Section A-Research paper
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Multiclass's Classification of Rice Diseases Using Pre-Trained Deep Neural Networks

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Abstract

One of the main problems that directly lower the quality of agricultural production is plant disease. The primary tasks to enhance the overall quality of plant cultivation for economic development are recognizing and categorizing plant diseases. The same holds true for the rice crop, since approximately 520 million metric tons of rice are used annually. Using a digital image collection of rice leaf datasets, a group of researchers has presented various methods for disease identification. However, such methods don't achieve the expected perfection because of their complex algorithms and inability to give an effective solution in terms of identifying clear boundaries among the given data classes for making the final decisions. For this problem, deep neural networks (DNN) can be proposed because a DNN is a multi-layer architecture model whose layers learn to represent the data at multiple abstract levels. Further, to learn large databases semantically at a high level and deep feature learning, emerging its applications in object detection and recognition. The present work is the result of a similar motivation, hence proposed a pre-trained model known as Inception_v3 for multiclass's classification of rice diseases. For the simulation of inception_v3, a publicly available dataset containing images belonging to multiple rice diseases has been used. This dataset contains three diseases belonging to rice leaves known as Bacterial Leaf Blight, Blast, and Brown Spot. The proposed technique is found to be effective in the given context.

Keywords: Rice Diseases, Multiclass, Classification andInception_v3.

1. Introduction

Indians primarily rely on agriculture as a source of income. They are entirely reliant on the production of various food grain kinds and horticultural goods. The most recent data, published in 2021, estimates that 13497.30 million hectares worldwide are used for agriculture. In India, 328.73 million hectares (2.44%) of the total area were used for agriculture placing India ninth globally after the Russian Federation, Canada, the United States, China, Brazil, and Australia [1].

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India comes in second place globally behind China in terms of rice output, accounting for 23.71% of the global total (749.19 million metric tons) [1].

Moreover, the demand for rice is rising daily as a result of the population's rapid growth. The most recent research estimates that the nation would produce a record 308.65 million metric tons of food grain in 2020–21, an increase of 11.14 million metric tons over what was produced in 2019–20. Additionally, the production of food grain in 2020–21 will be higher than the average output over the preceding five years (2015–16 to 2019–20) by 29.77 million metric tons. It is anticipated that rice production will reach a record high in 2020–21. 12,270,000 tones. It exceeds the average production over the previous five years of 112.44 million metric tons by 9.83 million metric tons [1]

India has made progress towards its goal in recent years, but to prevent such catastrophes, pesticide use has increased. Compared to 59.67 thousand metric tons in 2018–19, the use of pesticides has increased to 61.70 thousand metric tons in 2019–20. The most common diseases affecting rice crops include sheath blight, leaf blast, bacterial blight, neck blast, etc.

Plant diseases have been a major issue for agriculture and food security, leading to significant losses in crop yield and quality. India is one of the world's largest food producers, with its agriculture sector contributing significantly to the country's economy. This not only impacts the farmers' livelihoods but also the food security of the country. However, the crop yield loss due to plant diseases in India is estimated to be around 15-20% every year, resulting in an annual loss of approximately 45,000 crores ($6000 million) [2]. Plant diseases have a significant impact on agriculture and food production worldwide. According to recent reports, plant diseases account for up to 20% of crop losses globally, which can have severe consequences for food security and the economy [3]. With the world population projected to reach 9.7 billion by 2050, it is crucial to find solutions to mitigate the impact of plant diseases on crop yield and quality. To mitigate the need for food in India, the use of pesticides has been increased to cure the crop from various diseases. To implement the application of targeted pesticides and to reduce the input cost to provide benefits to the environment, various machine learning-based techniques have been presented nowadays for monitoring and detecting diseases. For example, the author in [4] proposed an image processing and machine learning-based technique for diagnosing the deficiencies from rice plant leaf images. The color color and texture of plant leaf images were analyzed. These features were used with an MLP classifier for the identification of spots of deficiencies and achieved 88.56% accurate results. Similarly in [5], the author demonstrated a software program for spotting illnesses in rice plants. In this system, the segmentation of the infected portion of the rice plant leaf was done using a threshold-based method. Based on information gathered with the zooming technique, the segmented images were identified using a SOM neural network. Instead of an original image, it was found that images in the frequency domain had a poor categorization rate. In [6], the author employed machine learning techniques to classify and identify illnesses in rice plant leaves. Following the segmentation of the photos

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using the threshold values recommended by the Ostu approach, the color, shape, and texture features were retrieved. These characteristics were utilized to classify rice infections using a support vector machine classifier, and the results were 97.2% accurate. However, due to significant similarities in both types of disease patterns, 11.1% of cases were incorrectly classified. Author in [7], developed a system for classifying illnesses affecting rice plants in a lab setting. With the aid of a digital camera, the photos were gathered, and the BP neural network was used to classify them. 90% of the photos in the entire data set may be processed by this classifier that was created. The system's output demonstrated its viability in distinguishing brown spots from rice leaves. However, the intended system proved unable to identify diseases in the various natural lighting scenarios. In [8], the author processed the leaves of the citrus fruit plant to detect illnesses. Using an improved input image and an optimized weighted segmentation technique, the citrus lesion spots are retrieved. Then, a codebook is created by combining geometrical elements, color, and texture. A hybrid feature selection method that combines PCA score, entropy, and a skewness-based covariance vector is also used to choose the best features. For the final classification of citrus diseases, the chosen characteristics are input to the Multi-Class Support Vector Machine (M- SVM). In a similar context, the author of [9] developed a deep learning method using colorimetric spaces and vegetation indices from the UAV photos to detect vine diseases. Convolutional neural networks (CNN) and color information were used as the basis of the technique to find symptoms in vineyards. CNNs with YUV color space combined with ExGR vegetation index and CNNs with a combination of ExG, ExR, and ExGR vegetation indices produce the best results with accuracy greater than 95.8% in this comparison of the performances of CNNs using various color spaces, vegetation indices, and the combination of both information. In [10], the author detected waterlogging stress based on hyperspectral images of oilseed rape leaves. In the article, support vector machine (SVM), quadratic discriminate analysis (QDA), and k-nearest neighbor (KNN) classifiers were used to create classification models for contrasting the images and spectra of samples under various levels of water logging among the three datasets, as well as for training and prediction. It was observed that the classification performance of the QDA mode was better, with identification accuracies of 100% and 94.44%, respectively. Overall, the classification outcomes for VNIR were better than those for images. These findings demonstrated the viability and use of hyper-spectral imaging technology for the identification of oilseed rape water-logging stress. Similarly in [11], the author employed smartphone digital images and machine learning to estimate the chlorophyll content of soybean leaves infield. It was discovered that the SVM model had the capability of directly predicting the chlorophyll with the unprocessed RGB input without the necessity for the standard calibration board. The developed methodology of image processing with machine learning modeling and conversion relationship of measuring the chlorophyll content of infield soybean leaves is effective, affordable, does not require a standard calibration board, and is easily adaptable to other large-scale aerial imaging platforms and field crops. In [12], the author created a technique based on support vector machines and deep learning for identifying and forecasting four diseases affecting rice, including rice blast, red blight, stripe blight, and sheath blight. The suggested approach generated an average correct identification percentage of 96.8%. The author of [13]created a way to find different rice plant leaf diseases. The Moore-Penrose pseudo-inverse Weight-related DCNN approach is employed in the suggested algorithm to identify diseases from the picture data set.The experiment has seen an average of 4% improvement in existing systems like Deep Convolutional Neural Networks (DCNN), AlexNet, Convolutional Neural Networks (CNN), and Support Vector Machines (SVM) with Deep Features [14][15][16].

Nonetheless, several methods have been put forth in the past for the early detect various leaf diseases of rice plants. Unfortunately, none of these methods accurately draws the edges, predicts the maximum size, or quantitatively quantifies the affected area. A deep learning approach is an effective solution for that in previous studies. Hence, the same has been employed in this work. Furthermore, deep convolutional neural network research has advanced throughout time by introducing different methods to attain astounding outcomes. The foundation of this research is the selection of an ideal hyper-parameter to lower the network error rate for a pre-trained deep learning model and simulate the same on a publicly available dataset containing images belonging to multiple rice diseases [17][18][19].

2. Proposed Methodology

In this section, details of the dataset used for the present research and the proposed methodology have been described [20][21].

2.1 Dataset

The dataset used in this work is composed of moderate-resolution rice plant leaves diseases. The dataset consists of 2500 images with an expansion of 432x288 pixels. Figure 1, shows the sample images in the dataset [22][23][24].

(a) (b)

Figure 1: Sample images for rice leaf diseases (a) bacterial_leaf_blight(b)blast

2.2 Pre-processing

The rice leaf diseases dataset is preprocessed with a median filter with a 9*9 contour size before classification. Preprocessing is one of the most crucial steps in the image processing process since it is used to enhance specific aspects of photos or eliminate undesirable distortions. Preprocessing is a crucial stage in the creation of stronger features in the given dataset. The proposed study's preliminary processing step involves research on noise reduction utilizing median filtering for this. Figure 2, depicts the methodology followed in this research study [25][26][27].

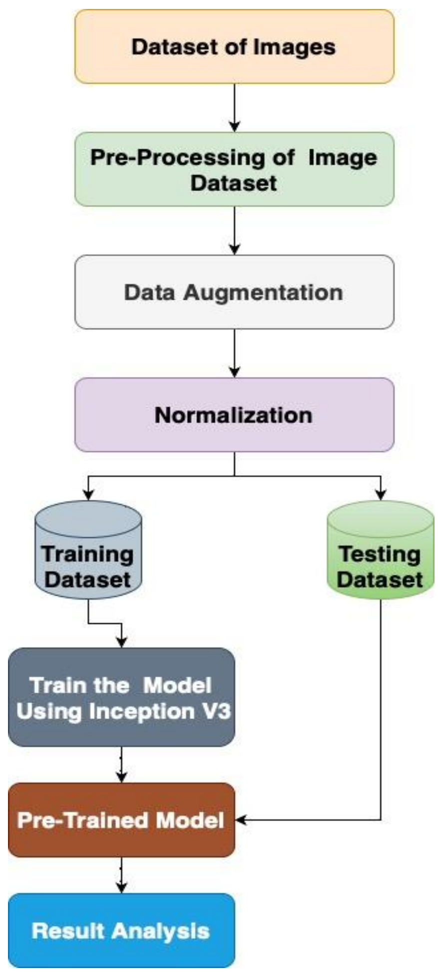

Figure 2: Proposed Methodology

2.3 Data augmentation

It is a technique that was used to boost the number of images in the dataset. Various approaches including rotation, shifting, shearing, and zooming, were employed to supplement existing data. The dataset originally contained 2500 images, which is very less for training the DL model, but after data augmentation, it has grown to 55000 images [28][29].

2.4 Normalization

To maintain numerical stability for CNN designs, normalization of the image is used. The RGB representation of given images is used at first, and each pixel's value has been normalized to fall between the range of 0 and 1 by multiplying it by 1/255. This has been done to scale down the weight's values, which results in less computation time for modal learning when normalization has been used. The dataset of images was divided into two different datasets namely the training set (70% of the total dataset) and the testing set (30% of the total dataset) [30].

2.5 Pre-trained model

Inception V3 is a so-called deep learning model based on the CNN framework, which is usually used to classify images. In the context of image classification-based problems, if the data gets overfitted when numerous deep levels of convolution are employed in a predictive algorithm, the inception model employs the concept of having many filters of various sizes on the same level to prevent this from occurring. Thus, in the inception models, parallel layers are used in place of deep layers, rendering the model larger rather than deeper. Various Inception modules make up the Inception model [31].

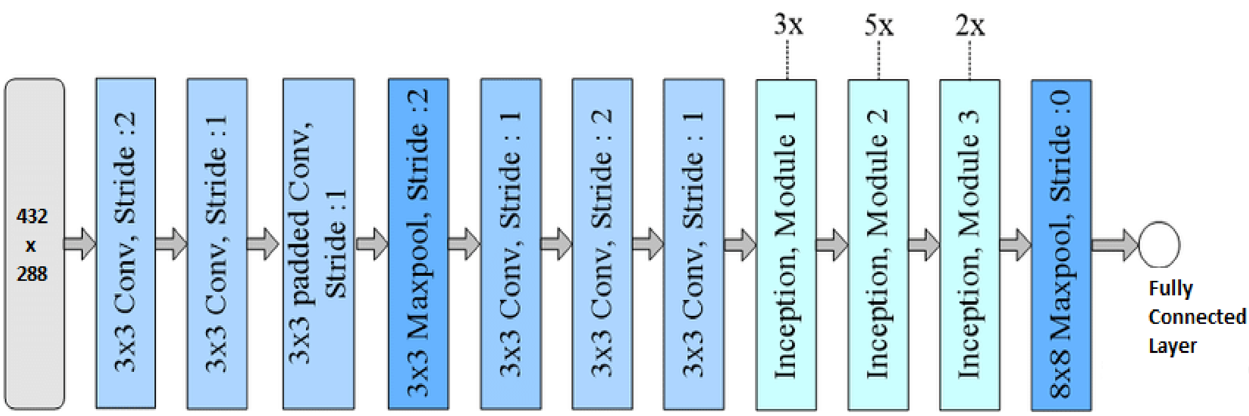

Figure 3: Architecture of Inception V3 [13]

The model has been composed of reduction blocks, inception blocks and auxiliary classifiers. An image model block called an Inception Module that seeks to simulate an ideal local sparse structure in the model. Simply said, it enables the combination of several filter sizes into a single image block rather than being limited to a single filter size, which then passes subsequent layers. Other than this, a tiny CNN is used as an auxiliary classifier, which is placed between layers during training and adds its loss to the loss of the primary network. As Inception v3 uses an auxiliary classifier serves as a regularizer.

2.6 Simulation parameters

The various parameters for the Inception V3 model simulation on a given dataset have been given below.

Table 1: Simulation Parameters of the Inception V3

Parameters	Value
Input Shape	432x288 pixels
Model	Sequential
Layers	42 layers
Activation Function for Dense Layer	Rectified linear units
Loss Function	categorical_crossentropy
Optimizer	Adam
Metrics	Accuracy
Epochs	30

The layer's description of the model and learnable parameters details has been shown in Figure 4.

```
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
keras_layer (KerasLayer)     (None, 2048)              21802784
_________________________________________________________________
flatten (Flatten)            (None, 2048)              0
_________________________________________________________________
dense (Dense)                (None, 512)               1049088
_________________________________________________________________
dropout (Dropout)            (None, 512)               0
_________________________________________________________________
dense_1 (Dense)              (None, 3)                 1539
=================================================================
Total params: 22,853,411
Trainable params: 1,050,627
Non-trainable params: 21,802,784
_________________________________________________________________
```

Figure 4: Layer's description of the model

2.7 Experimental Setup

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To obtain the results of the simulation using an approximated dataset, an experiment was carried out using an NVIDIA 128GB GPU, which is available on personal machines. Along with this, the experiment has used hardware with memory sizes of 16GB and 1TB, RAM and ROM, respectively. The model has been assessed using its accuracy and loss.

3. Results and analysis

This section gives a detailed analysis of the results of the experiment performed to detect diseases belonging to rice leaves known as Bacterial Leaf Blight, Blast, and Brown Spot.

3.1 Results of accuracy and loss

The pre-trained model Inceptions V3 has been simulated on the given dataset for the classification of the rice leaf diseases dataset into three classes. Based on the training of the model up to 30 epochs the results have been obtained for accuracy which is presented below in Figure 5.

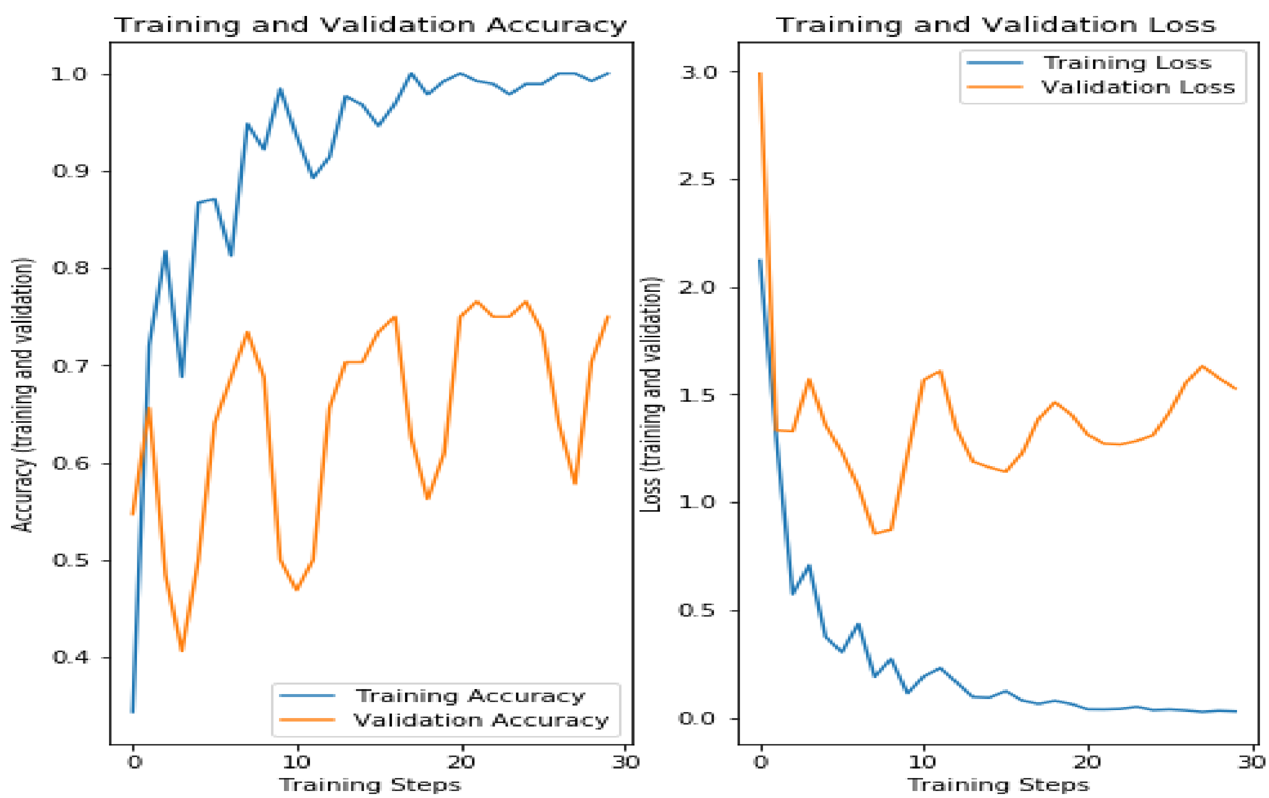

Figure 5: Accuracy loss curve

Figure 5, has shown the accuracy loss curve for the deep learning model inception C3 while simulating on the given dataset. As per the graph, the model has obtained a training accuracy of

1.0000, val_loss (validation loss) of 1.5269 and val_accuracy(validation accuracy) of 0.7500. The same results have been depicted in Figure 6.

```
Epoch 20/30
2/2 [==============================] - 42s 21s/step - loss: 0.0635 - accuracy: 0.9922 - val_loss: 1.4066 - val_accuracy: 0.6094
Epoch 21/30
2/2 [==============================] - 34s 17s/step - loss: 0.0386 - accuracy: 1.0000 - val_loss: 1.3136 - val_accuracy: 0.7500
Epoch 22/30
2/2 [==============================] - 41s 21s/step - loss: 0.0383 - accuracy: 0.9922 - val_loss: 1.2713 - val_accuracy: 0.7656
Epoch 23/30
2/2 [==============================] - 35s 17s/step - loss: 0.0424 - accuracy: 0.9892 - val_loss: 1.2674 - val_accuracy: 0.7500
Epoch 24/30
2/2 [==============================] - 34s 17s/step - loss: 0.0472 - accuracy: 0.9785 - val_loss: 1.2843 - val_accuracy: 0.7500
Epoch 25/30
2/2 [==============================] - 34s 17s/step - loss: 0.0327 - accuracy: 0.9892 - val_loss: 1.3109 - val_accuracy: 0.7656
Epoch 26/30
2/2 [==============================] - 34s 17s/step - loss: 0.0381 - accuracy: 0.9892 - val_loss: 1.4174 - val_accuracy: 0.7344
Epoch 27/30
2/2 [==============================] - 42s 21s/step - loss: 0.0339 - accuracy: 1.0000 - val_loss: 1.5540 - val_accuracy: 0.6406
Epoch 28/30
2/2 [==============================] - 34s 17s/step - loss: 0.0235 - accuracy: 1.0000 - val_loss: 1.6316 - val_accuracy: 0.5781
Epoch 29/30
2/2 [==============================] - 41s 21s/step - loss: 0.0324 - accuracy: 0.9922 - val_loss: 1.5765 - val_accuracy: 0.7031
Epoch 30/30
2/2 [==============================] - 34s 17s/step - loss: 0.0333 - accuracy: 1.0000 - val_loss: 1.5269 - val_accuracy: 0.7500
```

Figure 6: Training results of the model

3.2 Classification results

Here in this section, the author has presented the classification outcome of the proposed model. The results in terms of classified images have been shown in Figure 7 given below.

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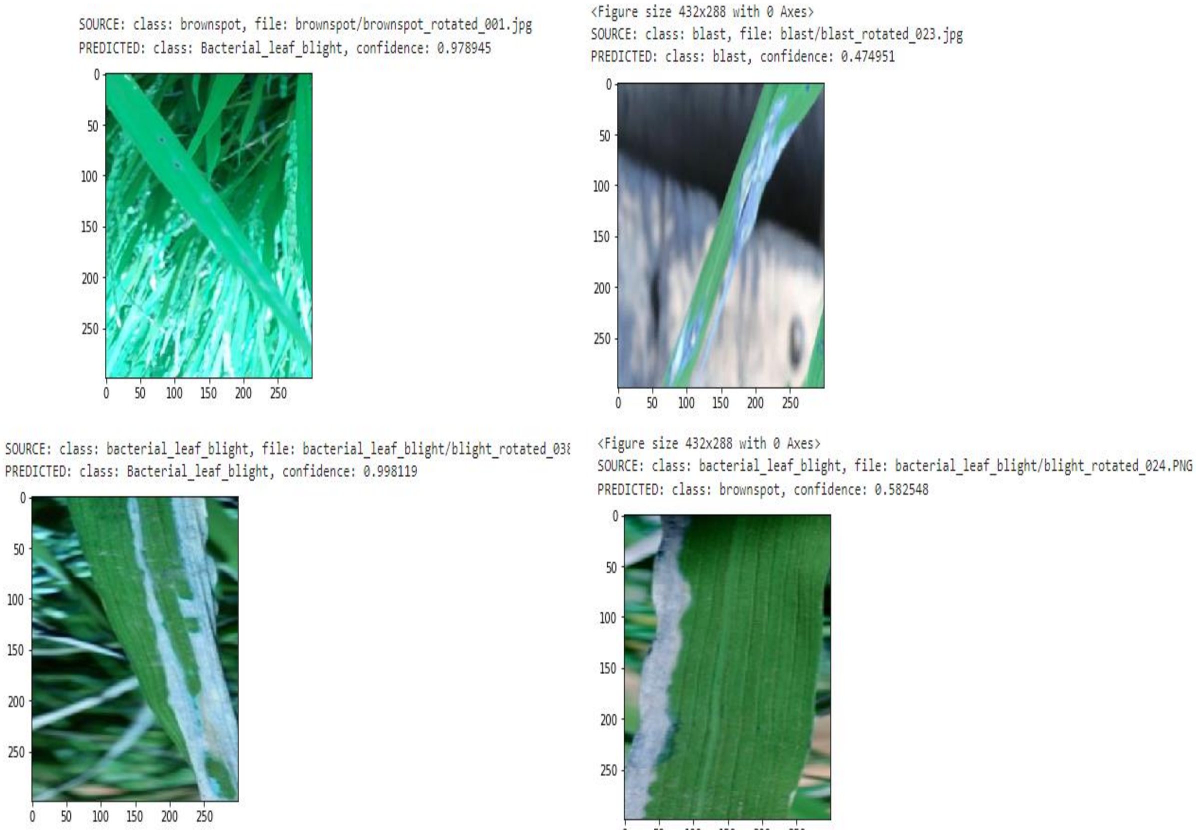

Figure 7: Classified images of the dataset

4. Conclusion

Globally, continuous urbanization, population growth, and rapid industrialization are impeding grain production, particularly in developing nations and metropolitan areas where the demand for crop output is rising. The management of crop diseases, however, can be a solution rather than increasing crop productivity. The same holds true for the rice crop since approximately 520 million metric tons of rice are used annually. Using a digital image collection of rice leaves, a group of researchers has presented multiple strategies for disease identification in rice leaves. Here machine learning has been proposed being a solution to this problem. Hence, the pre-trained model Inception_v3 has been used for the multiclass classification of rice diseases. A publicly accessible dataset containing samples from several rice diseases has been used for the simulation of inception_v3. The diseases Bacterial Leaf Blight, Blast, and Brown Spot are three that affect rice leaves and are included in this dataset. In the given setting, it is observed that the suggested technique works well with a training accuracy of 100% and a validation accuracy of 75%.

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References

1. Agricultural Statistics at a Glance, 2021. , Government of India, Ministry of Agriculture & Farmers Welfare Directorate of Economics and Statistics https://eands.dacnet.nic.in/PDF/Agricultural%20Statistics%20at%20a%20Glance%20-%202021%20(English%20version).pdf. (January, 2023)
2. Pradhan, D., & Sharan, P. (2017). Plant disease detection and diagnosis through image processing: A review. *Journal of Agricultural Informatics, 8(1), 1-14.*
3. Savary, S., Willocquet, L., Pethybridge, S. J., Esker, P., McRoberts, N., & Nelson, A. (2019). The global burden of pathogens and pests on major food crops. *Nature Ecology & Evolution*, 3(3), 430-439.
4. Sanyal, P. et al. 2007. "Color Texture Analysis of Rice Leaves to Diagnose Deficiency in the Balance of Mineral Levels towards Improvement of Crop Productivity." *Proceedings - 10th International Conference on Information Technology, ICIT 2007*: 85–90.
5. Phadikar, S. and Sil, J., 2008, December. Rice disease identification using pattern recognition techniques. In *2008 11th International Conference on Computer and Information Technology* (pp. 420-423). IEEE.
6. Yao, Qing Yao Qing et al. 2009. "Application of Support Vector Machine for Detecting Rice Diseases Using Shape and Color Texture Features." *2009 International Conference on Engineering Computation*: 79–83.
7. Liu, Libo, and Guomin Zhou. 2009. "BP Neural Network." In *2009 International Conference on Computational Intelligence and Software Engineering*, , 9–11.
8. Sharif, M., Khan, M. A., Iqbal, Z., Azam, M. F., Lali, M. I. U., &Javed, M. Y. (2018). Detection and classification of citrus diseases in agriculture based on optimized weighted segmentation and feature selection. *Computers and Electronics in Agriculture*, *150*, 220–234.
9. Kerkech, M., Hafiane, A., & Canals, R. (2018). Deep leaning approach with colorimetric spaces and vegetation indices for vine diseases detection in UAV images. *Computers and Electronics in Agriculture*, *155*, 237–243.
10. Xia, J. A., Cao, H. X., Yang, Y. W., Zhang, W. X., Wan, Q., Xu, L., Ge, D. K., Zhang, W. Y., Ke, Y. Q., & Huang, B. (2019). Detection of waterlogging stress based on hyperspectral images of oilseed rape leaves (Brassica napus L.). *Computers and Electronics in Agriculture*, *159*, 59–68.
11. Hassanijalilian, O., Igathinathane, C., Doetkott, C., Bajwa, S., Nowatzki, J., & Haji Esmaeili, S. A. (2020). Chlorophyll estimation in soybean leaves infield with smartphone digital imaging and machine learning. *Computers and Electronics in Agriculture*, *174*.
12. Jiang Feng, Lu Yang, Chen Yu, Cai Di & Li Gongfa (2020), Image recognition of four rice leaf diseases based on deep learning and support vector machine. *Computer and Electronics in Agriculture*, *1-9.*

13. Phadikar, S. and Sil, J., 2008, December. Rice disease identification using pattern recognition techniques. In *2008 11th International Conference on Computer and Information Technology* (pp. 420-423). IEEE.
14. Awasthi, Shashank, Naresh Kumar, and Pramod Kumar Srivastava. "An epidemic model to analyze the dynamics of malware propagation in rechargeable wireless sensor network." Journal of Discrete Mathematical Sciences and Cryptography 24.5 (2021): 1529-1543.
15. Tyagi, Neha, et al. "Data Science: Concern for Credit Card Scam with Artificial Intelligence." Cyber Security in Intelligent Computing and Communications. Singapore: Springer Singapore, 2022. 115-128.
16. Sawhney, Rahul, et al. "A comparative assessment of artificial intelligence models used for early prediction and evaluation of chronic kidney disease." Decision Analytics Journal 6 (2023): 100169.
17. Paricherla, Mutyalaiah, et al. "Towards Development of Machine Learning Framework for Enhancing Security in Internet of Things." Security and Communication Networks 2022 (2022).
18. Tyagi, Lalit Kumar, et al. "Energy Efficient Routing Protocol Using Next Cluster Head Selection Process In Two-Level Hierarchy For Wireless Sensor Network." Journal of Pharmaceutical Negative Results (2023): 665-676.
19. Narayan, Vipul, A. K. Daniel, and Pooja Chaturvedi. "E-FEERP: Enhanced Fuzzy based Energy Efficient Routing Protocol for Wireless Sensor Network." Wireless Personal Communications (2023): 1-28.
20. NARAYAN, VIPUL, A. K. Daniel, and Pooja Chaturvedi. "FGWOA: An Efficient Heuristic for Cluster Head Selection in WSN using Fuzzy based Grey Wolf Optimization Algorithm." (2022).
21. Faiz, Mohammad, et al. "IMPROVED HOMOMORPHIC ENCRYPTION FOR SECURITY IN CLOUD USING PARTICLE SWARM OPTIMIZATION." Journal of Pharmaceutical Negative Results (2022): 4761-4771.
22. Babu, S. Z., et al. "Abridgement of Business Data Drilling with the Natural Selection and Recasting Breakthrough: Drill Data With GA." Authors Profile Tarun Danti Dey is doing Bachelor in LAW from Chittagong Independent University, Bangladesh. Her research discipline is business intelligence, LAW, and Computational thinking. She has done 3 (2020).
23. Narayan, Vipul, et al. "Enhance-Net: An Approach to Boost the Performance of Deep Learning Model Based on Real-Time Medical Images." Journal of Sensors 2023 (2023).
24. Ojha, Rudra Pratap, et al. "Global stability of dynamic model for worm propagation in wireless sensor network." Proceeding of International Conference on Intelligent Communication, Control and Devices: ICICCD 2016. Springer Singapore, 2017.
25. Shashank, Awasthi, et al. "Stability analysis of SITR model and non linear dynamics in wireless sensor network." Indian Journal of Science and Technology 9.28 (2016).

26. Gupta, Sandeep, Arun Pratap Srivastava, and Shashank Awasthi. "Fast and effective searches of personal names in an international environment." Int J Innov Res Eng Manag 1 (2014).
27. Srivastava, Arun Pratap, et al. "Fingerprint recognition system using MATLAB." 2019 International conference on automation, computational and technology management (ICACTM). IEEE, 2019.
28. Kumar, Neeraj, et al. "Parameter aware utility proportional fairness scheduling technique in a communication network." International Journal of Innovative Computing and Applications 12.2-3 (2021): 98-107.
29. Awasthi, Shashank, et al. "A New Alzheimer's Disease Classification Technique from Brain MRI images." 2020 International Conference on Computation, Automation and Knowledge Management (ICCAKM). IEEE, 2020.
30. Awasthi, Shashank, et al. "Modified indel treatment for accurate Phylogenetic Tree construction." 2020 International Conference on Computation, Automation and Knowledge Management (ICCAKM). IEEE, 2020.
31. Mohseni, S., Yang, F., Pentyala, S., Du, M., Liu, Y., Lupfer, N., ... & Ragan, E. (2021, May). Machine learning explanations to prevent overtrust in fake news detection. In Proceedings of the International AAAI Conference on Web and Social Media (Vol. 15, pp. 421-431)