Rice Leaf Disease Identification using Attention Network

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***Abstract*—This study tackles the major problem of diagnosing rice diseases in agriculture, highlighting how important early detection is to preventing large financial losses for farmers. According to the International Rice Research Institute, pests and diseases cause an average of 37% of rice harvests to be lost each year. To enable accurate AI-assisted rice illness categorization, the paper presents a novel attention network built on the ResNet152V2 architecture and featuring a channel attention mechanism. The model strategically focuses on key aspects for disease identification by using attention modules to uncover contextual relationships inside images. We performed cross-validated classification tests using a publically available rice illness dataset [1] of 2627 photos. The suggested machine learning technique shows effectiveness in automatically identifying symptoms, making it a useful tool for farmers and improving agricultural disease management. Its test set accuracy of 96.40%, which beats out the state-of-the-art models, highlights how AI could be widely used in agricultural disease diagnosis.**

***Index Terms*—Rice Leaf disease, Deep Learning, AttentionNet, ResNet-152v2**

I. Introduction

The lack of comprehensive research on rice plant disease diagnosis poses a significant challenge, especially when compared to the abundance of studies addressing diseases in crops like tomatoes and peaches. While methodologies for identifying illnesses in these crops may be considered analogous, the dearth of investigations specifically targeting rice diseases remains pronounced. Moreover, while certain rice leaf diseases are widespread across different regions, Sri Lanka harbors a unique set of diseases exclusive to its agricultural landscape, including [2] ”Pecky rice,” ”Grain spotting,” ”Brown spot,” ”Leaf scald,” ”Root-knot,” ”Narrow Brown Leaf spot,” ”Bacterial blight,” ”False smut,” ”Sheath rot,” ”Bacterial leaf streak,” ”Rice blast,” and ”Rice sheath blight” (see table 1). Consequently, this research endeavors to explore various approaches, assessing their merits and drawbacks to address this critical gap in the field of rice plant disease diagnosis.

Crop disease diagnosis systems can be categorized into two types based on how they select leaf image features: handcrafted representation-based and deep representation-based. Currently, handcrafted representation-based methods have shown promising results in image identification. However, they have limitations, such as limited feature extraction that can result in a semantic gap in the image and the need for time-consuming image pre-processing. These limitations directly affect the precision and speed of crop disease diagnosis. On the other hand, deep representation-based methods often utilize deep convolutional neural networks, capable of extracting global features and context from images. However, current research on deep representations primarily focuses on crop disease identification in simple backgrounds. When applied to real-world scenarios, the accuracy of these methods significantly decreases as they cannot efficiently extract local information from complex backgrounds. This makes it challenging for the recognition results to meet the requirements of real-world applications.

In this study, we propose a novel approach to identifying rice diseases that leverages the ResNet-152V2 architecture, a powerful deep learning model, and the attention network mechanism. The attention network mechanism allows the model to focus on relevant areas of the input image, enhancing the precision and effectiveness of disease diagnosis. The intricate design of ResNet-152V2 enables it to extract complex patterns and features from the input data, improving the model’s ability to distinguish between healthy and diseased rice plants.

We conducted extensive testing on a large dataset of rice leaf images to evaluate the effectiveness of our proposed method. Our findings indicate that the attention network mechanism, combined with ResNet-152V2, significantly improves the accuracy and efficiency of rice disease detection compared to other approaches. This study contributes to ongoing efforts to develop innovative solutions for plant disease management and precision agriculture.

There is a growing interest in using computer-assisted diagnostics for disease detection and classification, as the traditional method of diagnosing rice leaf diseases is time-consuming and challenging. Convolutional Neural Networks (CNNs), a subset of Deep Neural Networks (DNNs), have shown remarkable generalization capabilities in image processing. A recent study demonstrated the potential of CNNs in detecting plant diseases by introducing a Deep Residual Network with attention mechanisms for identifying viruses in tomato leaves [3].

Author [4] proposed the novel concept of the kernel attention mechanism, which is applied to segmenting remote-sensing images. Remote-sensing imagery plays a crucial role in monitoring and identifying newly emerging urban areas due to urbanization. To classify rice diseases rather than segment them, this study modifies the kernel attention concept, focusing on extracting the most relevant information.

TABLE I
RICE PLANT DISEASES AND REMEDIES

Name of Disease	**Bacilli/Fungi**	**Contagious part of the plant**	**Symptoms**	**Remedies**
Blast (leaf and collar)	Magnaporthe oryzae	Leaf, collar, parts of panicle, leaf sheath	Lesions or patches with dark green borders that range in color from white to gray-green.	Modify the planting timing. When applying nitrogen fertilizer, divide it up into two or more applications.
Bacterial blight	Pv. oryzae / Xan-thomonas oryzae	Weeds and stubbles	Turning yellow on the leaves or seedlings withering.	Make use of pro-portionate quantities of nitrogen and other plant nutrients. Make sure nurseries and fields have enough drainage.
Leaf Scald	Microdochium oryzae	Wounded leaves, seeds and crop stubbles.	In mature leaves, lesions are oblong and have light brown halos. Tips and edges of leaves that glow.	Employ resilient cultivars. Don't use fertilizer excessively. Use nitrogen in divided doses.
Narrow Brown Spot	Sphaerulina oryzina	Leaves, panicles, sheaths.	It's also possible to see brown blemishes on rice plant stems.	Use resistant varieties. Keep fields clean. Use balanced nutrients.
Brown Spot	Pseudomonas cerevisiae pv. cerevisiae	Coleoptile, panicle branches, glumes, and spikelets.	Lesions on sensitive variety measure 5–14 mm in length.	Improve soil fertility. Soak seeds in 53–54°C boiling water for ten to twelve minutes.

II. RELATED WORKS

The concept of a classifier using a BP neural network. was presented by the author Libo Liu in order to distinguish between the diseased and healthy portions of rice leaves. Brown spot is the rice disease under consideration here. The findings demonstrate the accuracy with which rice brown spot illnesses may be detected using image analysis and BP neural networks [5].

Neural network techniques for detecting and tracking fruit plant disease from plantation to harvesting were proposed by author M. Jhuria. Total 3 distinct feature vectors were retrieved i.e. morphology, color, and texture. As opposed to the other two vectors, the morphological characteristics yield 90% of the accurate outcomes [6].

The concept of diagnosing plant diseases with computers was put out by author H. Q. Cap et al in 2018. With a frame rate of 2.0, our approach attained 78% detection performance in the F1-measure [7].

The computer vision approach method was presented by B. S. Ghyar to identify rice crop diseases caused by pests. For the leaf's diseased section, three characteristics were taken off. Utilizing a genetic algorithm, the pertinent traits are chosen. Using the ANN and SVM classification, the accuracy is 92.5% and 87.5%, respectively [8].

In previous studies, Convolutional Neural Networks (CNNs) have demonstrated their efficacy in detecting rice leaf diseases. For instance, a study by Wang [9] introduced a CNN-based approach for rice leaf disease classification, achieving commendable accuracy rates. However, CNNs have inherent limitations in focusing on critical areas or features within an image.

To address this issue, recent advancements in deep learning have introduced attention mechanisms. These mechanisms enable models to selectively focus on significant areas or features within an image, thereby enhancing the capacity of model to extract relevant information for disease detection. The kernel attention technique, pioneered by researchers [10] initially applied to the division of images from remote sensing, holds promise in improving CNN performance in image recognition tasks.

Additionally, Residual Networks (ResNets), a class of CNN architectures, have gained popularity for their effectiveness in training very deep networks. The ResNet 152V2 model, a variant of ResNet incorporating architectural enhancements, has shown superior effectiveness in image recognition tasks.

In the context of agricultural disease diagnosis, a study by Liu [11] proposed a ResNet 152V2-based method for detecting diseases in tomato leaves. This research provided evidence that ResNet 152V2 is a valuable tool for classifying agricultural diseases.

Using the InceptionResNetV2 model, Krishnamoorthy [12] presented a transfer learning strategy in their work. With an identification accuracy of 95.67%, our approach uses weight-shaped characteristics along with hyperparameter adjustments to identify three distinct rice illnesses.

With a 93.3% accuracy rate, Rahman and colleagues [13] correctly diagnosed rice illnesses by modifying the VGG16 and Inception V3 models. These results demonstrate how deep learning and image processing may be used to identify agricultural diseases with promising results. Wang Chunshan and his team [14] implemented grouped convolution operations, revised the connection approach for residual layers, and constructed a multi-scale residual network. They also developed a multi-scale feature extraction module using resnet18. An accuracy rate of 93.5% was achieved when utilizing self-gathered real-world environmental illness image data.

A deep convolution network was used by Qiu and associates

[15] to build a model for the identification of rice illness. By adjusting the kernel of convolution widths and pooling functions, they examined the grouping and identification of 3 rice illnesses in order to train this model using the Keras deep learning framework. Over 90% accuracy was attained.

III. Proposed Method

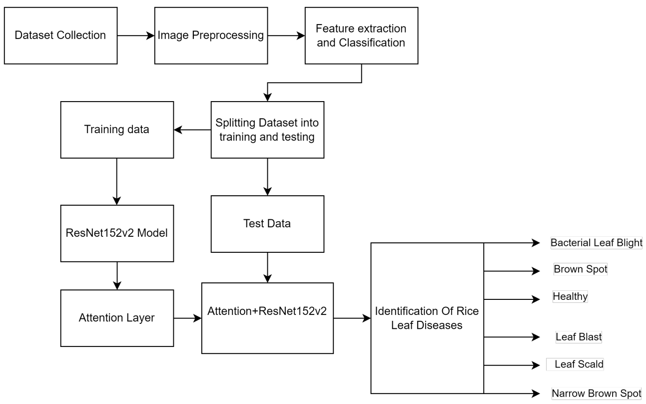

Fig. 1. Block diagram of the proposed work

Fig.1 represents the workflow of the entire work.

A. Dataset Collection

A comprehensive dataset for diagnosing rice diseases should encompass a variety of images, including those depicting both healthy rice plants and those afflicted with diseases. It is essential to ensure that this dataset captures a diverse range of conditions and variations reflective of real-world situations. The dataset, comprising a total of 2627 images, is sourced from Kaggle [1]. (Fig.2) illustrates the photos of sample images.

To establish a baseline for healthy plants, collect images of robust rice plants from diverse sources, encompassing agricultural databases, field research, and research facilities. These images will serve as a reference for healthy plants, providing a foundation for comparative analysis.

Incorporate images of rice plants affected by a spectrum of diseases, including but not limited to ”Narrow Brown Leaf spot,” ”Brown spot,” ”Leaf scald,” ”Rice blast,” ”Bacterial blight,” and ”Rice sheath blight.” It is crucial that the dataset represents various stages and severity levels for each disease, offering a comprehensive representation of the different manifestations observed in real-world scenarios.

B. Data Preprocessing

The subsequent step involves preprocessing the images to ensure uniformity in size and normalization of pixel values. This is crucial to establish consistent input dimensions and pixel value ranges, contributing to enhanced model performance and stability during the training process.

Ensuring uniformity involves setting identical measurements for all images. Standardizing pixel values across photos is achieved by normalizing them to a particular range, such as [0, 1] or [-1, 1]. This normalization process supports in the model’s quicker convergence during training. Each image is appropriately labeled based on its category, distinguishing between healthy and diseased plants. The dataset is then partitioned into two distinct sets: training and testing. The testing set serves to calculate the model’s ultimate results, while the training set is utilized for model training.

In addition, data augmentation techniques, including scaling, rotating, mirroring, and introducing noise, have been applied to augment the dataset. These techniques contribute to increased diversity within the dataset, facilitating a more robust training process.

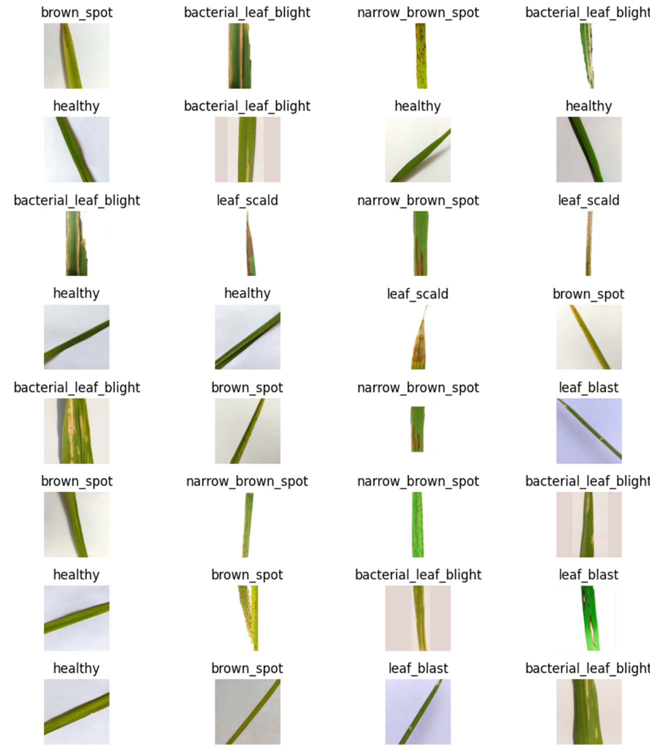

Fig. 2. Sample of images of disease from Plant-Village dataset [16]

C. Feature extraction and Classification

In the feature extraction phase, we identify traits that serve as distinguishing characteristics, such as color, texture, and shape, to differentiate healthy from unhealthy sections in rice plant images. These features are extracted from segmented regions of the images, resulting in feature vectors that represent each area. These feature vectors become inputs for models of machine learning, such as support vector machines or neural networks, enabling the classification of regions as either healthy or diseased. For supervised classification, the crucial step involves gathering known pixels, which are utilized to train the classifier. This trained classifier can then accurately classify different images based on the learned traits. On the other hand, unsupervised classification, specifically clustering, groups pixels based on their intrinsic characteristics, eliminating the need for pre-existing labeled data. The user determines the number of clusters or groups formed during this process. Unsupervised classification becomes particularly valuable in scenarios where labeled pixels are unavailable, offering a flexible approach to categorizing image content based on inherent similarities.

D. Model Architecture

In identifying the illness in the rice crop we use the Resnet152V2 model as the base model for the classification task with the attention mechanism (channel wise attention) integrated in it using the transfer learning technique. The main motive of integration of the attention mechanism is made the model to focus on the most relevant features of the images for making precise predictions. The fully connected layers at the top of the network have been left out, and the model is initialized using pre-trained weights from ImageNet. This enables the model to utilize the knowledge learned from the ImageNet dataset, customizing it for the intended use of rice leaf disease classification. Fig.3 represents the Resenet 152v2 model architecture.

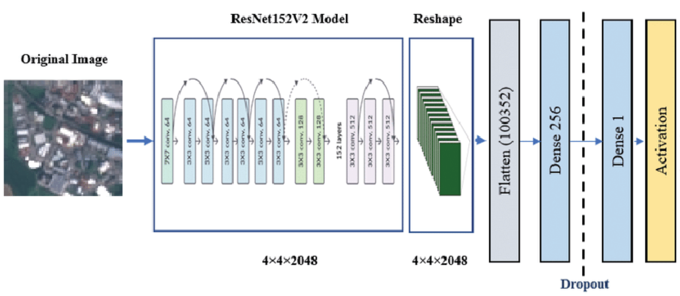

Fig. 3. ResNet 152v2 Model [17]

- Fine-Tuning: In this stage, the ResNet152V2 architecture is employed as the base model for rice leaf disease classification. The uppermost layers of the network that are fully connected are excluded, and model initialization is achieved by using weights that have been pre-trained from ImageNet. To prevent updates to the weights in the initial layers, freezing is applied up to the conv5_block1_preact_bn layer. Subsequently, the layers following this block are set to be trainable, helping the final convolutional layers to be fine-tuned. This strategic approach allows the model to adapt its pre-learned knowledge from ImageNet to the specific task of rice leaf disease classification.
- Attention Mechanism: The next step involves enhancing the model with a channel-wise attention mechanism. This mechanism comprises a GlobalAveragePooling2D layer, a softmax activated Dense layer to generate attention likelihoods, and a multiplication operation with the output of the GlobalAveragePooling2D layer. This addition empowers the model to selectively focus on the most pertinent features during predictions, enhancing its ability to identify and classify rice leaf diseases effectively.
- Fully Connected Layers: Following the attention mechanism, fully connected layers are introduced to further refine the model's features. An activation of ReLU and a Dense layer containing 256 units are added, followed by an output layer containing the quantity of units corresponding to the distinct output groups as well as a softmax activation mechanism. These fully connected layers contribute to the final stages of feature extraction and classification, completing the comprehensive architecture designed for accurate rice leaf disease identification.

E. Model Compilation and Model Training

The accuracy metric, categorized cross-entropy loss function, and Adam optimizer are utilized to create the model. Training is conducted on the designated training set, and performance is evaluated on the validation set. Hyperparameter adjustments can be made based on the model's efficiency during training. The figure (Fig.4) illustrates how the accuracy varies with an increase in the number of epochs.

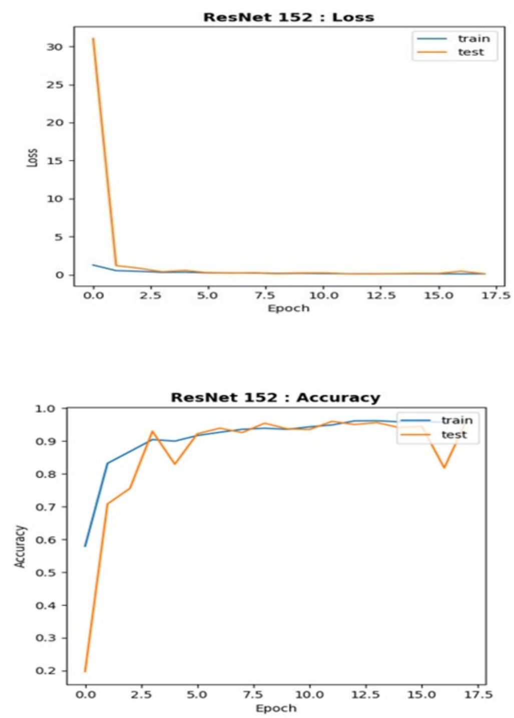

Fig. 4. Accuracy vs Number of Epochs

IV. RESULTS AND DISCUSSION

Subsequently, the model's effectiveness is assessed on the testing set. To gauge its effectiveness, the results are compared with those of other state-of-the-art models, including VGG16, VGG19, AlexNet, and ResNet50. Remarkably, our ResNet152V2 model outperforms these counterparts, demonstrating superior accuracy in rice leaf disease classification (see table 2).

This comprehensive evaluation establishes our model's effectiveness and positions it as a robust solution for accurate

TABLE II
MODEL PERFORMANCE METRICS

Models	Accuracy	Precision	Recall	F1-score
ResNet50	0.447	0.377	0.447	0.393
Vgg19	0.273	0.180	0.273	0.212
Vgg16	0.167	0.027	0.167	0.0476
AlexNet	0.313	0.289	0.313	0.265
ResNet152v2	0.964	0.9644	0.964	0.9633

and reliable identification of rice leaf diseases.

In this research, we introduced a unique attention network on the ResNet152V2 architecture for rice disease classification, featuring a channel attention mechanism strategically focus on key aspects for disease identification Our experimental results demonstrated the usefulness of the attention based strategy in direct the model, achieving test set accuracy of 96.40%, outperforming state-of-the-art models. The attention mechanism let the model concentrate on the greatest number of features, resulting in improved accuracy and robustness. The model's high test set accuracy highlights the potential of AI to be widely used in agricultural disease diagnosis, potentially reducing financial losses for farmers and improving crop yields. The suggested approach can serve as a standard for upcoming research on rice disease classification and can be adapted to other plant disease classification tasks. The results of this study have significant implications for agricultural disease management, enabling accurate AI-assisted diagnosis and improving crop yields. The attention mechanism used in this study is a simple yet effective way to allow the model to concentrate on the most important aspects, making it a promising approach for rice disease classification. Overall, this research paper indicates a novel and effective solution for rice disease classification, contributing to the development of AI-assisted agricultural disease management. The system utilized for training this model should have a minimum of 12 GB of RAM and 128 GB of storage. Figures 5, 6, 7, and 8 depict the accuracy, precision, recall value, and F1-score of various models, respectively. These figures graphically represent the data presented in Table 2.

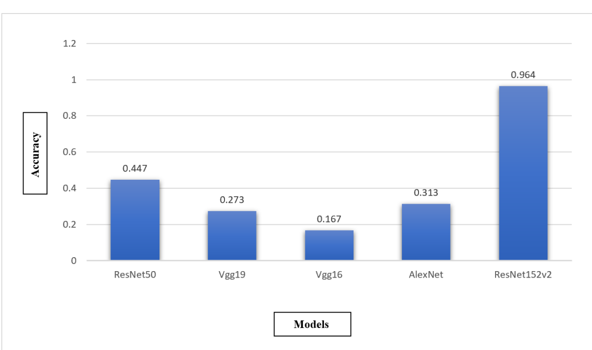

Fig. 5. Accuracy Value Graph

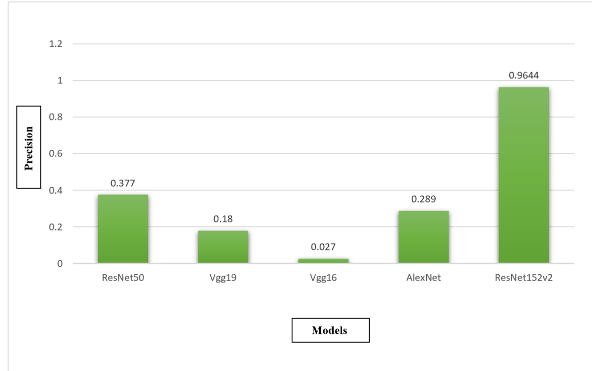

Fig. 6. Precision Value Graph

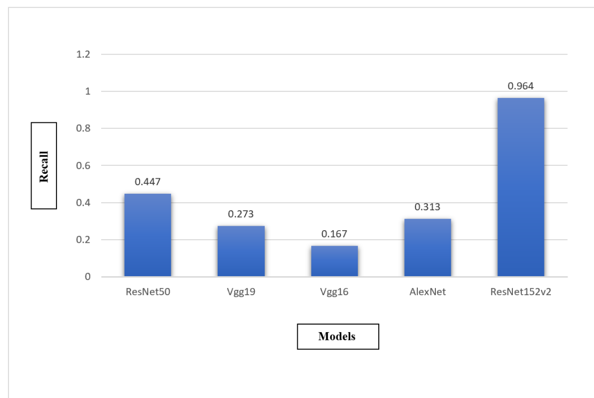

Fig. 7. Recall Value Graph

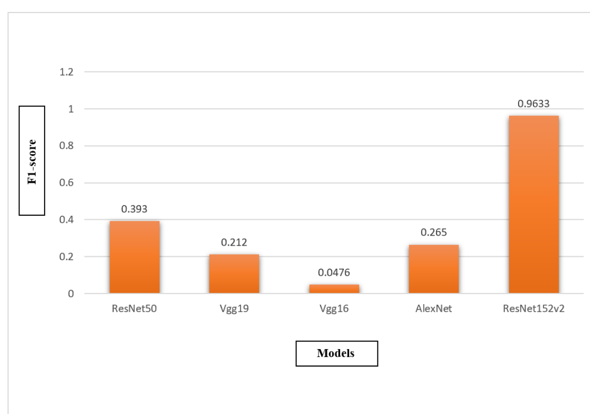

Fig. 8. F1-score Value Graph

Rice Leaf Diseases	Sensitivity of Models				
	ResNet152 v2	ResNet 50	Vgg16	Vgg19	Alex Net
Bacterial Leaf Blight	0.989	0.443	0.001	0.132	0.43
Brown Spot	0.8409	0.189	0.043	0.213	0.387
Healthy	0.997	0.761	0.001	0.254	0.476
Leaf Blast	0.966	0.238	0.112	0.287	0.298
Leaf Scald	0.989	0.556	0.098	0.318	0.416
Narrow Brown Spot	0.988	0.682	0.054	0.264	0.216

Fig. 9. Sensitivity of various models

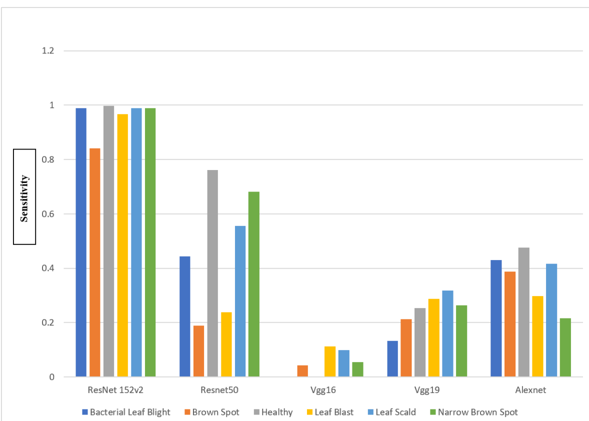

Fig. 10. Sensitivity graph

Fig.9 represents the sensitivity of different models for various diseases, while Fig.10 provides a graphical representation of the same data.

V. Conclusion and Future scope

In conclusion, since quick and precise detection of rice diseases is essential to averting huge financial losses for farmers and increasing crop yields, our work has important implications for agricultural disease management. The suggested model can function as a foundation for further studies on rice disease classification and may be modified for use in other activities involving the classification of plant diseases. This study's attention mechanism is a straightforward yet efficient technique to let the model concentrate on the most important characteristics, which makes it a potential method for diagnosing agricultural diseases. In the future, this project will enable us to identify and mitigate diseases using advanced technologies, ultimately reducing crop wastage and facilitating the production of high-quality rice.

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