Paddy Crop Leaf Disease Classification By Using CNN And Transfer Learning Approach

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Abstract: *Agriculture and its allied sectors are one of the main pillars of Indian economy. The experiences during and after the covid-19 pandemic proved that agriculture will always be a leading sector in driving the nation. The paddy crop is one of the major staple crops in India. The yield of this crop may be affected due to several diseases affecting at various stages of crop cycle. There is a lot of research progressing on the crop diseases prediction. Presently, a lot of literature is available on crop disease prediction using image processing and machine learning approaches. The main aim of this research paper is to develop a paddy crop disease classification system by using convolutional neural network architecture and transfer learning using VGG16. The Mendeley dataset consisting of 5932 images of four different paddy crop diseases namely bacterial blight, blast, brown spot and tungro are used in this proposed work. The model is trained and tested by using CNN and VGG16 and the accuracies are obtained as 92.04% and 99.70% respectively. This model has achieved better accuracy with transfer learning approach compared to CNN architecture.*

Keywords: Paddy crop diseases, CNN, VGG16

1. Introduction

India is the second largest producer and largest exporter of rice in the world. As per 4th Advance Estimate of production of major agricultural crops for 2020-21 released by the Department of Agriculture and Farmers Welfare, a record 308.65 million tonnes of food grains have been produced out of which the estimated production of rice is estimated at record 122.27 million tonnes. It is higher by 9.83 million tonnes than the last five years' average production of 112.44 million tonnes. The record food grains are being produced due to the tireless efforts of farmers, the skill of agricultural scientists and the farmer friendly policies of the Government of India. As per the observed records, it is a welcome scenario but there exist huge efforts and challenges being faced by the farmers at the field level. The farmer who is the backbone of agriculture undergoes tireless efforts starting from ploughing the field to selling the final agricultural produce in the market.

The agriculture involves many stages like soil nutrient management, seed selection and sowing, manure and fertilizer usage, providing irrigation facilities, crop protection from weeds and pests, harvesting, storage and final selling in the market. Each stage is associated with many challenges. Proper care needs to be taken at each stage.

Even though there is a lot of progress in agriculture, most of the farmers in the country are still following traditional practices in their agricultural work. There are many reasons for going through traditional methods such as implementation costs involved above their regular expenditure, lack of awareness to the advanced technologies. There is a need for user friendly methods to help the new generation farmers and it is possible by adopting deep learning technologies like convolutional neural networks in agriculture.

The main aim of this research work is to propose a simplified solution for crop disease classification in paddy crop by using deep learning techniques. The proposed model classifies the paddy crop diseases namely bacterial blight, blast, brown spot and tungro by using CNN architecture and transfer learning using VGG16

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2. Literature Survey

Singh, Ashutosh Kumar, et al. [1] proposed a Hybrid Feature-Based leaf Disease Detection method. This research paper presented the detection of leaf diseases for corn, apple, tomato, rice, and potato leaves by extracting the deep features, texture, color features and followed by BPSO based feature selection, and comparing Bayesian optimized SVM and random forest classifications. This method achieved a maximum accuracy of 96.1%. Sharma, Rahul, et al. [2] proposed a novel approach for automatically evolving the CNN architecture using big bang–big crunch (BB–BC) algorithm. The CNN architecture is validated using the 5932 on-field rice leaf images infected with bacterial leaf blight, rice blast, brown leaf spot and tungro diseases. This approach performed better than CNN evolved using genetic algorithm, SVM, KNN, decision tree, random forest with the test accuracy of 98.7%. Sharma, Mayuri, et al. [3] discussed about various machine learning and deep learning techniques for detection of rice diseases namely bacterial blight, rice blast, and brown spot. The detailed analysis proved the superiority of transfer learning techniques over conventional machine learning techniques. It is observed that InceptionResNetV2 achieved the best results with an accuracy of 98.9%, whereas Xception achieved 97.65%, ResNet50 achieved 97%, MobileNet achieved 96.65% and InceptionV3 achieved 95.85% accuracies. Krishnamoorthy, N., et al. [4] utilized InceptionResNetV2 CNN model with transfer learning for recognizing diseases such as leaf blast, bacterial blight and brown spot in rice leaf images. The simple CNN model achieved the accuracy of 84.75% by running 15 epochs whereas InceptionResNetV2 has attained an optimized accuracy of 95.67% using 10 epochs. Anandhan, K., et al. [5] proposed a method to detect various rice leaf diseases such as brown spot, sheath blight, blast and leaf streak disease by using mask R-CNN and faster R-CNN algorithms and proved that mask R-CNN is best and the accuracy for brown spot, sheath blight and blast were obtained as 95%, 94.5% and 96%. Sankar, et al. [6] proposed an intelligent crop health assessment system to find out the leaf diseases by using deep learning based on CNN and the accuracy was obtained as 85%. Limkar, et al. [7] proposed a method of classification of rice crop diseases and its prediction by using PNN and CNN approaches and achieved the accuracies of 99.8% and 94.4%. Jadhav, et al. [8] proposed a method of identification of soybean crop disease using AlexNet and GoogleNet CNN models and achieved accuracies of 98.75% and 96.25%. Das, Sujay, et al. [9] proposed a probabilistic model for detection of three paddy crop diseases using CNN. Purbasari, et al. [10] proposed a method of detection of four rice crop diseases using CNN and obtained 91.41% training accuracy along with an average of 51.2% testing accuracy. Ghosal, et al. [11] proposed the CNN architecture based on VGG-16 for leaf disease detection in rice and the accuracy is obtained as 92.46%. Das, Ankur, et al., [12] proposed the method for prediction of rice leaf diseases using CNN which generates the features automatically and classifies the diseases using softmax layer. This method achieved the accuracy of 91.07%. Rahman, Chowdhury R., et al., [13] demonstrated the different CNN architectures namely VGG16, InceptionV3, MobileNetv2, NasNet Mobile, SqueezeNet and Simple CNN. Among these architectures Fine-tuned VGG16 obtained the best accuracy of 97.12%. Vardhini, et al., [14] proposed a method of disease detection in paddy crop using Raspberry Pi and CNN. The various diseases encountered by the paddy crop are stored in the database of Pi and whenever the diseased image is taken through mobile application, it gives the result of details affected disease based on the artificial intelligence and CNN. Hasan, Md Jahid, et al. [15] adopted the SVM classifier along with deep CNN to detect and classify the nine different rice crop diseases and achieved the accuracy of 97.5%. Francis, Mercelin, et al. [16] implemented a CNN method to detect whether the leaf is healthy or not in apple and tomato plants and achieved the accuracy of 88.7%. Emebo, Onyeka, et al. [17] proposed the method for detection of tomato septoria leaf spot and tomato mosaic diseases using deep CNN and Raspberry Pi and achieved a validation accuracy of 99.01%. Orano, Jonah Flor V., et al. [18] proposed a method to detect and diagnose the jackfruit damages caused by pests and diseases by using CNN method and achieved the overall success rate of 97.87%. Ahila Priyadharshini, et al. [19] proposed a method by using Modified LeNet deep CNN architecture to classify the diseases in Maize leaves. The model achieved the accuracy of 97.89%. Singh, Uday Pratap, et al. [20] proposed a Multilayer Convolutional Neural Network (MCNN) for the classification of Mango leaves infected by a fungal disease named Anthracnose. The accuracy of 97.13% is achieved in this model. Jiang, Peng, et al. [21] proposed a SSD with Inception module and Rainbow concatenation model based on improved CNN architecture for real-time detection of various leaf diseases in Apple plant. This model achieved the accuracy of 78.80%. Mique Jr, et al. [22] proposed a model based on CNN to detect the pests and diseases in rice crops and this model achieved an accuracy of 90.9%. Kosamkar, Pranali K., et al. [23] proposed a method to detect various leaf diseases of different crop species by using CNN with five, four and three layers to train the model and achieved the highest accuracy of 95.05% with 5 layers. Zhang, Xihai, et al. [24] proposed a maize leaf disease identification method by using the improved GoogLeNet and Cifar10 models based on deep CNN and achieved the accuracies of 98.9% and 98.8%. Watchareeruetai, Ukrit, et al. [25] proposed the method of detecting five types of nutrient deficiencies i.e., Ca, Fe,K, Mg, and N deficiencies in black gram plants by using CNN model and proved that CNN based methods are efficient over trained humans in detecting nutrient deficiencies in plants. Ouppaphan, et al. [26] proposed the disease identification in corn leaf images by using CNN and achieved the accuracy of 97.09%.

3. Proposed Methodology

The proposed methodology is implemented by using 5932 paddy crop images from Mendely dataset consisting of four diseases bacterial blight, blast, brown spot and tungro. The image data is split into the train-test ratio of 75:25 and feed to the CNN and VGG16 models. Python programming is used for the development of the models and the performance evaluation parameters in terms of accuracy and loss for both CNN and VGG16V are done through Google Colab. The Figure1 shows the block diagram of the proposed methodology.

A) Convolutional Neural Networks:

CNNs are generally used for classification and computer vision applications. They bring forth the ascendable ways for image processing and the tasks associated with object recognition. The superior performance of the CNNs with image and audio signal inputs makes them more preferable as compared to other neural networks. There are three main types of layers in CNN.

- Convolutional layer
- Pooling layer
- Fully-connected (FC) layer

The first layer of the convolutional network is the convolutional layer. The convolutional layer will be followed by additional convolutional layers also called as pooling layers. The final layer is the fully-connected layer. The CNN increases in its complexity with each layer and identifies the greater portions of the image. The starting stages focus on simple features like colors and edges. The next layers starts to recognize larger elements of the object as the image data progresses through the layers of CNN and finally identifies the intended object.

Convolutional Layer

This is the core building block of CNN as the majority of computation takes place in this stage. It requires input data, a filter and a feature map. The feature detector known as kernel or a filter will move across the receptive fields of the image to check the presence of features. This is called as the process of convolution.

The feature detector is a weighted two-dimensional (2-D) array that represents a portion of the image. The filter size, which can vary in size, is usually a 3x3 matrix, which also affects the size of the receptive field. The filter is then applied to a portion of the image, and the dot product between the input pixels and the filter is determined. The output array receives this dot product. The filter then shifts by a stride, and the procedure is repeated until the kernel has swept across the entire image. A feature map, activation map, or convolved feature is the ultimate output of a series of dot products from the input and the filter.

Each feature map output value does not have to correspond to each pixel value in the input image. It simply has to be connected to the receptive field, which is where the filter is applied. Convolutional (and pooling) layers are often referred to as "partially connected" layers because the output array does not have to map directly to each input value. This trait, however, can also be represented as local connection.

The feature detector's weights stay fixed as it advances over the image, which is also known as parameter sharing. Backpropagation and gradient descent are used to change some parameters, such as weight values, during training. However, there are three hyperparameters that determine the output volume size that must be specified before the neural network can be trained. Among them are:

i. **Number of filters**: The depth of the output is affected by the number of filters used. Three distinct filters, for example, would result in three different feature maps, giving a depth of three.

ii. **Stride:** The kernel's stride is the number of pixels it traverses across the input matrix. While stride values of two or more are uncommon, bigger strides result in smaller output.

iii. **Zero-padding:** When the filters don't fit the input image, zero-padding is utilised. All members outside of the input matrix are set to zero, resulting in a larger or similarly sized output. Padding comes in three varieties:

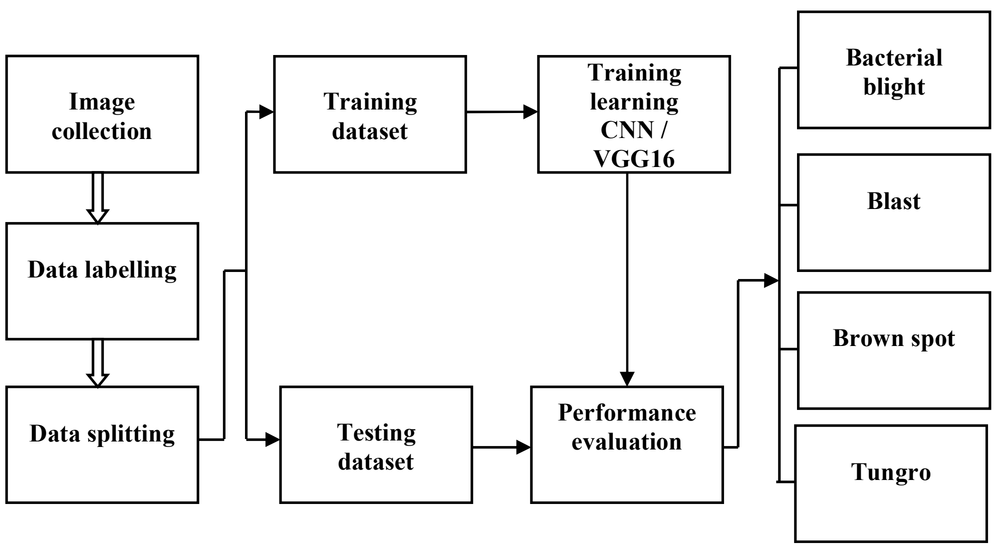

Figure 1. Block diagram of the proposed paddy crop disease classification system

Valid padding: No padding is also known as valid padding. If the dimensions do not align, the last convolution is discarded.

Same padding: The same padding ensures that the output layer and the input layer are the same size.
Full padding: This type of padding enhances the output size by padding the input border with zeros.
A CNN adds a Rectified Linear Unit (ReLU) adjustment to the feature map after each convolution operation, introducing nonlinearity to the model. After the initial convolution layer, another convolution layer can be added. When this happens, the CNN's structure might become hierarchical, as later layers can perceive pixels within earlier layers' receptive fields. Finally, the convolutional layer turns the image to numerical data, allowing the neural network to analyse and extract meaningful patterns.

Pooling Layer
Downsampling, also known as pooling layers, is a dimensionality reduction technique that reduces the number of factors in the input. The pooling process sweeps a filter across the entire input, similar to the convolutional layer, however this filter does not have any weights. Instead, the kernel uses an aggregation function to populate the output array from the values in the receptive field. Pooling can be divided into two categories:

- **Max pooling**: The filter selects the pixel with the highest value to send to the output array as it advances across the input. In comparison to average pooling, this strategy is employed more frequently.
- **Average pooling**: As the filter passes over the input, the average value within the receptive field is calculated and sent to the output array.

While the pooling layer loses a lot of information, it does provide some advantages for the CNN. They assist in reducing complexity, increasing efficiency, and reducing the risk of overfitting.

Fully-Connected Layer
The full-connected layer's name is self-explanatory. In partially linked layers, the pixel values of the input image are not directly connected to the output layer, as previously stated. Each node in the output layer, on the other hand, connects directly to a node in the previous layer in the fully-connected layer.
This layer performs classification tasks based on the features retrieved by the previous layers and their various filters. While convolutional and pooling layers typically utilise ReLu functions to categorise inputs, fully connected layers typically use a softmax activation function to produce a probability from 0 to 1.

B)VGG-16:
The network's input is a two-dimensional image (224, 224, 3). The first two layers have the same padding and 64 channels of 3*3 filter size. Then, after a stride (2, 2) max pool layer, two layers of convolution layers of 256 filter size and filter size (3, 3). This is followed by a stride (2, 2) max pooling layer, which is the same as the preceding layer. There are then two convolution layers with filter sizes of (3, 3) and a 256 filter. Following that, there are two sets of three convolution layers, as well as a max pool layer. Each has 512 filters of the same size (3, 3) and padding. This image is then fed into a two-layer convolution stack.
The filters that are utilised in these convolution and max pooling layers are 3*3. It also employs 1*1 pixels in some of the layers to adjust the amount of input channels. After each convolution layer, a 1-pixel padding (same padding) is applied to avoid the image's spatial information from being lost.
We received a (7, 7, 512) feature map after stacking the convolution and max-pooling layers. The output is labelled as bacterial blight, blast, brown spot, and tungro using the softmax function.

C) Paddy crop diseases:

The paddy crop will be affected by many diseases from its plantation stage to the yield stage. The effect of damage by the diseases clears shows its results on the final yield. This paper is focused on four major diseases that come across in paddy crops; bacterial blight, blast, brown spot and tungro.

Bacterial blight **Blast** **Brown spot** **Tungro**

Figure 2. Diseases in paddy crops

Bacterial blight:

This is caused by *Xanthomonas oryzae* pv. *oryzae*. This is one of the most important serious diseases in paddy crops. It results in wilting of seedlings and yellowing and drying of leaves. There will be high crop loss to the yield if it attacks the crop at earlier stages.

Blast:

This is caused by the fungus *Magnaporthe oryzae.* It can affect all parts above the ground of a rice plant: leaf, collar, node, neck, parts of panicle, and sometimes leaf sheath. This is one of the most destructive diseases of paddy. A leaf blast infection can kill seedlings or plants up to the tillering stage. At later growth stages, a severe leaf blast infection reduces leaf area for grain fill, reducing grain yield. This disease can kill rice plants at seedling stage and cause yield losses in cases of severe infection.

Brown spot:

Brown spot is a fungal disease that infects the coleoptile, leaves, leaf sheath, panicle branches, glumes, and spikelets. Its most observable damage is the numerous big spots on the leaves which can kill the whole leaf. When infection occurs in the seed, unfilled grains or spotted or discolored seeds are formed. Brown spot can occur at all crop stages, but the infection is most critical during maximum tillering up to the ripening stages of the crop.

Tungro:

This disease is caused by the combination of two viruses, which are transmitted by leafhoppers. It causes leaf discoloration, stunted growth, reduced tiller numbers and sterile or partly filled grains. Tungro infects cultivated rice, some wild rice relatives and other grassy weeds commonly found in rice paddies. Tungro is one of the most damaging and destructive diseases of rice in South and Southeast Asia. In severe cases, Tungro susceptible varieties infected at an early growth stage could have as high as 100% yield loss. Once tungro is present in the field, it increases rapidly in young rice plants. Leafhopper vectors prefer to feed on young rice plants. They also acquire tungro viruses more efficiently from younger infected plants.

4. Experimental Results

The proposed model is executed for 5 epochs by train-test split ratio of 75:25 for 5932 images and the accuracy of training set is obtained as 99.60% and the test accuracy is obtained as 99.70% in the CNN VGG16 model. Similarly, the model is executed for 8 epochs by train-test split ratio of 75:25 for 5932 images and the accuracy of training set is obtained as 93.61% and the test accuracy is obtained as 92.04% in the CNN model. The CNN model without transfer learning has 3 Convolution layers each of which is followed by ReLU, Maxpooling and dropout layer followed by Fully Connected Layer and SoftMax. Table 1 shows the comparison of accuracy of the proposed CNN model with VGG16 and CNN without VGG16.

Model	Training Accuracy	Test Accuracy
CNN with VGG16	99.60%	99.70%
CNN without VGG16	93.61%	92.04%

Table 1: Performance of comparison of CNN model with and without VGG16

Layer (type)	Output Shape	Param #
conv2d (Conv2D)	(None, 150, 150, 32)	2432
max_pooling2d (MaxPooling2D)	(None, 75, 75, 32)	0
conv2d_1 (Conv2D)	(None, 75, 75, 64)	18496
max_pooling2d_1 (MaxPooling 2D)	(None, 37, 37, 64)	0
conv2d_2 (Conv2D)	(None, 37, 37, 96)	55392
max_pooling2d_2 (MaxPooling 2D)	(None, 18, 18, 96)	0
conv2d_3 (Conv2D)	(None, 18, 18, 96)	83040
max_pooling2d_3 (MaxPooling 2D)	(None, 9, 9, 96)	0
flatten (Flatten)	(None, 7776)	0
dense (Dense)	(None, 512)	3981824
activation (Activation)	(None, 512)	0
dense_1 (Dense)	(None, 4)	2052
Total params: 4,143,236 Trainable params: 4,143,236 Non-trainable params: 0		

Table 2: CNN Model Parameters

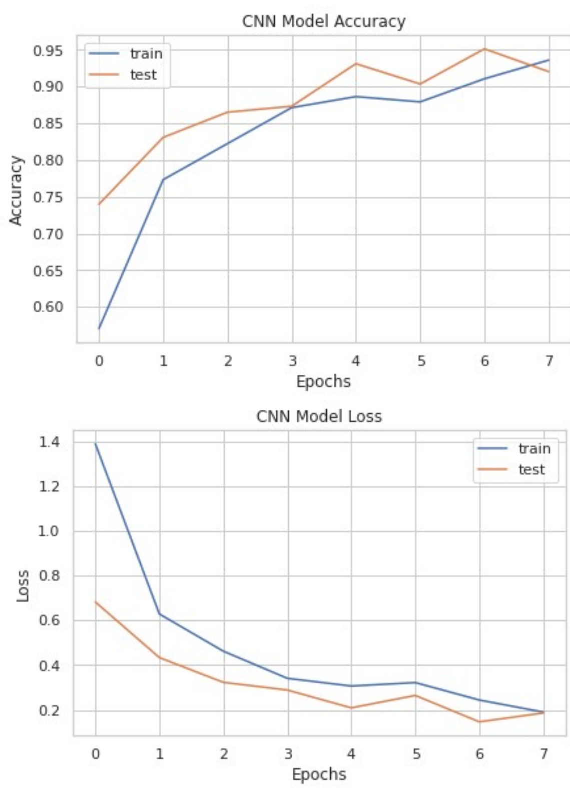

Figure 3. Plot of CNN Model Accuracy & Loss

Layer (type)	Output Shape	Param #
input_1 (InputLayer)	[(None, 224, 224, 3)]	0
block1_conv1 (Conv2D)	(None, 224, 224, 64)	1792
block1_conv2 (Conv2D)	(None, 224, 224, 64)	36928
block1_pool (MaxPooling2D)	(None, 112, 112, 64)	0
block2_conv1 (Conv2D)	(None, 112, 112, 128)	73856
block2_conv2 (Conv2D)	(None, 112, 112, 128)	147584
block2_pool (MaxPooling2D)	(None, 56, 56, 128)	0
block3_conv1 (Conv2D)	(None, 56, 56, 256)	295168
block3_conv2 (Conv2D)	(None, 56, 56, 256)	590080
block3_conv3 (Conv2D)	(None, 56, 56, 256)	590080
block3_pool (MaxPooling2D)	(None, 28, 28, 256)	0
block4_conv1 (Conv2D)	(None, 28, 28, 512)	1180160
block4_conv2 (Conv2D)	(None, 28, 28, 512)	2359808
block4_conv3 (Conv2D)	(None, 28, 28, 512)	2359808
block4_pool (MaxPooling2D)	(None, 14, 14, 512)	0
block5_conv1 (Conv2D)	(None, 14, 14, 512)	2359808
block5_conv2 (Conv2D)	(None, 14, 14, 512)	2359808
block5_conv3 (Conv2D)	(None, 14, 14, 512)	2359808
block5_pool (MaxPooling2D)	(None, 7, 7, 512)	0
flatten_1 (Flatten)	(None, 25088)	0
dense_2 (Dense)	dense_2 (Dense)	100356
Total params: 14,815,044 Trainable params: 100,356 Non-trainable params: 14,714,688		

Table 3. VGG16 Model Parameters

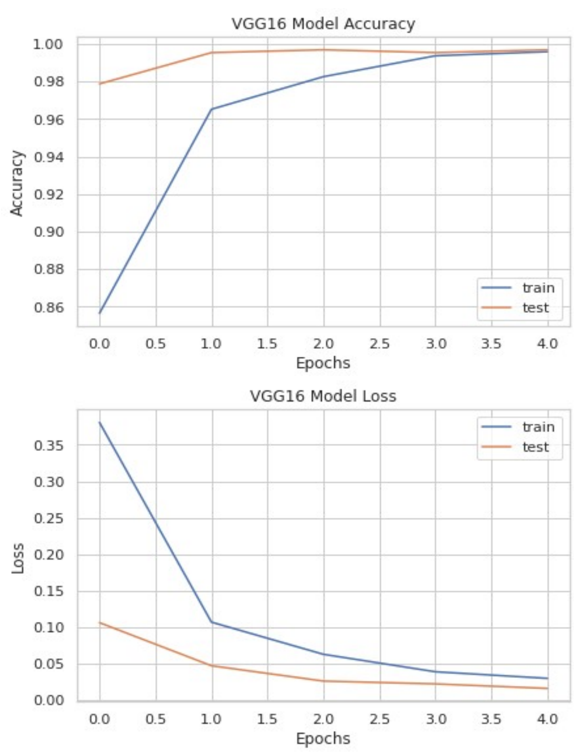

Figure 4. Plot of VGG16 Model Accuracy & Loss

5. Conclusion

This paper proposed the paddy crop disease classification system by using CNN and VGG16 models and the accuracies are better as compared to some previous works [11]. The VGG16 approach performed better as compared to CNN with accuracy of 99.70%.
In the future, this work will be utilized for development of IoT based applications combined with these approaches for application in real time in the agricultural fields.

6. References

[1] Singh, Ashutosh Kumar, et al. "Hybrid Feature-Based Disease Detection in Plant Leaf Using Convolutional Neural Network, Bayesian Optimized SVM, and Random Forest Classifier." *Journal of Food Quality* 2022 (2022).
[2] Sharma, Rahul, and Amar Singh. "Big bang–big crunch-CNN: an optimized approach towards rice crop protection and disease detection." *Archives of Phytopathology and Plant Protection* 55.2 (2022): 143-161.
[3] Sharma, Mayuri, Chandan Jyoti Kumar, and Aniruddha Deka. "Early diagnosis of rice plant disease using machine learning techniques." *Archives of Phytopathology and Plant Protection* 55.3 (2022): 259-283.
[4] Krishnamoorthy, N., et al. "Rice leaf diseases prediction using deep neural networks with transfer learning." *Environmental Research* 198 (2021): 111275.
[5] Anandhan, K., and Ajay Shanker Singh. "Detection of paddy crops diseases and early diagnosis using faster regional convolutional neural networks." *2021 International Conference on Advance Computing and Innovative Technologies in Engineering (ICACITE)*. IEEE, 2021.
[6] Sankar, Pagadala Rohit Sai, et al. "Intelligent Health Assessment System for Paddy Crop Using CNN." *2021 3rd International Conference on Signal Processing and Communication (ICPSC)*. IEEE, 2021.
[7] Limkar, Suresh, et al. "Classification and prediction of rice crop diseases using CNN and PNN." *Intelligent Data Engineering and Analytics*. Springer, Singapore, 2021. 31-40.
[8] Jadhav, Sachin B., Vishwanath R. Udupi, and Sanjay B. Patil. "Identification of plant diseases using convolutional neural networks." *International Journal of Information Technology* 13.6 (2021): 2461-2470.
[9] Das, Sujay, et al. "A model for probabilistic prediction of paddy crop disease using convolutional neural network." *Intelligent and Cloud Computing*. Springer, Singapore, 2021. 125-134.
[10] Purbasari, I. Y., B. Rahmat, and CS Putra PN. "Detection of Rice Plant Diseases using Convolutional Neural Network." *IOP Conference Series: Materials Science and Engineering*. Vol. 1125. No. 1. IOP Publishing, 2021.
[11] Ghosal, Shreya, and Kamal Sarkar. "Rice leaf diseases classification using CNN with transfer learning." *2020 IEEE Calcutta Conference (CALCON)*. IEEE, 2020.
[12] Das, Ankur, Chirantana Mallick, and Soumi Dutta. "Deep learning-based automated feature engineering for rice leaf disease prediction." *Computational Intelligence in Pattern Recognition*. Springer, Singapore, 2020. 133-141.
[13] Rahman, Chowdhury R., et al. "Identification and recognition of rice diseases and pests using convolutional neural networks." *Biosystems Engineering* 194 (2020): 112-120.
[14] Vardhini, PA Harsha, S. Asritha, and Y. Susmitha Devi. "Efficient Disease Detection of Paddy Crop using CNN." *2020 International Conference on Smart Technologies in Computing, Electrical and Electronics (ICSTCEE)*. IEEE, 2020.
[15] Hasan, Md Jahid, et al. "Rice disease identification and classification by integrating support vector machine with deep convolutional neural network." *2019 1st international conference on advances in science, engineering and robotics technology (ICASERT)*. IEEE, 2019.
[16] Francis, Mercelin, and C. Deisy. "Disease detection and classification in agricultural plants using convolutional neural networks—a visual understanding." *2019 6th*

International Conference on Signal Processing and Integrated Networks (SPIN). IEEE, 2019.
[17] Emebo, Onyeka, et al. "Development of tomato septoria leaf spot and tomato mosaic diseases detection device using raspberry Pi and deep convolutional neural networks." *Journal of Physics: Conference Series*. Vol. 1299. No. 1. IOP Publishing, 2019.
[18] Oraño, Jonah Flor V., Elmer A. Maravillas, and Chris Jordan G. Aliac. "Jackfruit Fruit Damage Classification using Convolutional Neural Network." *2019 IEEE 11th International Conference on Humanoid, Nanotechnology, Information Technology, Communication and Control, Environment, and Management (HNICEM)*. IEEE, 2019.
[19] Ahila Priyadharshini, Ramar, et al. "Maize leaf disease classification using deep convolutional neural networks." *Neural Computing and Applications* 31.12 (2019): 8887-8895.
[20] Singh, Uday Pratap, et al. "Multilayer convolution neural network for the classification of mango leaves infected by anthracnose disease." *IEEE Access* 7 (2019): 43721-43729.
[21] Jiang, Peng, et al. "Real-time detection of apple leaf diseases using deep learning approach based on improved convolutional neural networks." *IEEE Access* 7 (2019): 59069-59080.
[22] Mique Jr, Eusebio L., and Thelma D. Palaoag. "Rice pest and disease detection using convolutional neural network." *Proceedings of the 2018 international conference on information science and system*. 2018.
[23] Kosamkar, Pranali K., et al. "Leaf disease detection and recommendation of pesticides using convolution neural network." *2018 fourth international conference on computing communication control and automation (ICCUBEA)*. IEEE, 2018.
[24] Zhang, Xihai, et al. "Identification of maize leaf diseases using improved deep convolutional neural networks." *Ieee Access* 6 (2018): 30370-30377.
[25] Watchareeruetai, Ukrit, et al. "Identification of plant nutrient deficiencies using convolutional neural networks." *2018 International Electrical Engineering Congress (iEECON)*. IEEE, 2018.
[26] Ouppaphan, Pichayoot. "Corn disease identification from leaf images using convolutional neural networks." *2017 21st International computer science and engineering conference (ICSEC)*. IEEE, 2017.
[27] http://www.knowledgebank.irri.org/