AUTOMATIC RICE PLANT DISEASE RECOGNITION AND IDENTIFICATION USING CONVOLUTIONAL NEURAL NETWORK

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ABSTRACT : Increasing production of grain is necessary where quantity of the food is insufficient. Grain production can be increased by controlling the crop disease and pests in time so that crop loss can be reduced. Now days various image processing techniques are used to analyze the crop images for diagnosing the rice crop disease. Manual detection of these images is very time consuming and the result will depend upon the experience of the expert. So, computer aided techniques are used for fast processing and accurate result of the disease detection. The Deep learning model uses the Convolutional neural network (CNN) that automatically extracts the features and classify the image using fully connected network. In this paper, we have trained a Sequential convolutional neural network and obtained a prediction accuracy of up to 99.61

KEYWORDS: CNN, rice diseases and pests, image processing, deep Learning, Machine Learning**.**

I. INTRODUCTION

The crop production is very important in the areas that are lacking in the food. The grains can be loosed because of crop diseases or the pests. So, the timely detection of these diseases can save the crop loss and increase the production of crop [1]. Rice crop gives food security to nearly half of the world population [2] so the timely recognition and identification of rice crop disease plays an important role for high yield, high quality and high efficiency of rice [3]. The manual detection of rice disease requires lots of experience and knowledge of experts. Recently computer aided technique is adopted for automatic rice disease detection based on pattern recognition and machine learning. Pattern recognition techniques [4], Support vector machine [5] and digital image processing techniques [6]. However, these techniques are not only used for rice disease detection, but they are also using for disease detection of other crops also like wheat, soybean, cotton etc. Rice plants disease could be affected by various conditions like climate, lighting, humidity, fertilizer, water management, and various farming conditions. In recent years CNN is widely used

for image processing and machine learning due to its automatic feature extraction capability.

II. BACKGROUND STUDY & RELATED WORK

Jayme Garcia et. al. presented that the size and variety of the dataset impact the effectiveness of the deep learning methods in plant pathology. Their study is based on image database containing 12 plant species and each presenting very different characteristics that are number of samples, number of diseases and variety of conditions. In this paper Experimental results shows that the technical constraints linked to automatic plant disease identification have been largely overcome, the use of limited image datasets for training can brings many undesirable consequences [7].

Jiang, J et.al. presented that using five cross validation method for high performance of the RWR approach showed the robustness of the parameter r. In this paper the authors predicted a landscape of associations between known seeds and candidate genes [8].

Kodama, T et. al. processed the image by rice planted in paddy field to classify the healthy plants and the diseased plants. For the identification they had used the color information of the rice plant and the SVM classifier is constructed. The overall accuracy achieved in this paper is 90% [9].

Mique Jr, E. L et.al. proposed an application using convolutional neural network and image processing that will help farmers to identify type of disease and pests in rice plants. The preprocessing is done on collected images to train the model and after successful implementation the model gives the accuracy of 90.9% [10].

Aukkapinyo, K et.al. proposed a solution to localization and classification of rice grains in an image. In this paper the authors have presented the watershed algorithm method for image preprocessing, auto-alignment using the major axis orientation, and image enhancement using the contrast-limited adaptive histogram equalization (CLAHE) technique.

In an input image Region based convolutional neural network is used to classify rice grains. Transfer learning is used to improve the performance and to prevent the over fitting dropout is used.

The presented method is validated using many conditions of experiments, reported in the forms of mean average precision (mAP) and a confusion matrix. It achieves above 80% mAP for main conditions in the experiments [11].

Chen, J., Chen et. al. presented the use of transfer learning of deep convolution neural network for plant disease identification and consider using the pre-trained model learned from the typical massive datasets, and then transfer to the specific task trained by our own data. The authors in this paper used the VGGNet pre-trained on ImageNet and Inception module. The experimental result in this paper shows the validation accuracy not less than 91.83% on the public dataset [12].

To increase the crop yield weeding is an important way. **Jiang, H et.al.** presented a CNN feature-based graph convolutional network (GCN) based approach to improve weed and crop re- cognition accuracy. In this paper a GCN graph was constructed based on extracted weed CNN features and their Euclidean distances. The proposed GCN-ResNet-101 approach achieved 97.80%, 99.37%, 98.93% and 96.51% recognition accuracies on four different weed datasets respectively, which outperformed the state-of-the-art methods (AlexNet, VGG16 and ResNet-101) [13].

Sethy. P et. al. presented a review from 2007 and 2018 for diagnosing rice plant disease. They have compared their studies are based on image segmentation, feature extraction, feature selection and classification. The authors also presented the current achievements, limitations and suggestions for future research associated with the diagnosis of rice plant diseases [14]. The physical characteristics of an organism are predicted from knowledge of its genotype and environment is known as phenotype prediction. **Nastasiya F. Grinberg et.al.** presented the three phenotype prediction problems: one simple and clean (yeast), and the other two complex and real-world (rice and wheat). In this paper the authors had compared standard machine learning methods such as elastic net, ridge regression, lasso regression, random forest, gradient boosting machines (GBM), and support vector machines (SVM), with two classical statistical genetics methods such as genomic BLUP and a two-step sequential method based on linear regression. The result in this paper shows that the application of machine learning methods to phenotype prediction problems capture great security [15].

Liang et.al. presented a CNN based novel rice blast recognition method. For training and testing the CNN a dataset of 2906 positive samples and 2902 negative samples is established. The result in this paper shows that the high-level features extracted by CNN are more discriminative and effective than traditional manual features extraction methods including local binary patterns histograms (LBPH) and Haar-WT (Wavelet Transform). The authors had concluded that CNN model is a top performing method for rice disease recognition [16].

Zhou . C et. al. implemented a panicle detection and counting system to improve the accuracy of rice detection and counting in the field, that is based on improved region-based fully convolutional networks. To train and test the system experiments were conducted in target areas and used a rotor light vehicle equipped with a high-definition RGB camera to collect images. In this paper after training the model achieved the precision of 0.868 on a held-out test set [17].

Qi Yang et.al. presented convolutional neural network (CNN) architecture to learn the important features related to rice grain yield from low-altitude remotely sensed imagery. To investigate the ability of CNN in rice grain yield estimation a 160-hectare site with over 800 management units was chosen in one major region for rice cultivation of Southern China. A fixed wing unmanned aerial vehicle (UAV), which was mounted with a digital camera and multispectral sensors is used for data collection. In this paper the network was trained with different datasets and compared against the traditional index-based method. The experimental results showed that the CNNs trained by RGB and multispectral datasets perform much better than VIs-based regression model for rice grain yield estimation [18].

Dengshan L et. al. presented a deep learning-based video detection architecture for detecting plant diseases and pests in video. In this paper the authors first transformed the video into immobile frame, then sent the frame to the immobile-image detector for detection, and finally synthesized the frames into video. Faster-RCNN is used as the framework and to detect relatively blurry videos image-training models are used. Experimental result shows in the presented system that custom backbone was more suitable for detection of the untrained rice videos than VGG16, ResNet-50, ResNet-101 backbone system and YOLOv3 [19].

Sudarshan S. Chawathe presented a method for automatic classification of rice plant disease by analyzing photographs of rice leaves. The author used image processing algorithms to detect leaves and disease-induced lesions in the leaves. The different attributes of leaves like the numbers and shapes of lesions, as well the color characteristics of lesions and intact portions of leaves are used to build the classification model. The method is evaluated using a publicly available database of rice leaf images [20].

Chowdhury R. Rahman et. al. presented the deep learning-based approaches for detecting diseases and pests from rice plant images. In this paper the author presented their work in two phases fold: (i) large scale architectures such as VGG16 and InceptionV3 is adopted and fine-tuned for detecting and recognizing rice diseases and pests. (ii) Since large scale architectures are not suitable for mobile devices, a two-stage small CNN architecture such as MobileNet, NasNet Mobile and Squeeze Net is presented. The presented architecture can achieve the accuracy of 93.3% with a significantly reduced model size (e.g., 99% smaller than VGG16) [21].

III. PROPOSED METHOD

This paper presented the automatic detection of rice disease detection using deep learning methodology. We have used CNN architecture for image classification. Using the Kaggle dataset we are using input images which are labeled as healthy and leaf_blast. In this work CNN was trained using RGB color model with 1000 samples of rice crop. The proposed architecture to distinguish between healthy and leaf_blast rice crop is shown in figure 1.

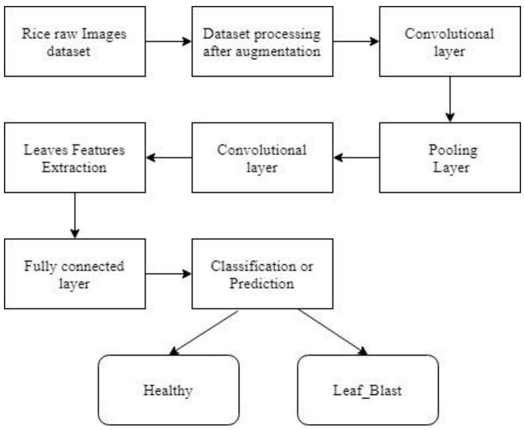

Figure 1:Model Process Flow

3.1 Image Preprocessing

An image is having various redundant pixels that are not used to display any information regarding image. In the machine learning compression techniques is uses to remove these redundant pixels. In implementation of our model for preprocessing of rice images we have used OpenCV library of python.

3.1.1 Feature Extraction

For classification of images Feature extraction is the important step. Past studies show that machines are very susceptible to pattern as compare to the human brain that is susceptible to shape [23]. So automatic feature learning will be different from the manual learning. In the visual representation of rice plant images leaf_blast images have spots on the images. We have used CNN model to process the images with the labeled class such as healthy & leaf blast. Weights are updated automatically in the training process of CNN that will be able to extract the features of the image. In our proposed architecture CNN model is having 2 layers.

(i) Convolutional layer
(ii) Pooling Layer

After the convolutional process the number of filters are used to increase the depth of the input and after that pooling layer is used that remains the same depth with reduced size.

3.1.2 Classification

In the classification process of this model, flattened weighted feature map are used that are received from the final pooling layer and it will be used as an input to the fully connected layer that calculates the loss and accuracy and according to the result weights of the internal nodes will be modified automatically to improve the result. After the preprocessing the output of the last layer is taken as the final output as usual.

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IV. CONVOLUTIONAL NEURAL NETWORK FOR AUTOMATIC IDENTIFICATION OF DISEASE IN RICE LEAF AS HEALTHY OR INFECTED WITH LEAF_BLAST

Here we are discussing the process to identify whether the crop of rice is healthy or the infectious by the rice crop images. For the implementation of same we have used Kaggle dataset that is having data in 2 classes (i) Healthy (ii) Leaf_blast. Total numbers of images used from the Kaggle dataset in this model are 1000. The dataset is split into 80% training and 20 % testing samples.

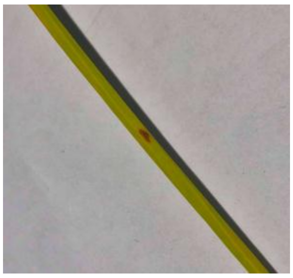

Figure2 (a): Healthy **Figure 2 (b): Leaf_Blast infected**

Ref: Kaggle Dataset [22]

This model is developed in Python language by using the deep learning libraries: numpy, opencv and Keras. We used a batch size of 32 that is a hyper-parameter to adjust in deep learning. Data augmentation is also used to artificially create large training set from the existing dataset. We have implemented an image generator object which performs random rotations, shifts, flips, crops, and sheers on our image dataset. This allows us to use a smaller dataset and still achieve high results. In the model Our CONV layer has 32 filters with a 3 x 3 kernel and RELU activation (Rectified Linear Unit), pooling layer of size 3x3 and dense layer with ReLu and Softmax activation function. After that we have applied 25% (0.25) dropout, batch normalization and max pooling. Visualization is done after every layer and adam optimizer is used with epoch value of 20.

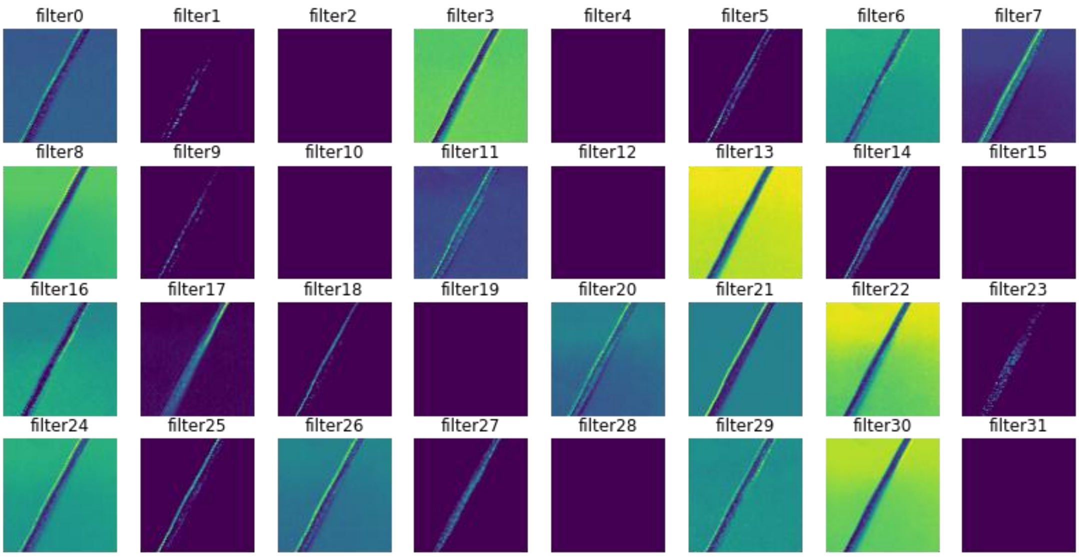

Figure 3 (a): Visualization of layers (conv2d_1)

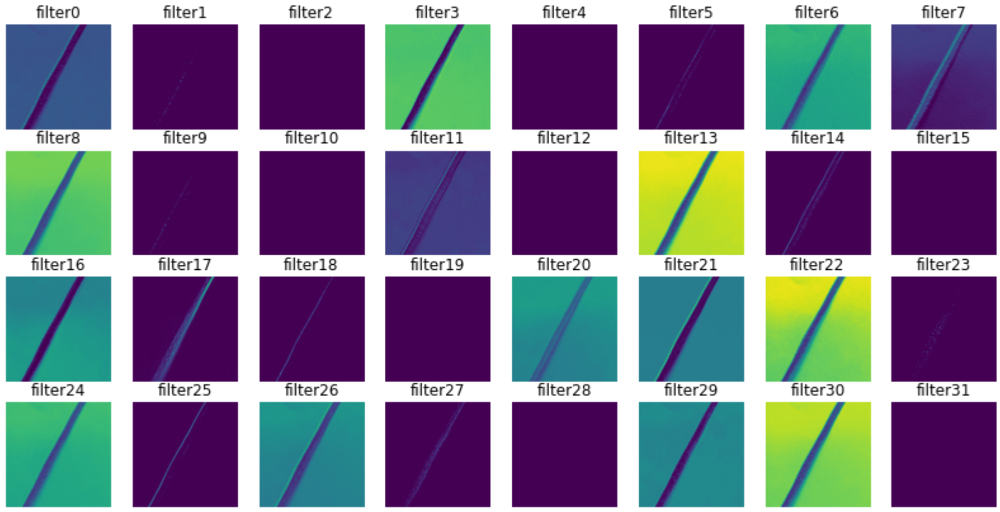

Figure 3(b): Visualization of layers (max_pooling2d_1)

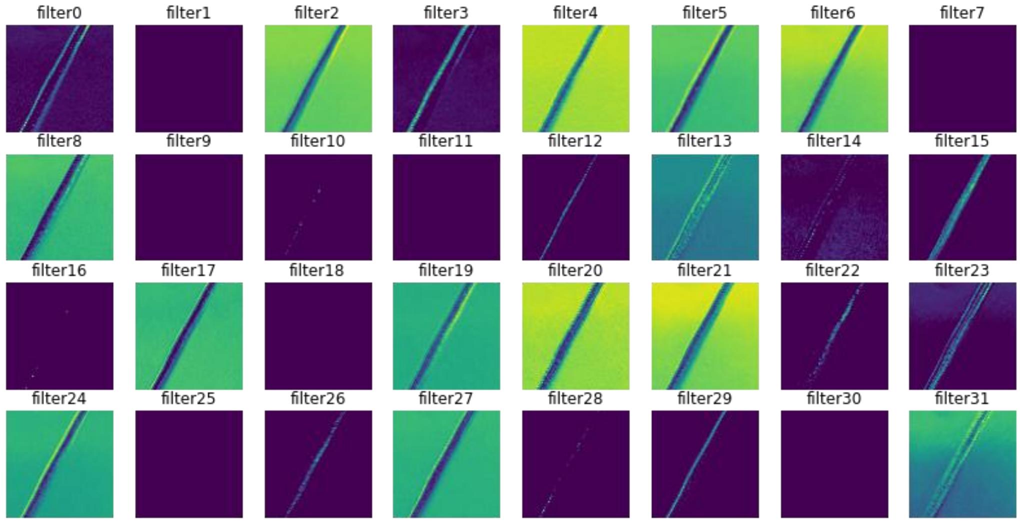

Figure 3 (c): Visualization of layers (conv2d_2)

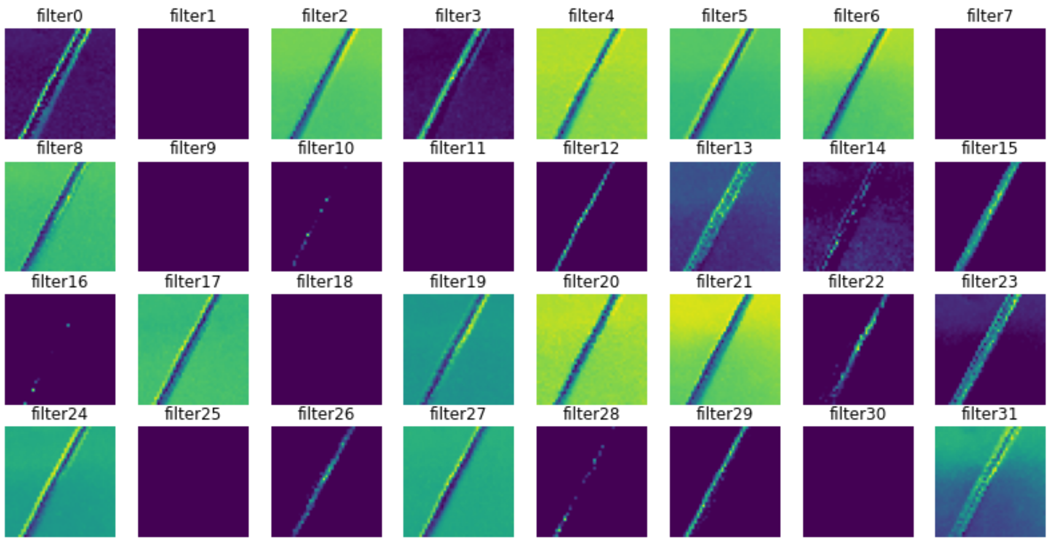

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Figure 3 (d): Visualization of layers (max_pooling2d_2)

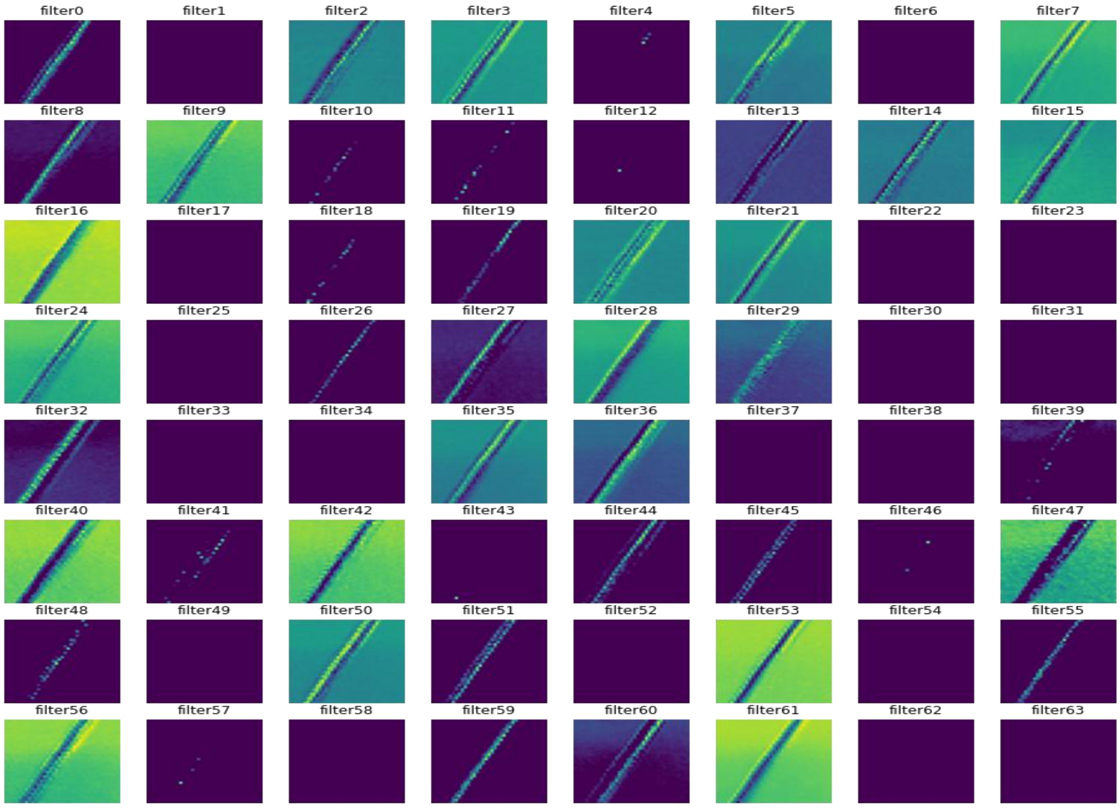

Figure 3 (e): Visualization of layers (conv2d_3)

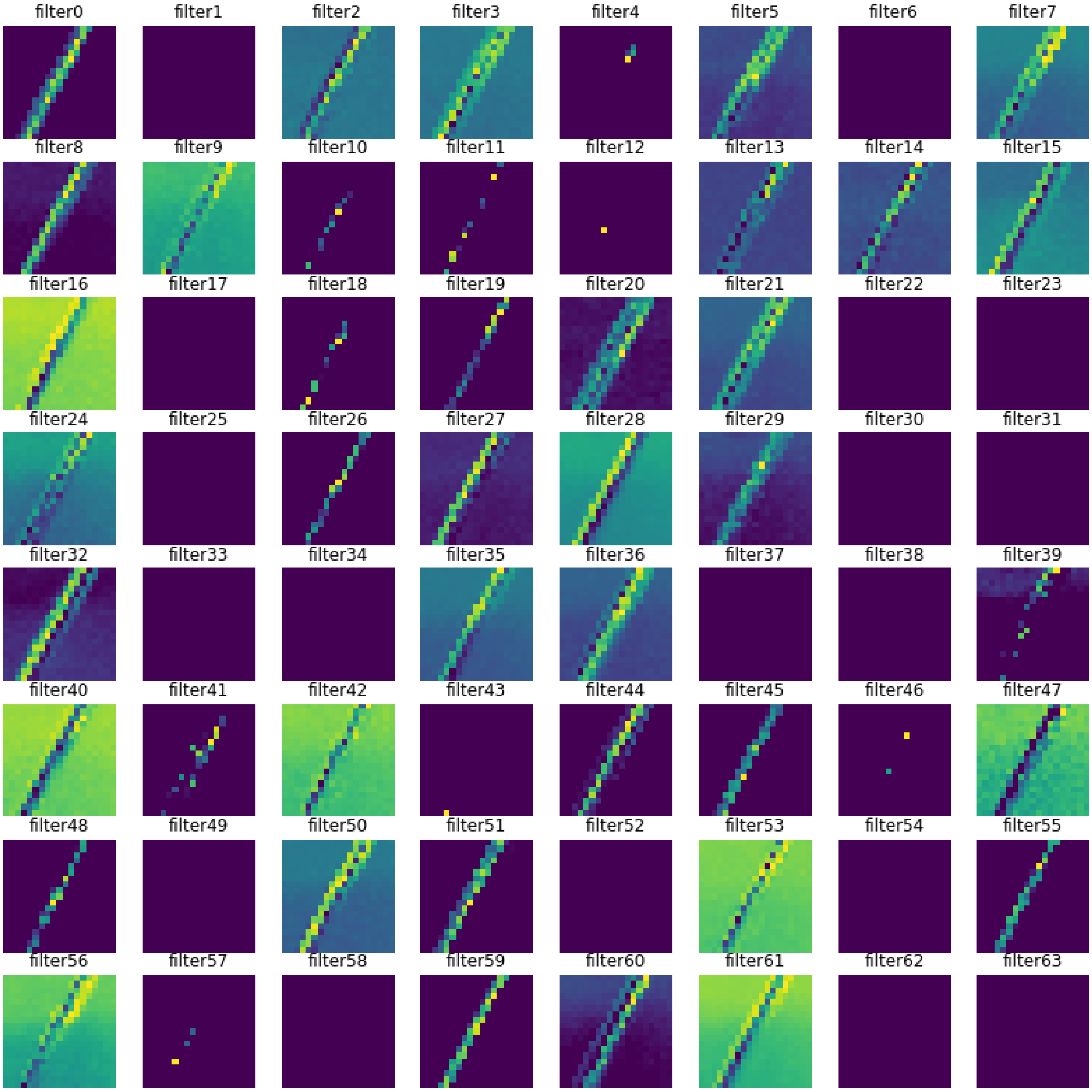

Figure 3 (f) Visualization of layers (max_pooling2d_3)

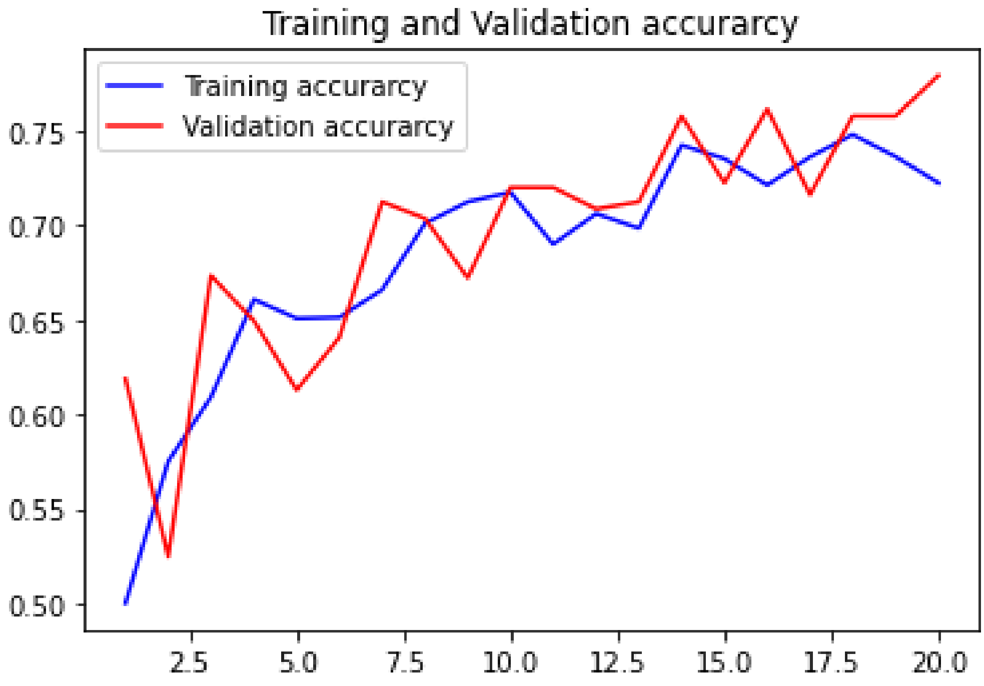

Figure 4: Training & Validation Accuracy

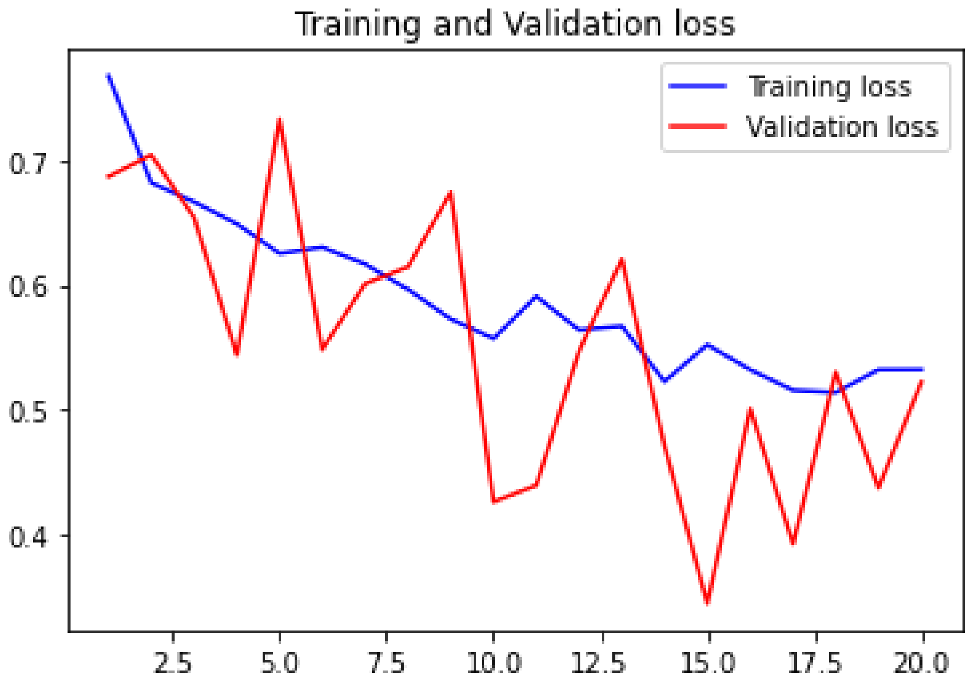

Figure 5: Training & Validation Loss

In these graphs (Figure 4 & 5) losses are decreasing and accuracy is increasing that shows that our model is trained in a better way.

4.1 Prediction of Image

After the successful implementation following prediction output is generated for the healthy or infectious rice leaves.

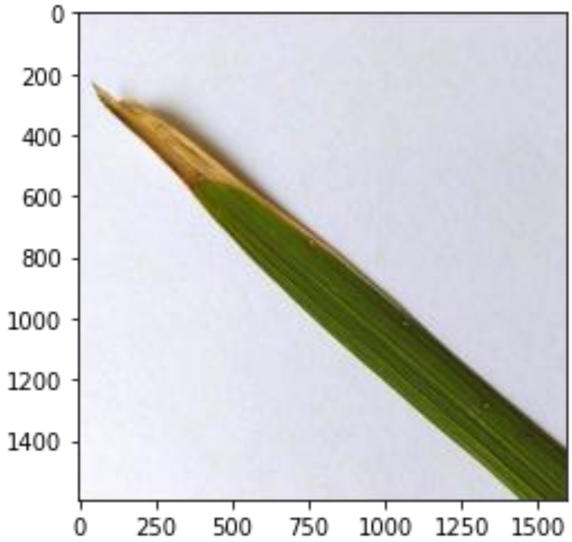

Figure 6: Leaf_Blast Image

V. CONCLUSION

Rice crop disease detection & recognition in deep learning by using rice images is a signal in the field of agriculture. It has provided the new opportunities for researcher as there are no of undiscovered areas that can be exposed by techniques and tools of machine learning and deep learning. We may obtain improved results by of disease detection by altering the network design and parameters. As an improvement to the proposed method, in future one can implement an autoencoder instead of manually reducing image size. It can compress data without losing the important features, because autoencoders can regenerate up to 90% of the original images.

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