deep Learning. J. inf. commun. technol. robot. appl.2022; 13(1):31-38.*

Funding Source: *Nil*
Conflict of Interest: *Nil*

INTRODUCTION

Rice is a species of grass and is commonly known as Oryza sativa. It grows in aquatic and warm places like ponds and wetlands. It is well suited for regions where the cost of labour is low and heavy rainfall areas. Rice was one of the most-eaten foods consumed in 2019-2020, with 493.13 million metric tons and 509.87 million metric tons consumed in 2021-2022 [1]. It is the third number in terms of production of agricultural commodities. It produces 21% per capita energy and 15% protein for humans globally. From the cereals, rice protein is considered of good quality. Along with it, this is a good source of other nutrients like vitamins, fiber, minerals etc. It is a good source of manganese, protein, iron and vitamin B. Rice is an important food to deal with malnutrition globally for fulfilling food demands. Traditionally it has been used in medicines to cure gastric and skin problems. Rice is an important source of income for most farmers worldwide. Rice is indeed an important food crop globally and plays a critical role in addressing malnutrition by providing essential nutrients such as carbohydrates, vitamins, and minerals [2]. In many countries, rice is a staple food that is consumed daily and is a key component of many traditional diets.

Apart from its nutritional value, rice has also been traditionally used for medicinal purposes, especially in Asian countries. Rice has been found to be effective in treating various health issues, including digestive problems, skin conditions, and even fever. In addition to its importance in addressing malnutrition and as a medicinal crop, rice also plays a vital role in the economy of many countries. Many farmers worldwide rely on rice cultivation as a source of income, and the rice industry supports many other industries, including transportation, packaging, and marketing.

Rice production needs to be grown in synchronization with the increasing population worldwide. Increase in the human population also enhances the food demand [3, 4]. The excessive use of chemicals badly effects the plants growth and production [5] . The most essential thing in agriculture that affects the quality and quantity of crop is the plant diseases [6-10]. The wrong farming methodologies like over irrigation and wrong use of insecticides can harm the growth of rice plants. The majority of world's population lacks sufficient food and plant diseases plays major role in its reduction. Crop diseases affects the productivity and quality of crops [11, 12]. Diagnosis of rice diseases in the early stages is essential. Because reduction in production of rice can not only affect the life of individuals but also can disturb the economy of agricultural countries.

There are several rice diseases. These diseases can affect the rice seeds during germination or effects the rice plant leaves. These diseases decrease the production of rice by effecting the rice plant leaves [13]. Main diseases that harm the rice plant leaves are brown spots, tungro, leaf blasts, bacterial blight, etc. Brown spots causes prominent marks to appear on leaves [14]. It harms coleoptile, leaf sheath, glumes, panicle branches, coleoptile, and spikelets. Its indication involves various big leaf marks that can harm the whole leaf. 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 occurs due to Xanthomonas oryzae pv. Wilting of seedling is caused due to it. It mainly occurs due to heavy rains and strong winds due to which disease spreading bacteria spreads in the infected plants. Leaf blast occurs due to a fungus named magnaporthe oryzae. The parts that are affected due to leaf blast are nodes, collar, parts of penicile and neck of rice plants. Leaf blast can occur in places of spores [15]. Its presence is found in low moisture soil, heavy rain areas and cold temperatures during the day. Appropriate fertilizers and fungicides can be used to control the blast in rice plants. Initial signs of this disease include green lesion with border. These lesions can be of elliptical shape or spindle shaped. Tungro disease usually spreads due to leafhoppers because these grasshoppers are fed on infected tungro plants. It is among the main destructive rice diseases that can cause even 100% yield loss. Rice plants can get infection at any stage but mostly it occurs in vegetative phase. Yellow or orange discolorations are majorly noticeable in the infected plants. The appearance of infected plants are also stripped or molded.

Traditionally, most widely used methods for rice crop disease detection was based on manual judgment and appearance [16, 17]. For helping farmers in detection and treatment of rice diseases, several methodologies have been used like machine learning, Support Vector Machine (SVM) and Neural Networks etc. Feature extraction is an essential step in the identification process. Features are extracted from the dataset for training of deep learning models. For achieving high accuracy, transfer learning models can be used in identification process. These models automatically extract the features while training on the dataset. These learned features are further used for identification and classification of rice diseases.

The architecture of deep neural networks is designed to simulate the way the human brain processes information, with each layer of the network learning to recognize different features of the input data. The output from one layer is used as the input to the next layer, allowing the network to build increasingly abstract representations of the input data [18, 19]. Deep learning generally learns from experiences. Deep learning uses multi layered algorithm structure known as neural network. These neural network structures identify patterns and classify the input information. Algorithms of deep learning work in layers. On the left, an input layer is present that has sensors for collecting input data from outside of the world. The output layer is present on right hand side for prediction of results from the network.

Between the input and output layer there are hidden layers for processing inputs and generation of output. Increasing these hidden layers adds complexity to the network but also gives correct prediction in majority cases.

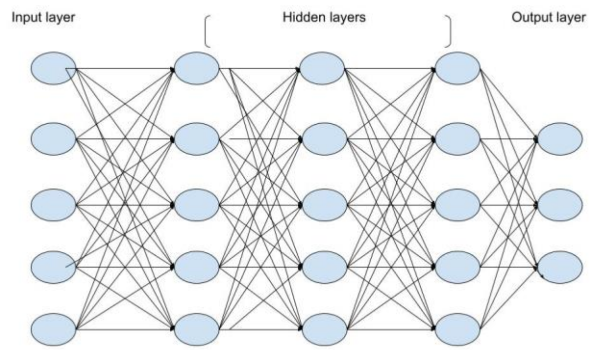


Figure 1. Neural network

In figure 1, raw input data regarding images are provided to the first input layer. Then these input layers determine patterns and with respect to color and luminosity features are differentiated. Then some features are identified by the first hidden layer and other by next subsequent layers. All these features are then sent to the output layer for prediction of output. The goal of this approach is to develop a reliable and accurate system for early detection of rice leaf diseases, which can help farmers take appropriate action to prevent further spread and minimize crop damage. This approach has the potential to improve rice crop management and increase crop yields, ultimately contributing to food security and the economic well-being of rice-growing regions.

LITERATURE REVIEW

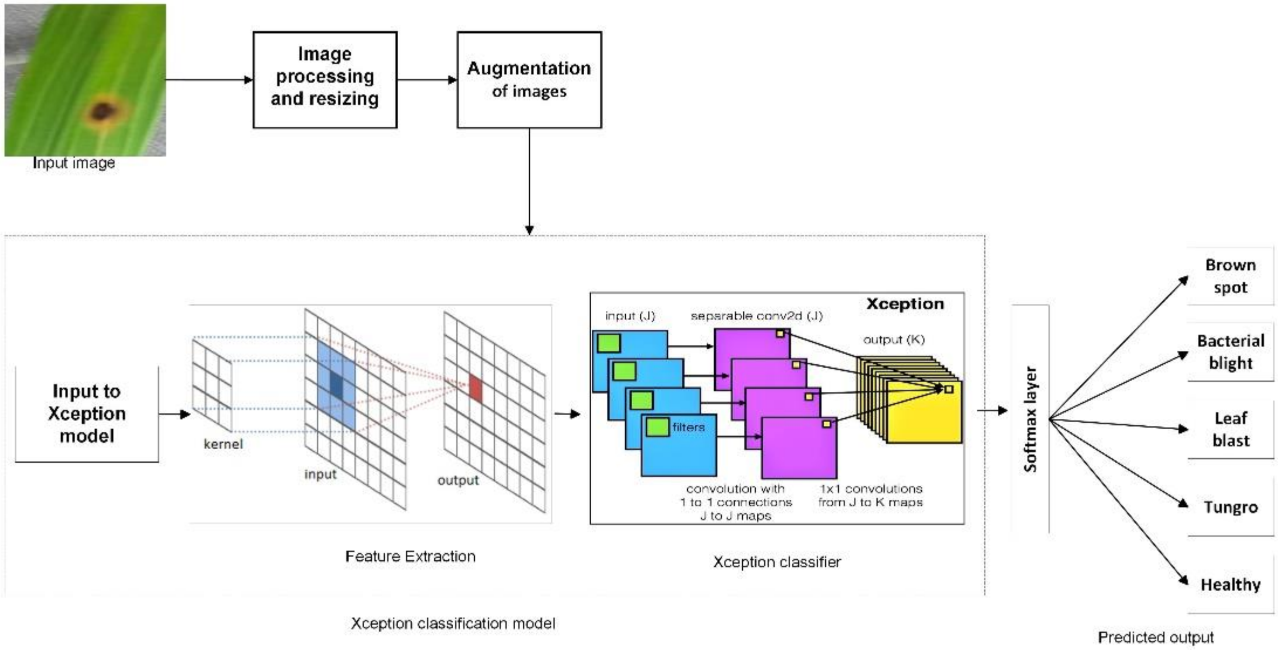
Vimal et al [20] proposed Classification of rice diseases using pre trained deep neural networks. In this paper, a transfer learning approach has been used. Various transfer learning models have been used like Alex Net, Vgg16, ResNet152V2, inception V3, InceptionResnetV2, Xception, Mobile Net, DenseNet169, NasNetMobile and NasNetLarge. These models are trained on dataset that have 1216 images of rice. These images belong to seven categories i.e., bacterial blight, rice blast, sheath blight, brown spot, sheath rot, false smut, and healthy leaves. Vgg16 model has performed better than all the other models by achieving 93.11% accuracy.

Muhammad et al [21] proposed detection of rice leaf diseases using Yolo 5. Here several diseases are considered for detection like bacterial blight, brown spots, leaf blast and tungro. Deep learning model Yolo 5 is used for detection as its accuracy is better than Yolo3 and Yolo4. The dataset is obtained from Google having 400 images of rice leaves. The number of epochs are set to 100. Precision, mAP and recall values obtained are 1.0, 0.62 and 0.92 respectively. Sherin et al [22] proposed identification of rice diseases using deep learning. The Inception V3 model has been used for identification of rice diseases. Dataset is split into ratio of 80:20. One hot encoding is used for conversion of categorical images into numerical images. The number of epochs are set to 500. Learning rate of 0.001 used and batch size is set to 32. Accuracy of 97.1% is obtained.

Rakesh et al [23] proposed use of deep learning for detection of rice diseases. Rice diseases like false smut, leaf blast, bacterial stripe disease, neck blast, sheath blight, and brown spot were detected. Ensemble model has played vital role in success of method. Three models i.e., DenseNet-121, ResNet-50 and SE-ResNet-50 were used. Dataset contains 300 images belonging to 6 categories. The number of epochs used is 100. Confusion matrix is also calculated.

Junde et al. [24] proposed Rice plant disease detection using deep learning. MobInc-Net architecture is used for disease recognition. Enhancement of inception module is done by replacing the convolutions with point wise and depth wise convolutions. After this, already trained MobileNet was combined with the modified inception. Mobile Net was used for extracting the features from images. Softmax layer is used for prediction of diseases. For efficiency of model, transfer learning with two stages is used. On public dataset, it has obtained 99.21% accuracy and 97.89% on local dataset.

Latif et al [25] proposed improved CNN model for detection of rice diseases. Transfer learning approach is used for correct diagnosis. Modified Vgg19 model is used. Six categories were used like brown spot, narrow, healthy, leaf blast, leaf scald and bacterial blight. Accuracy of 96.08% is obtained using augmented dataset. Values of precision, specificity, recall and F1-score obtained were 0.9620, 0.9617, 0.9921, and 0.9616 respectively. Ramesh et al [8, 26] proposed detection of



rice blast disease using machine learning. Feature extraction of disease infected rice images is performed. Dataset contains 300 images of rice blast. Test accuracy of 90% is obtained for infected images.

Kawcher et al [26] proposed detection of rice diseases using machine learning. Three common diseases like bacterial blight, leaf smut and brown spot are detected. Different machine learning algorithms like Naive Bayes, K-Nearest Neighbor, Decision Tree, and Logistic Regression were used. After 10-fold cross validation, 97% accuracy is achieved. Heri et al [27] proposed detection of rice diseases using smartphone application. Machine learning applications were installed on cloud server and smartphone applications were developed. Smartphone application is used for capturing rice leaves and then these leaves are passed on to server for obtaining the result of classification.

RESEARCH METHODOLOGY

Rice disease classification is a multi-step process where various operations are carried out for recognition of the multiple stages as given in figure 2. Rice disease classification is comprised of some major steps like Feature extraction, model training, model evaluation and Disease prediction. Eventually, presence of disease in the rice leaf can be detected using the trained model as given in figure 2.

Figure 2 Disease Recognition process

Dataset

Rice leaf images are collected from two datasets [44,62] by merging them. These are publicly available or open-source datasets. The dataset contains sixty-five hundred and forty images belonging to five diseases. Dataset is divided into two sub parts i.e. train and test. Train and test categories are further divided into five classes with respect to the diseases. Each category in the train set contains nine hundred images and the test set contains four hundred and eight images. Target size is set to 299x299 for 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.

Image Preprocessing

Images are collected randomly, and these can vary in size. So, these images are preprocessed and transformed into uniform size. The dataset images are resized to 224X224 for vgg16 model and 299X299 for xception and inception v3 model. This is the default input size of the models. So, to improve the performance of models, image resizing has been performed.

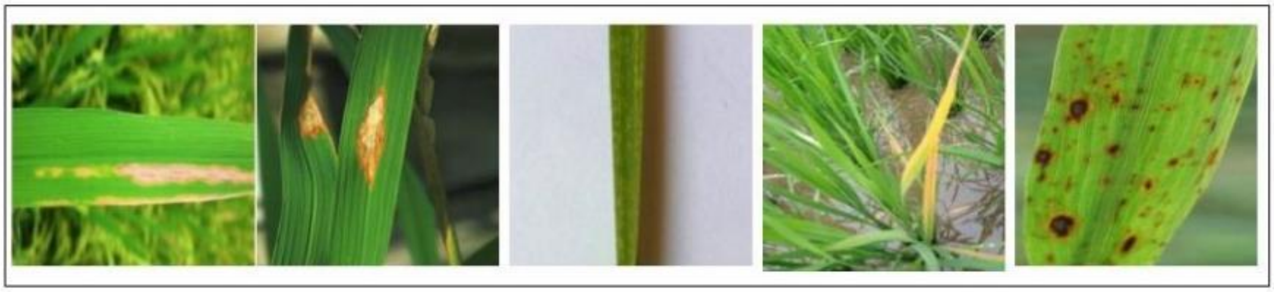


Figure 3 Dataset sample

Image Augmentation

Image augmentation technique is used to increase the volume of dataset. It is also used for providing input to the training models. Generally, there are several augmentation techniques that can be performed. In this thesis, I have used different augmentation techniques like zoom, horizontal flip, shear, and rescaling using Image Data Generator in Keras for generation of new images.

Xception Classification Model

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(hnorm) and by scale and shift(hi) operations.

$$\mu = \frac{1}{m}\sum h_i \qquad (1)$$

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

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

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

In (1), 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. Finally, 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. The architecture of xception model is provided in figure 4.

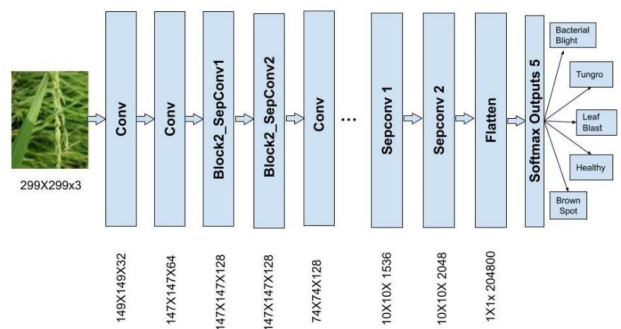


Figure 4. Xception Architecture

RESULTS

The implementation of rice leaf diseases classification is accomplished using the Xception model to accurately detect whether a rice leaf image is healthy or infected with one of the four diseases: bacterial blight, leaf blast, tungro, or brown spots. The dataset used in this study was divided into 70% for training and 30% for testing. The Xception model was chosen due to its effectiveness in image classification tasks, particularly in cases with limited training data. The model was trained on the training dataset, which consisted of 4500 images, using transfer learning techniques. Transfer learning involves using pre-trained models to classify new images, which allows for better accuracy even with small datasets.

Models Specifications

For achieving optimal accuracy, the Adam optimizer is used. Several hyper parameters were set during the implementation of rice leaf disease classification using the Xception model. The Adam optimizer was used to optimize the model's weights and biases during training. Categorical cross-entropy was chosen as the loss function to measure the model's performance during training. The batch size, which represents the number of training samples utilized in each iteration of training, was set to 32. The number of epochs used in the training phase was set to 10. An epoch represents a complete iteration through the entire training dataset. A learning rate of 0.001 was utilized during training to determine the step size at each iteration while adjusting the model's weights and biases. Additionally, an input size of 299x299x3 was set in the Xception model. This input size specifies the dimensions of the input image that the model can accept. Hyperparameters were chosen based on their effectiveness in training the Xception model for image classification tasks, and their optimal configuration was determined through experimentation and tuning.

Accuracy and Loss Evaluation of the Xception model

The Inception V3 model has obtained 0.9864 train accuracy and 0.9392 test accuracy. Train loss is 0.0425, and the test loss value is 0.1602 loss during training. The accuracy graph obtained during the training of the xception model is given in figure 5.

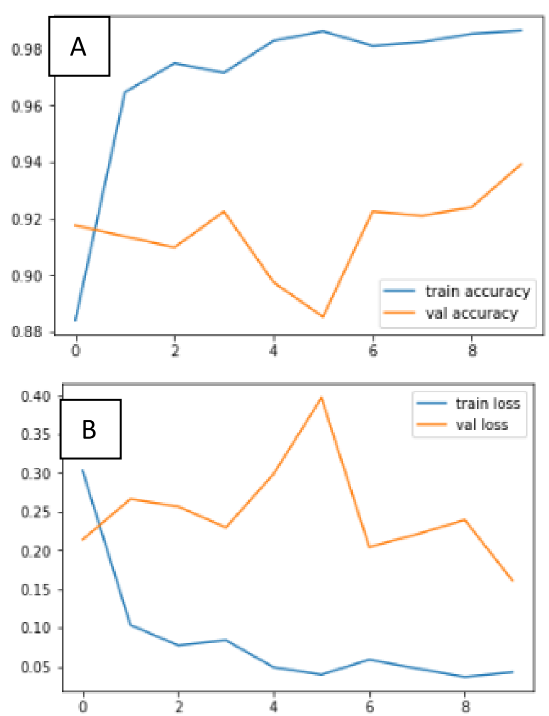


Figure 5. Xception Model (A) Accuracy (B) Loss

The precision recall and F1 score value obtained by the xception model is 0.94. The calculations of the confusion matrix has also been done as given in fig 6.

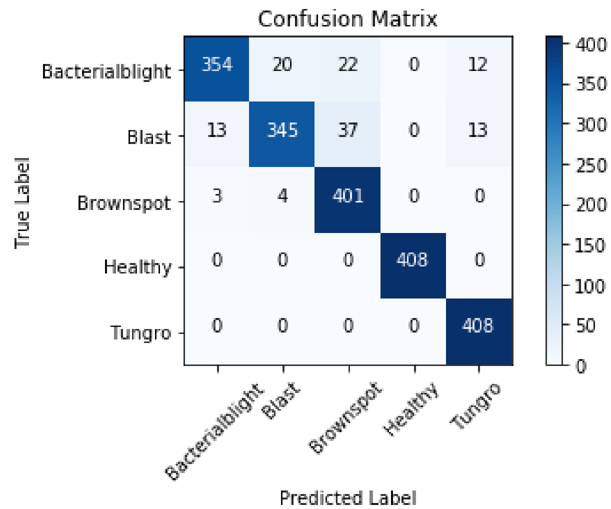


Figure 6 Confusion matrix of the Xception Model

The models initially did not give better accuracy due to some parameter values like input size, batch size, optimizer, loss function. But when these parameters are set to input size=299, batch size =32, adam optimizer instead of RMSprop, categorical cross entropy as loss function, epochs=10, and learning rate=0.001, results were improved. The model gave us optimal results.

After the successful training of deep learning model, prediction of the rice diseases can be performed by taking infected leaf sample and passing it to deep learning model. Deep learning model then performs prediction of disease in infected leaf by returning the name of the disease by classifying it. In this paper, we have used xception model for identification of rice diseases. Xception model is transfer learning model whose fine tuning is performed for identification of rice diseases. 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.

CONCLUSION

This study demonstrates the potential of deep learning approaches for the early detection and accurate classification of rice leaf diseases. The classification of rice leaf diseases is performed using transfer learning model. Xception model is used for the detection of rice diseases. Xception model for the classification of five different types of rice leaf diseases, including brown spots, bacterial blight, leaf blast, tungro, and healthy leaves. The dataset was obtained from two sources and merged to obtain optimal accuracy. Accuracy obtained for xception model is 93.92%. Evaluation metrics such as precision, recall, F1 score, and confusion matrix have been calculated. The Xception model achieved an impressive test accuracy of 93.92% for the detection of rice leaf diseases. Evaluation metrics, including precision, recall, F1 score, and confusion matrix, were calculated to verify the model's performance. The weighted average of precision, recall, and F1 score for Xception was found to be 0.94, indicating the model's high accuracy and reliability.

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