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Research Paper

Rice Crop Disease Detection Using Classification Technique

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ABSTRACT
Rice (Oryza sativa) is a principal cereal crop in the world. It is consumed by greater than half of the world's population as a staple food for an energy source. The rice grain's yield production quantity and quality are affected by abiotic and biotic factors such as precipitation, soil fertility, temperature, pests, bacteria, viruses, etc. For disease management, farmers spend a 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 in the automatic identification of infectious organisms in the rice plants' leaves. The convolutional neural network algorithm (CNN) is one of the algorithms in deep learning that has been triumphantly invoked for solving computer vision problems like image classification, object segmentation, image analysis, etc.We are going to use a publicly available data-set that contains 4 different types of diseases on rice plants. We are going to use data augmentation techniques on images as we have a small data-set. Typically, we are exploring the possibility of making this application in the real world which helps the farmers easily identification of diseases. We are hosting our model in TF Hub for further cases for the developers to explore and update the model.

KEYWORDS
Crop disease detection, InceptionResNetV2

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I.INTRODUCTION

In the agriculture sector, rice plants are facing serious problem due to diseases which affect the quality and quantity of the crops. This necessitates automatic plant disease identification and detection, to improve the yield. In our country, rice is the one of the most important cereal crops and rice farming is considered to be the major agricultural economy. During the rice growth, the diseases that occur in the plant are the major problems faced by the farmer, and will cause huge loss, apart from other problems like pest and environmental factors. Although several methods are available to detect diseases in the crop, like image processing methods and remote sensing etc., the accuracy of such systems is poor. This paper proposes a method which is based on machine learning algorithm to detect the blast disease in the rice plant in an effective way. The agriculture field is monitored and images of the rice crops are captured using camera. The appropriate features are extracted and the images are classified either as infected or healthy, using artificial neural networks (ANN). Section II contains the Literature survey, section III describes the proposed method, section IV explains the Classification, and section V presents the Experimental results and Section VI provides conclusion. II.LITERATURE SURVEY The author Libo Liu et al (2009), proposed the concept of BP neural network classifier to identify the disease and healthy part of the rice leaves. The rice disease considered here is brown spot. The results shows that the image analysis and BP neural networks are accurately detect the rice brown spot diseases [1]. The author M. Jhuria et al (2013) proposed the neural networks algorithms to detect and monitor the disease for the fruits plants from plantation to harvesting. Total of three features vectors were extracted which includes colour, morphology and texture. The morphology features provides 90% of the correctly results when compared to other two vectors [3]. The author H. Q. Cap et al (2018) proposed the concept of computer based methods to detect the plant diseases. This method obtained the 78% of detection performance in F1- measure at 2.0 fps.

II. LITERATURE SURVEY

Khirade et al. [1] proposed algorithm for plant disease detection using image processing. They likely employed techniques such as image segmentation, feature extraction, and machine learning to identify and classify plant diseases from images. Specific results and evaluation parameters are not provided in the reference. You may need to access the original paper for detailed results. Shah et al. [2] Proposed Algorithm conducted a survey on the detection and classification of rice plant diseases. This paper likely summarizes various algorithms and techniques used for rice plant disease detection, rather than proposing a specific algorithm.

Since this paper is a survey, it does not present specific results or evaluation parameters. It provides an overview of existing research in the field. Ramesh et al. [3] applied machine learning techniques for the detection of blast disease in South Indian rice crops. The algorithm likely involved data preprocessing, feature extraction, and a machine learning model for classification. Specific results and evaluation parameters are not provided in the reference. You may need to access the original paper for detailed results.

Martinelli et al .[4] conducted a comprehensive review of advanced methods for plant disease detection. This paper summarizes various techniques and algorithms used in the field without proposing a specific algorithm.

Since this paper is a review, it does not present specific results or evaluation parameters. It provides an overview of existing research in the field.

Jackson et al.[5] paper primarily focuses on remote sensing techniques for detecting plant stress, including both biotic and abiotic factors. While it doesn't propose a specific algorithm for rice crop disease detection, it discusses the broader principles and approaches used in remote sensing for plant stress detection.

Specific results and accuracy percentages for rice crop disease detection are not provided in this reference. The paper discusses the methodology and principles of remote sensing for stress detection. Kobayashi et al. [6] describe a method for detecting rice panicle blast using multispectral radiometers and airborne multispectral scanners. The paper likely discusses the use of remote sensing technology for disease detection in rice crops.

Specific results and accuracy percentages for rice panicle blast detection are not provided in this reference. The paper focuses on the methodology and potential of remote sensing for this purpose. Vanitha et al.[7] presents a deep learning-based approach for rice disease detection.

Specific results and accuracy percentages for rice disease detection using deep learning are not provided in this reference. You may need to access the original paper for detailed results.

Rahman et al .[8] propose the use of convolutional neural networks (CNNs) for the identification and recognition of rice diseases and pests. Specific results and accuracy percentages for rice disease and pest identification using CNNs are not provided in this reference. You may need to access the original paper for detailed results.

Ahmed et al. [9] propose a dual-phase convolutional neural network-based system for rice grain disease identification. Specific results and accuracy percentages for rice grain disease identification using their system are not provided in this reference. You may need to access the original paper for detailed results. K. He et al. [10] introduces the concept of residual learning, which involves the use of residual blocks (ResNets) in deep neural networks.

The paper reports results on the ImageNet dataset and discusses the advantages of deep residual networks. However, this paper does not pertain to rice crop disease detection, and specific accuracy or evaluation parameters for that domain are not provided.

III. PROPOSED SYSTEM

Proposed systems leverage various technologies, from AI and machine learning to advanced sensors and imaging techniques, to enhance the accuracy and efficiency of rice crop disease detection. The choice of system depends on factors like the available resources, technological infrastructure, and the specific needs of the agricultural community.

Using deep learning for rice crop disease detection can also help to reduce the need for manual inspection of crops, which can be time-consuming and labor-intensive. By automating the process of disease detection, deep learning can help to save time and resources, and can potentially allow for large-scale monitoring of rice crops.

Dataset Collection and Preparation Rice plant disease dataset with 3600 images have been used in this experiment. This data set was created with images capturing by two smartphone mobiles (Gionee and LYF mobile phones having 5.0 megapixel) and a digital camera (Canon PowerShot SX530HS with 16.0 megapixel). Adobe Photoshop CS5 (64 Bit) software tool has been used to pre-process the images to remove the other information by making background black for the purpose of reducing the complexity and computational cost. All these images were acquired on various weather conditions from the agricultural field of Indira Gandhi Agricultural University that is situated in Raipur, Chhattisgarh state, India. The dataset contains seven classes: (a) Rice Blast (RB); (b) Bacterial Leaf Blight (BLB); (c) Brown Spot (BS); (d) Sheath Blight (SB); (e) Sheath Rot (SR); (f) False Smut (FS) and (g) Healthy Leaves (HL). Table 2 depicts the details of dataset along with few sample images. Moreover, we have provided a brief description about each class below: Rice Blast (RB): Rice Blast is caused by Magnaporthe Oryzae. This disease was first recorded in 1913 in India by Padmanabhan . This is one of the most destructive diseases in the world . In India, more than 266000 tons of rice was lost between 1960-61 . Further, a yield loss of 70-80% was reported in 2019 by Baskaran. The lesion of this type appears on the grains, panicles, nodes, leaves. The spots on leaf are elliptical with less or more pointed. The center is grayish or white and the outer margin is generally brown or reddish-brown. The spot usually starts with small water-soaked whitish grayish or bluish dots. Bacterial Leaf Blight (BLB): It is described by Xanthomonas Oryzae. It is a common disease occurring in all the states of India . Yield loss occurs between 6-60% in some state . Further, the yield loss is reported up to 80% in India . The symptoms of it appear as tiny water-soaked spots at the margin of fully developed leaves. Further it turns dry, yellow and whitish as it grows.

Fig.4 depicts the block diagrams of transfer learning technique. Here, Conv block represents convolutional layer and FC denote fully connected layer. The figure 2 shows general deep CNN pre-trained models on large dataset. This is the general deep CNN block diagram with transfer learning technique. Depending on the specific deep CNN model, number of convolutional, pooling and fully connected layers may vary. While training, all the layers of this model are frozen (nontrainable layers) except last layer (trainable layer). Due to this, only the weights of last layer are updated while training. Hence, it reduces the computational cost while achieving adequate performance.

3.1 Inception V3

The Inception V3 is a deep learning model for image categorization that is based on Convolutional Neural Networks. The Inception V3 is an improved version of the fundamental model Inception V1, which was introduced in 2014 as GoogLeNet. It was created by a Google team, as the name implies (Opengenius, 2022). The inception V3 model is simply an improved and optimized version of the inception V1 model. Several strategies were employed by the Inception V3 model to optimize the network for better model adaptability.

- It is more efficient.
- It has a larger network than the Inception V1 and V2 models, yet its speed is not affected.
- It is less computationally expensive.
- As regularizers, it employs auxiliary Classifiers.

The Inception v3 model, which was launched in 2015, features 42 layers and a reduced error rate than its predecessors. Let's have a look at the various optimizations that improve the Inception V3 model. The primary changes made to the Inception V3 model are as follows:

The inception V3 model has 42 layers in total, which is slightly more than the preceding inception V1 and V2 models. However, the efficiency of this model is quite outstanding. We'll get to it shortly, but first, let's take a closer look at the components that make up the Inception V3 model.

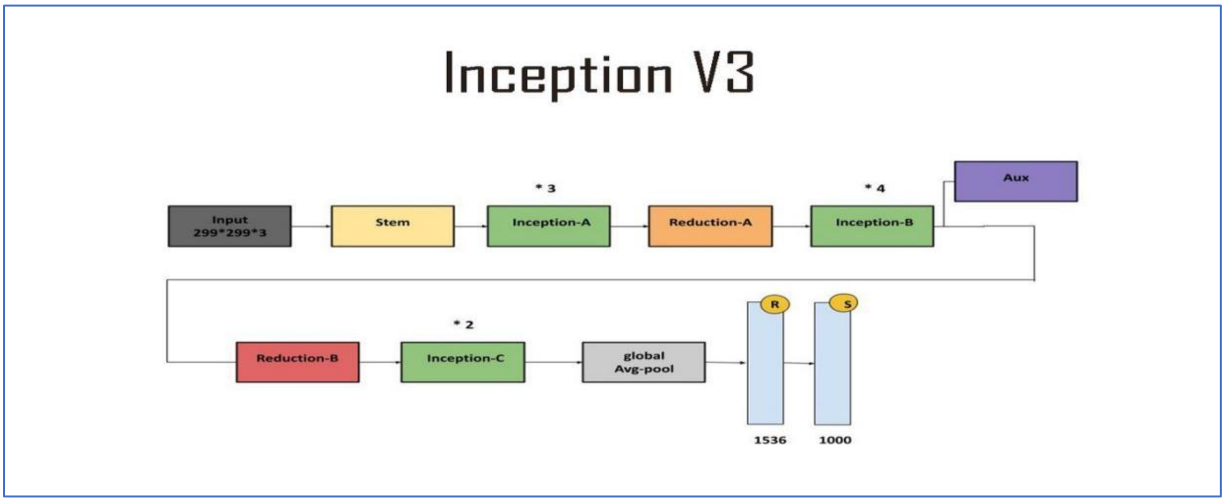


Figure 3.1: Inception V3 model architecture

3.2 ResNet50

Deeper neural networks are more difficult to train. When deeper networks can begin to converge, a degradation problem emerges: as network depth increases, accuracy becomes saturated (which is somewhat unsurprising) and rapidly deteriorate. Surprisingly, such degradation is not caused by overfitting, because adding more layers to a sufficiently deep model increases training error, as stated in and extensively validated by our tests. The degradation (of training accuracy) indicates that not all systems are similarly easy to optimize (Kahe, 2015). ResNet50 is a ResNet model version having 48 Convolution layers, 1 MaxPool layer, and 1 Average Pool layer. It can perform 3.8 x 109 floating point operations. It is a popular ResNet model. AlexNet won top place in the LSVRC2012 classification challenge in 2012. Since then, ResNet has been the most intriguing thing to happen in the computer vision and deep learning worlds. ResNet, short for Residual Networks, is a traditional neural network that serves as the foundation for many computer vision applications. In 2015, this model won the ImageNet challenge. Because of the foundation that ResNets provided, it was possible to train ultra-deep neural networks, which means that a network may have hundreds or thousands of layers and still function well. ResNet first introduced the concept of skip connection. The ResNet-50 has over 23 million trainable parameters.

ResNets were initially applied to image identification tasks, but as stated in the study, the framework can also be utilized for non-computer vision tasks to improve accuracy. ResNet reduces the top-1 error by 3.5% resulting from the successfully reduced training error.

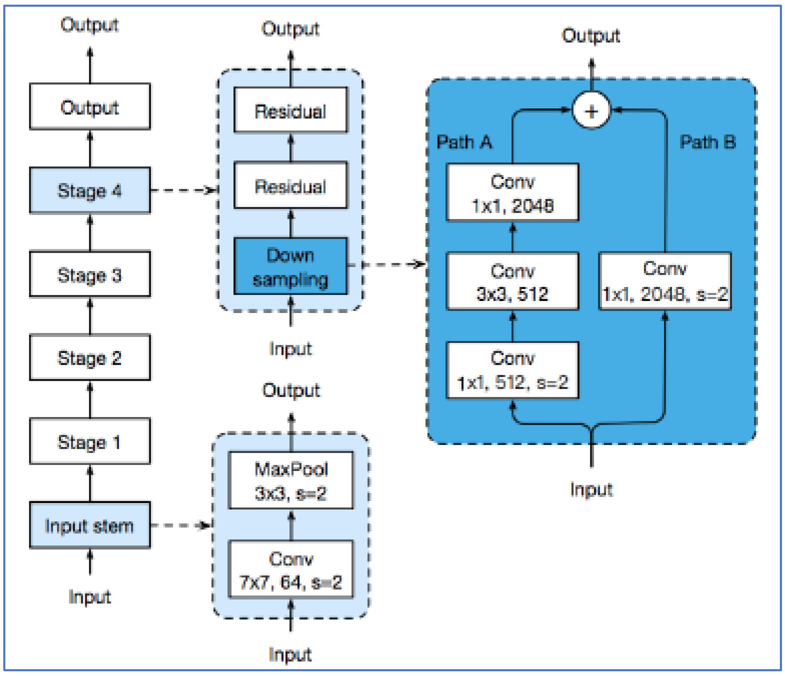


Figure 3.2: ResNet50 architecture

3.3 InceptionResNet V2

The Inception-ResNet-v2 convolutional neural network was trained on over a million photos from the ImageNet collection. The 164-layer network can categorize photos into 1000 object categories, including the keyboard, mouse, pencil, and many animals. As a result, the network has learned detailed feature representations for a diverse set of images. The network takes a 299-by-299 picture as input and returns a list of estimated class probabilities as output. It is created by combining the Inception structure and the Residual connection. Multiple-sized convolutional filters are mixed with residual connections in the Inception-Resnet block. The introduction of residual connections not only solves the degradation issue caused by deep structures but also shortens the training time.

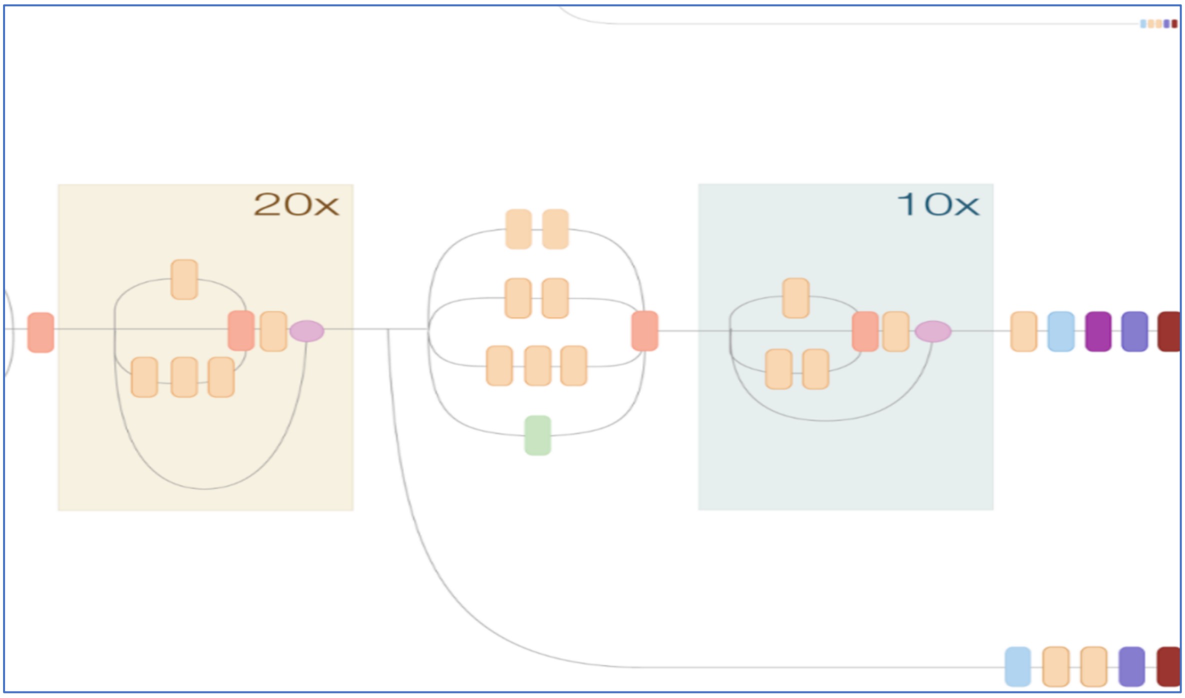


Figure 3.3: Inception Resnet V2 Architecture

IV. SYSTEM ARCHITECTURE

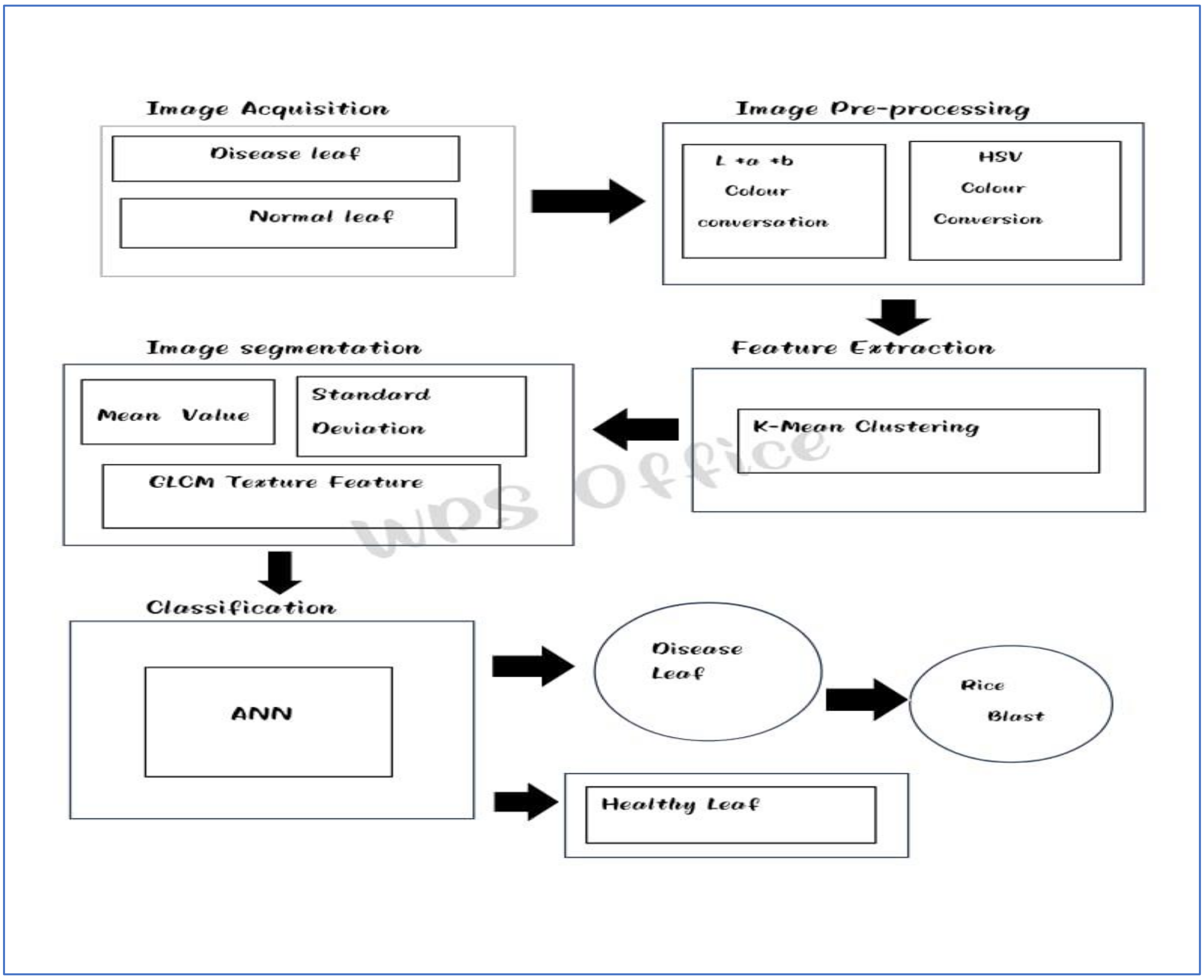


Fig 4: Proposed System

A.Image acquisition
Images are acquired from the rural area of the Panpoli Village, Shencottai taluk, Tirunelveli district, Tamilnadu. Total 300 leaf samples are taken from both normal and infected part of the field. Images are captured using Redmi Note 5 Camera with high resolution and then resized into 256x256pixels. The typical disease affected image is shown fig 2.

Fig.5. Blast disease affected Leaf

B. Image pre-processing
During image pre-processing, the RGB images are converted into HSV images, since working with HSV is very easier to separate the colors. The HSV represents the Hue, saturation and value part of the images. The steps of various image pre-processing are shown in the Fig 3.

Fig. 6.a Rgb Image

Fig 6.b Rgb to HSV

C. Image Segmentation
K-Means Clustering is used for Image Segmentation. The selections of K Values are very important in the k-means clustering technique. Out of three values selected using trial and error method, the value 3 is fixed for K. Results of k-means clustering is shown in the Fig 4.

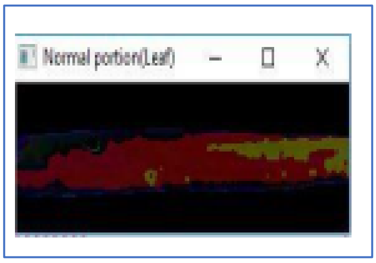


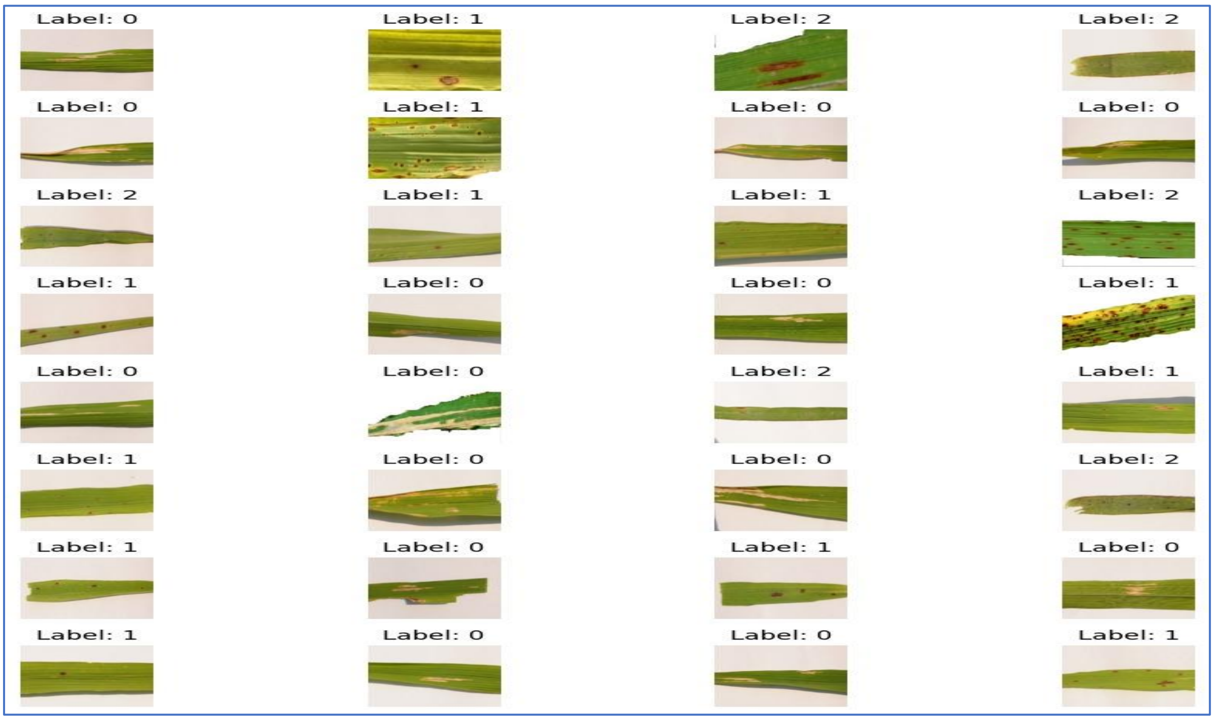
Fig.7. Results of K-Means Clustering

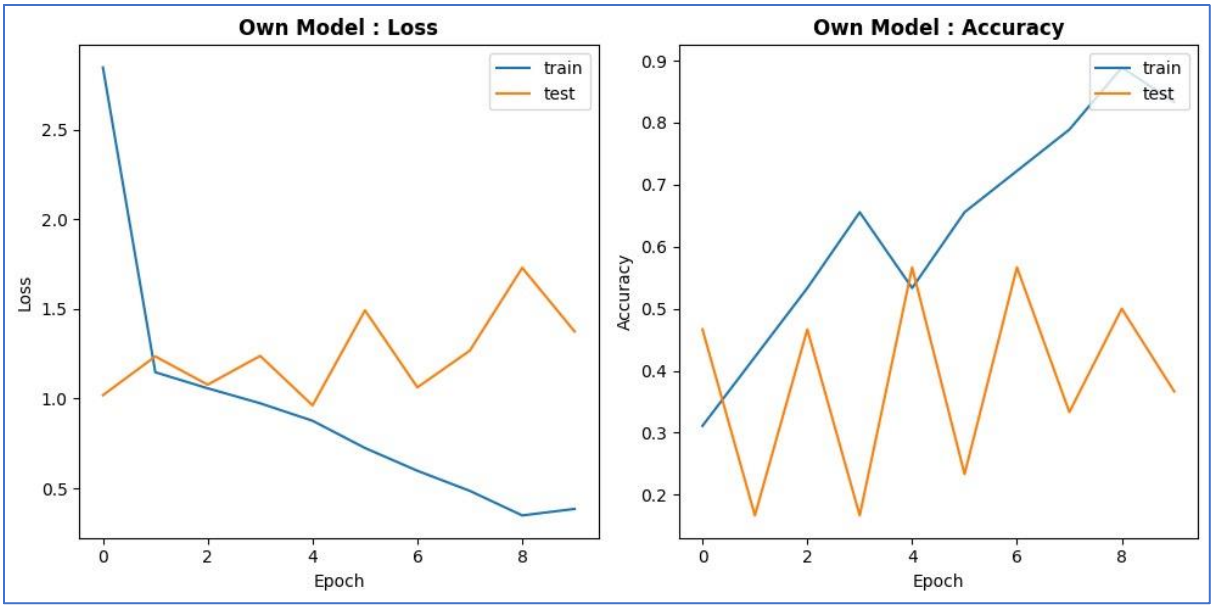
Feature extraction: Features such as the color, texture, and shape of the leaves may have been extracted from the image.

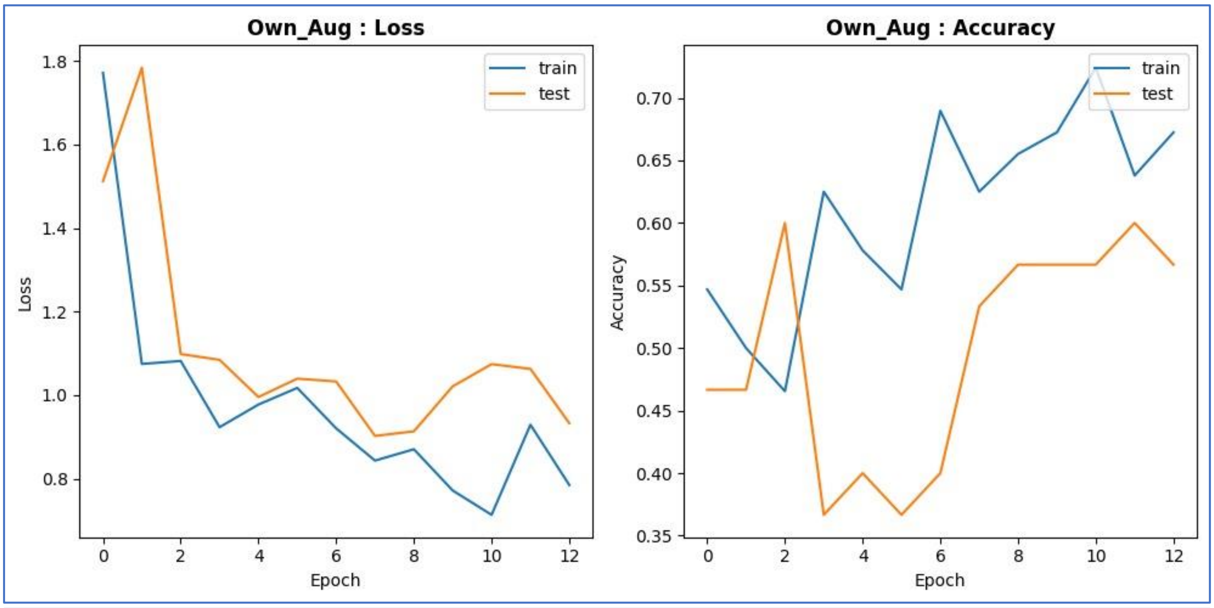
- Classification: The leaves in the image may have been classified as either healthy or diseased using a machine learning algorithm.
- Overall, the image shows the different steps involved in using image processing and machine learning to detect and classify rice blast disease.

V. RESULTS

Pictures displays the classification accuracy attained using 4 pre-trained deep CNN models on a test set of rice plant dataset. We demonstrated the classification's precision.
for each of the five trials, along with OA and STD. As can be seen, the VGG16 model was used to get the maximum OA of 93.11% with an STD of 3.02%.
It can be seen that the InceptionResNetV2 model performed most accurately for the SR, FS, and HL classes while having difficulty classifying the RB and BLB classes.



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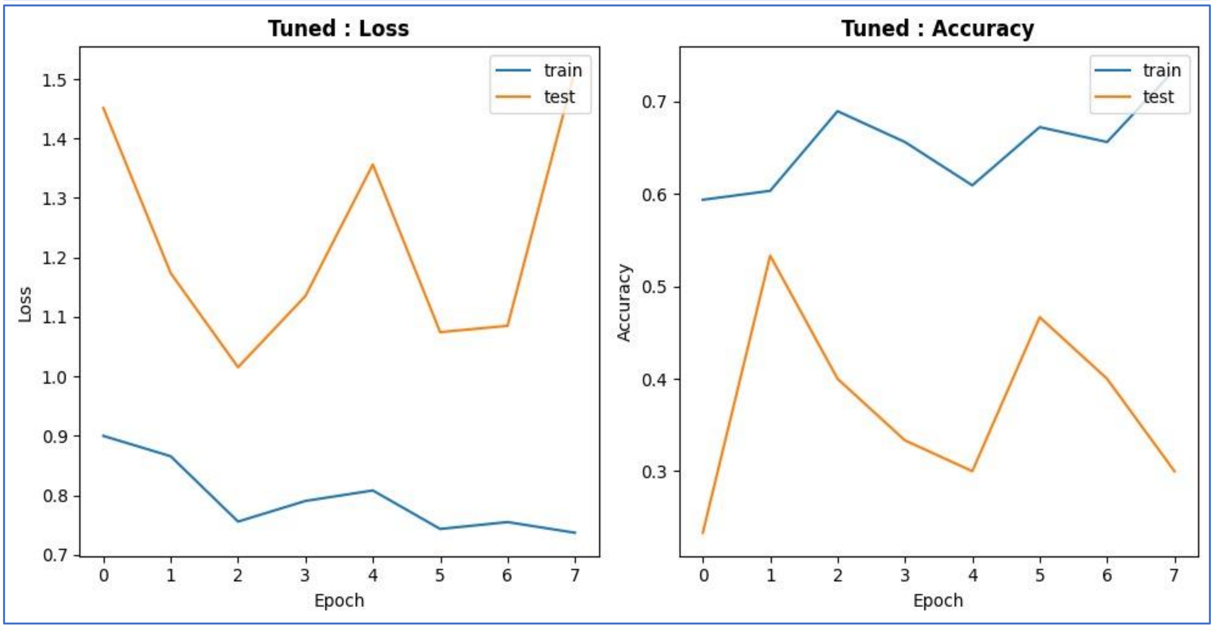
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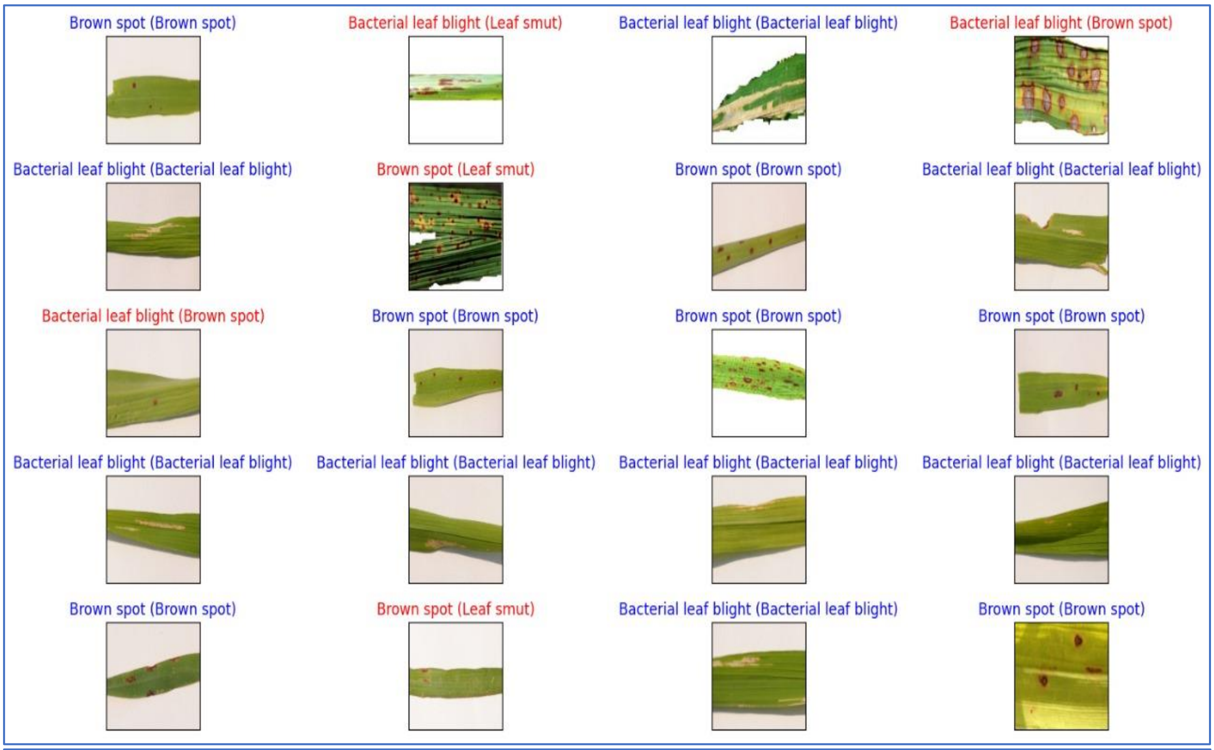

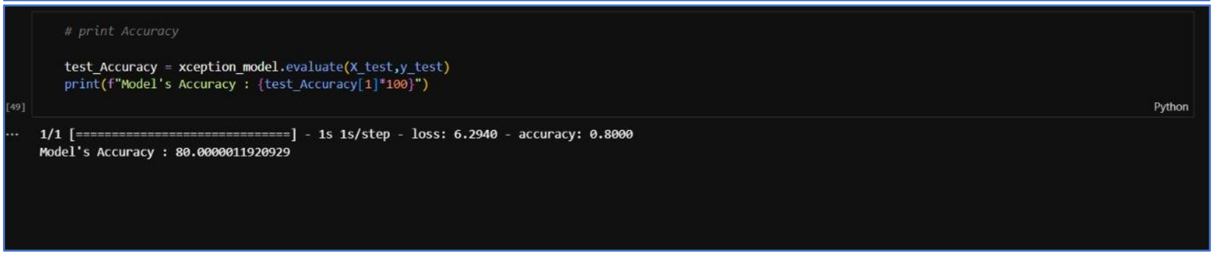

VI. CONCLUSION

In the research, transfer learning of deep CNN models is used to classify diseases of rice plants based on images. ResNet152V2, nceptionV3, InceptionResNetV2 were among the ten pre-trained deep CNN models we used. According to our findings, out of the 4 models, the InceptionResNetV2 model had the greatest classification accuracy (92.59%). Inception V3 may have performed better because of its larger number of parameters, which aid in fitting the new data. However, most other models have deeper depths than Inception V3, which takes longer epochs to fine-tune. Overall, the proposed transfer learning technique exhibits positive outcomes and proves its capacity to categorize illnesses affecting rice plants.

VII. FUTURE SCOPE

1. Improved Accuracy and Early Detection:

Multi-modal data integration: Combining visual data from leaves with other information like weather, soil conditions, and historical data can lead to more robust and accurate disease detection.

Advanced deep learning architectures: Exploring novel neural network architectures, like transformers and generative models, could further improve recognition accuracy and even predict disease outbreaks before visible symptoms appear.

2. Real-time Monitoring and Precision Agriculture:

Drone and aerial image capture: Integrating disease detection models with drones and other aerial imagery systems could enable real-time monitoring of large fields, facilitating timely interventions.Robotic applications: Combining disease detection with robotics could automate tasks like targeted pesticide application, minimizing resource waste and environmental impact.

3. Accessibility and User-friendliness:

Mobile applications: Developing user-friendly mobile apps with image recognition features would empower farmers to easily diagnose diseases in their fields.

Cloud-based platforms: Cloud-based platforms could democratize access to advanced disease detection models, even for small-scale farmers with limited resources.
4. Multi-disease and beyond:
Expanding to other crops: Adapting and enhancing existing models for disease detection in other crops can further revolutionize agricultural practices.
Pest and weed detection: Deep learning models could be extended to identify and manage pests and weeds alongside diseases, promoting holistic crop health management.
5. Sustainability and Environmental Impact:
Precision interventions: Early detection and targeted treatments can reduce pesticide overuse, promoting more sustainable agricultural practices.
Data-driven decision making: Insights from disease detection data can inform crop selection, planting practices, and resource allocation, contributing to long-term agricultural sustainabili

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