Deep Learning-Based Rice Disease Recognition Using VGG16 and Transfer Learning

Poreddy Jayaraju[1], Dr. Aashiq Banu[2]

[1] Phd Scholar ,Department of Computer science & Eng. Indian Institute of Technology Bhilai, Chhattisgarh, India.
[2]Assistant Professor Department of Computer Science Eng. Koneru Lakshmaiah Education Foundation, Hyderabad-500075, Telangana, India.

Abstract - *Rice is one of the major cultivated crops in India which is affected by various diseases at various stages of its cultivation. It is very difficult for the farmers to manually identify these diseases accurately with their limited knowledge. For disease management, farmers spending lot of time and resources and they detect the diseases through their penniless naked eye approach which leads to unhealthy farming. The advancement of technical support in agriculture greatly assists for automatic identification of infectious organisms in the rice plants leaves. The convolutional neural network algorithm (CNN) is one of the algorithms in deep learning has been triumphantly invoked for solving computer vision problems like image classification, object segmentation, image analysis, etc. In our work, VGG16 is a type of CNN model utilized with transfer learning approach for recognizing diseases in rice leaf images. The parameters of the proposed model is optimized for the classification task and obtained a good accuracy of 97.57%.*

Key Words: CNN Deep Learning Fine-tuning Rice leaf diseases Transfer learning

1.INTRODUCTION

Timely and accurate diagnosis of plant diseases is crucial for sustainable agriculture and resource management. While some diseases lack visible symptoms, most are identified through optical observation by experienced plant pathologists. However, climate changes and the spread of diseases can challenge even skilled pathologists. In India, a major rice producer, agriculture contributes 19.9% to the GDP, with rice being a staple crop. Diseases affecting rice can significantly impact farmers' profits. Thus, an automatic data processing expert system for early disease detection is essential. Deep learning, particularly convolutional neural networks (CNNs), offers robust solutions for plant disease classification and other agricultural challenges by effectively processing visual data and learning spatial relationships.

2.Related work

A lot of researchers have developed disparate architectures in the recent years for the plant leaf diseases diagnosis by using machine learning and deep learning algorithms. 2020). Convolutional Neural Network (CNN) is one of neural networks used most frequently in deep learning, Amit Kumar Singh et al. used Support Vector Machine (SVM) to classify normal rice leaves and diseased rice leaves, and the classification accuracy reached 82% (Duan et al., 2017). Mohsen Azadbakht et al. used wheat leaf hyperspectral data and machine learning methods to detect wheat leaf rust, and reached a conclusion that support vector regression had the best effects in this case after comparing the results of four machine learning methods (Azadbakht et al., 2019). Comparatively speaking; the performance is very ordinary. Unlike traditional machine vision algorithms, which require manual feature extraction and classification, CNN only needs to input the image data into the network, and the self-learning ability of the network can complete the image classification (Xie et al., 2020), this research uses CNN as the research method.

Deep learning has been applied rapidly in image recognition (Xiong et al., 2021; Naranjo-Torres et al., Krishnamoorthy N et al. (2021) proposed a InceptionResNetV2 (Convolutional Neural Network) with transfer learning to identify rice plant diseases (Krishnamoorthy N et al. 2021). In this classification Solemane Coulibalya et al. (2019) applied a VGG16 model with transfer learning approach for detecting the disease in millet crop (Coulibaly et al., 2019). This work collected 124 leaf images and split into mildew diseases and healthy categories. The VGG16 model obtained an accuracy of 95%

N. Nandhini et al. (2020) proposed a machine learning algorithms such as SVM, K-NN, and decision trees for classifying the diseases in the plant leaves (Nandhini and Bhavani, 2020).

Task, the authors used 6 classes of images for training and achieved an accuracy of 95.67% for InceptionResNetV2.

3. Materials and methods: In this section, the procedure of the projected work is segregated into seven steps processes for categorizing rice leaf diseases which shows in Fig. 1 (Fig. 2).

3.1. Rice disease types and dataset description: The rice image dataset has been collected over the past few months mostly from the cultivation fields of Raipur, The dataset consists of 4020 images, images of diseased leaves of rice consisting of five most common diseases namely Bacterial Leaf Blight, Brown Spot, False Smut, Leaf Blast, sheath blight There are 516 images of Healthy leaves. There were a number of difficulties faced while collecting the data like poor illumination and Each and every image has only one disease. The dataset has been split into 80% training, 10% validation and 10 % testing. The classification function was implemented using VGG16.

3.2. Image Pre-processing and Augmentation: Image pre-processing enhances raw input data, improving model accuracy and efficiency by promoting meaningful insights. In this study, the collected dataset images with RGB coefficients (0–255) and varying dimensions were rescaled and resized for consistency.

During pre-processing, image pixel values were rescaled to 0–1 and resized to 224x224x3 pixels. Image augmentation techniques, including rotation, vertical and horizontal flipping, shearing, and random zooming, were applied using the Image Data Generator class to expand the training dataset. (Fig. 4)

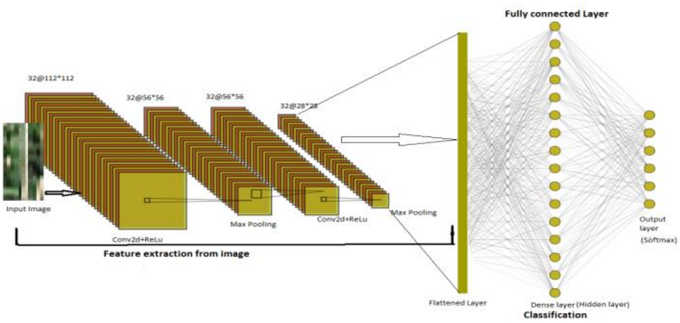


Fig. 5. Simple CNN model architecture.

4. Model building

4.1. CNN without transfer learning

It is a very simple neural network. It only has 6 layers, among which there are 2 convolution layers, 2 down sampling layers and 1 fully connected layer that are followed by the output layer. The input images are set to the size of 224x224x3.It consists of a series of convolution, activation and pooling layers in the feature extraction. The model used for the proposed system is shown in Fig. 5.

Convolutional layer is the building block of Convolutional Neural Network (Liu et al., 2018). Convolution layers use 3 by 3 filters with strides. It is used to derive the related features of the input image through the filters that have set of automatic learnable parameters (weights). Activation function used is ReLU. ReLU is an unsaturated activation elevates performance of the model better than saturated activation functions. Max pooling layers uses a 3 by 3 pooling window with stride value is 2 and functioning down sampling operation on input activation maps. It is a pooling operation that selects the maximum element from the region of the feature map covered by the filter. Flattening layer is used to transform the data into single dimensional array which is used as input to the fully connected layer. There are three sets of fully connected layer with 112,56 and 6 neurons which classifies the images into different classes that it belongs. Softmax activation function is used in the third fully connected layer. It returns the probability for each class and the target class will have the highest probability.

4.2. VGG16 with transfer learning

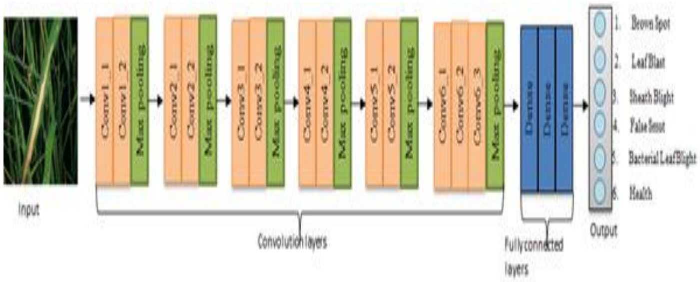


Fig. 8. VGG-16 Architecture fine–tuned with the last two layers with 128 Dense FC Layer and 6 Dense Softmax Layer as the output

images were resized to 224x224x3 pixels. Image augmentation techniques, including rotation and flipping, were applied using the Image Data Generator class. The model was compiled using the Adam optimizer and categorical_crossentropy loss function, and training was stopped at 200 epochs. A comparison with a custom CNN model showed superior performance of the VGG-16 based approach Figure 2 and Figure 8 depict the VGG-16 architecture and proposed model, respectively

4.3. Justification for the Chosen Model

Transfer learning leverages knowledge from pre-trained models to improve generalization and reduce training time, particularly useful when limited labelled data is available. We utilized the pre-trained VGG Net, fine-tuning it for our specific dataset to build an effective classification model.

5. Parameters for evaluation and Experimental Analysis (Metrics): We use the following metrics to analyze the performance of various models;

5.1. Confusion Matrix: Considering the statistics of correct detections (also known as true positives), misdetections (also known as false negatives), true negatives, and false positives, we can evaluate the performance of the models with the indicators including the Accuracy, Precision, Recall, and F1 Score as in equations 1, 2, 3 and 4.

5.2. Accuracy

It works well for balanced dataset and calculates a closeness of the evaluation with the actual value.

Accuracy=(TP+TN)/TP+FP+TN+FN) (1)

5.3. Precision

Precision=TP/(TP+FP) (2)

5.4. Recall

Recall=TP/(TP+FN) (3)

5.5. F1- score

F1−score=2TP/(2TP+FP+FN) (4)

This inference will be supportive for us to achieve a reliably skilled model for our plant leaf diseases recognition task. Where, true positive (TP), true negative (TN), false positive (FP), and false negative (FN) are the elements used in the evaluation metrics

6. Experimental setup

The experiment was accomplished with components of windows 11 PC, GPU runtime assigned by Google Colaboratory, Google drive 16 GB storage space, 64 bit operating system. The training and validation processes of the deep neural networks were enabled with the Keras 2.8.3 framework and TensorFlow backend.

7. Results and discussion

This portion shows and addresses the result derived by the proposed methodology. A fine-tuned pre-trained model and simple CNN were experimented with training and test sets contain 11236 and 2700 instances respectively.

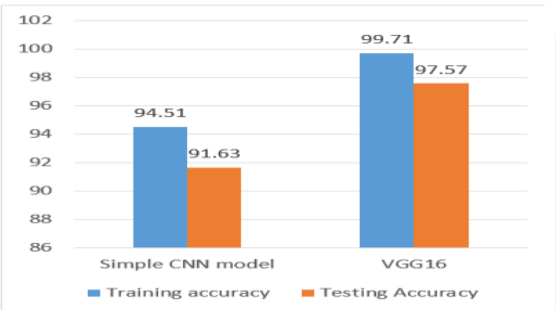


Fig. 10. Training and test accuracy of the proposed models.

Fig. 10 shows the accuracy of CNN models for rice leaf diseases classification. Fig. 11 illustrates the confusion matrix is evaluating the performance of the models on a classification task. It shows the classification accuracy score for discrete classes and it also useful to calculate the accuracy, precision, recall, and f1 score which show in Fig. 12.

7.1 Error Analysis

The Figure 11 illustrates images that are misclassified by the proposed Simple CNN model. The misclassifications are described in details in the below section for each of the disease type.

leaf Blast: Image belongs to leaf Blast but it is classified as Brown Spot as the image is blurred. The reason could be the presence of small brown spots in the same rice leaf.

Bacterial Leaf Blight: Images are classified as false smut but they belong to Blight category. The reason could be poor illumination and blurring of image.

Healthy: Images are healthy but it is classified as False smut probably because the image is blurred and contrast is poor.

Brown Spot: Images belong to Brown Spot but are classified as Blast and Sheath blight. One reason could be the presence of small blast lesions on the leaf. In the brown spot lesions resemble the blast lesion.

False smut: Images belong to False smut but are classified as brown spot and healthy. One reason could be the presence of small blast lesions on the leaf. In the brown spot lesions resemble the blast lesion and the image is blurred and contrast is poor.

Sheath blight: Images belongs to sheath blight but it is classified as Brown Spot and false smut as the image is blurred. The reason could be the presence of small brown spots in the same rice leaf.

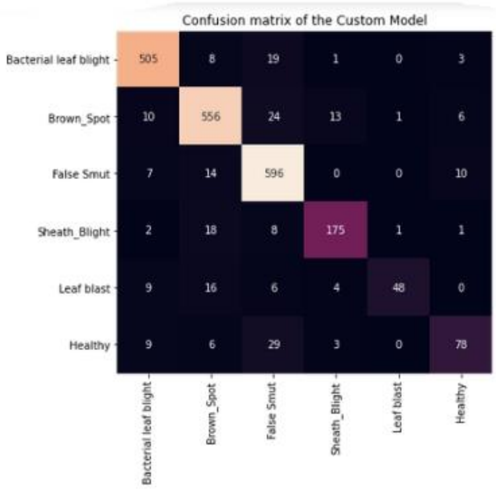
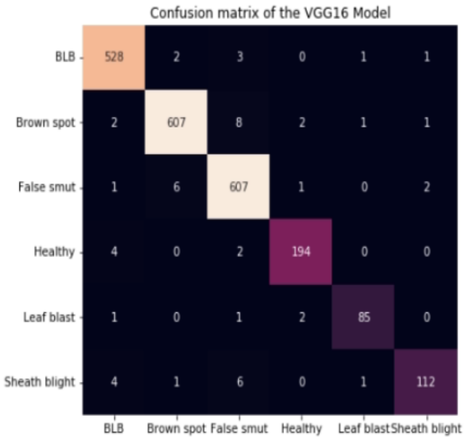


Fig. 11. Confusion matrix for proposed models i.e., a) Simple CNN, b) VGG16.

International Research Journal of Engineering and Technology (IRJET) e-ISSN: 2395-0056
Volume: 11 Issue: 06 | Jun 2024 www.irjet.net p-ISSN: 2395-0072



Observation: It produces significantly less false positive and false negative, as observed from the confusion matrix and Diagonal values are more.

Diseases types	Performance metrics of Simple CNN model			
	Precision	Recall	F1 Score	Support
BLB	0.93	0.94	0.94	536
Brown Spot	0.90	0.91	0.91	610
False smut	0.87	0.95	0.91	627
Sheath Blight	0.89	0.85	0.87	205
Leaf blast	0.96	0.58	0.72	83
Healthy	0.80	0.62	0.70	125

Fig. 12. Performance Metrics for proposed models i.e., a) Simple CNN, and b) VGG16

Diseases types	Performance metrics of VGG16			
	Precision	Recall	F1 Score	Support
BLB	0.98	0.99	0.98	536
Brown Spot	0.99	0.98	0.98	621
False smut	0.97	0.98	0.98	617
Healthy	0.97	0.97	0.97	200
Leaf blast	0.97	0.96	0.96	89
Sheath Blight	0.97	0.90	0.93	124

Fig. 12. Performance Metrics for proposed models i.e., b) VGG16

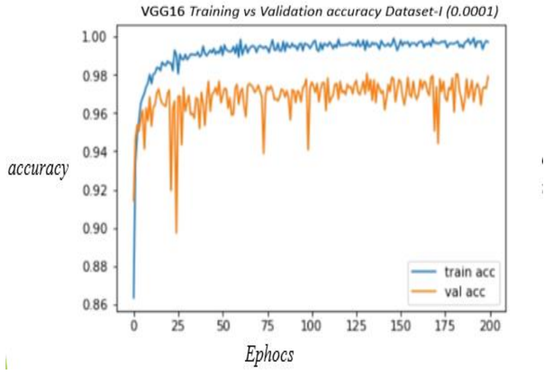
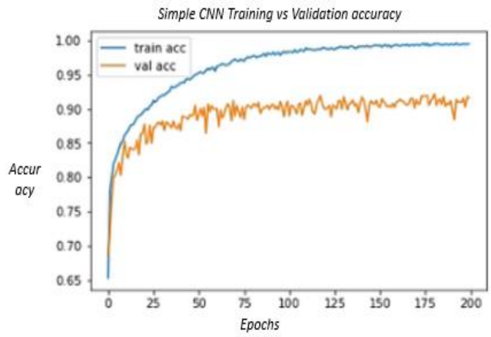


Fig. 13. Training and validation accuracies for proposed models i.e., a) Simple CNN, and



b) VGG16

Observation of Fig 13: In VGG16 Training and validation curves are moving closely whereas in simple CNN model curves are not moving together we could observe in the (a)

8. Conclusion

In this study, we demonstrated a pre-trained deep convolutional neural network of VGG16 with transfer learning approach for the detection of rice leaf diseases. The three major attacking diseases of rice plant Bacterial Leaf Blight, Brown Spot, False Smut, Leaf Blast, sheath blight and healthy class are considered for this research. The simple CNN model was fine-tuned using different hyper parameters and achieved the accuracy of 91.63% by running 200 epochs. VGG16 has attained an optimized accuracy of 97.57% using 200 epochs and by fine-tuning several hyper parameters. Future work will be the exploration on convolutional neural network for categorizing further types of rice diseases and other plant leaf diseases. And we will use the object detection algorithms to detect the diseases, Additionally, we like to utilize nature inspired algorithms for selecting the best hyper parameters automatically for fine-tuning the CNN.

REFERENCES

1. Sankaran, S., Mishra, A., Ehsani, R., Davis, C., 2010. A review of advanced techniques for detecting plant diseases. Comput. Electron. Agric. 72, 1–13. https://doi.org/10.1016/J.COMPAG.2010.02.007.

2. Arsenovic, M., Karanovic, M., Sladojevic, S., Anderla, A., Stefanovic, D., 2019. Solving Current Limitations of Deep Learning Based Approaches for Plant Disease Detection. Symmetry (Basel). 11,939. https://doi.org/10.3390/sym11070939.

3. Duan, Y., Liu, F., Jiao, L., Zhao, P., Zhang, L., 2017. SAR image segmentation based on convolutional-wavelet neural network and markov random fifield. Pattern Recogn. 64, 255–267.

4. Azadbakht, M., Ashourloo, D., Aghighi, H., et al., 2019. Wheat leaf rust detection at canopy scale under different LAI levels using machine learning techniques. Comput. Electron. Agric. 156, 119–128.

5. Xie, W., Ma, G., Zhao, F., et al., 2020. PolSAR image classification via a novel semi supervised recurrent complex-valued convolution neural network. Neurocomputing.

6. Coulibaly, S., Kamsu-Foguem, B., Kamissoko, D., Traore, D., 2019. Deep neural networks with transfer learning in millet crop images. Comput. Ind. 108, 115–120.

7. Nandhini, N., Bhavani, R., 2020, January. Feature extraction for diseased leaf image classification using machine learning. In: 2020 International Conference on Computer Communication and Informatics (ICCCI). IEEE, pp. 1–4.

8. Liu, B., Zhang, Y., He, D., Li, Y., 2018. Identification of apple leaf diseases based on deep convolutional neural networks. Symmetry 10 (1), 11

9. Zhang, R., Sathishkumar, V.E., Jackson Samuel, R.D., 2020. Fuzzy efficient energy smart home management system for renewable energy resources. Sustainability 12 (8), 3115.