Rice Leaf Disease Identification using Attention Networks

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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 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.**

Keywords—Rice Leaf disease, Early Detection, Deep Learning, Attention Network, Channel Attention Mechanism, 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.

The following is the Motivation for proposing our research writing over previous studies in this area: -

1. Rice is a vital staple food, but its cultivation faces significant threats from diseases. Traditional manual inspection methods are laborious and prone to errors.

2. Leveraging attention networks in deep learning presents an opportunity to revolutionize disease identification by automating the process and enhancing accuracy, addressing the urgent need for scalable solutions in sustaining rice production and ensuring global food security.

TABLE I. RICE PLANT DISEASES AND REMEDIES

Name of disease	***Bacilli/fungi***	***Contagi-ous 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 colour from white to grey-green.	When applying nitrogen fertilizer, divide it up into two or more applications.
Bacterial blight	Pv. oryzae / Xanthomonas oryzae.	Weeds and stubbles	Turning yellow on the leaves or seedlings withering.	Make use of proportionate quantities of nitrogen and other plant nutrients.
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.	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, and glumes	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 WORK

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, colour, 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.

According to the review, the various techniques for detecting plant diseases exhibit several limitations. BP neural networks, as used by Libo Liu, though accurate for detecting brown spot in rice leaves, may lack generalizability across different diseases and crops. M. Jhuria's approach, while effective with morphological features, might be less robust when other feature vectors are less distinguishable. The method by H. Q. Cap et al., despite a 78% detection performance, operates at a low frame rate of 2.0, making it impractical for real-time applications. B. S. Ghyar's approach using genetic algorithms for feature selection, combined with ANN and SVM classifiers, achieved high accuracy but may suffer from computational complexity and inefficiency in feature extraction. CNNs, although effective in studies such as Wang's work on rice leaf disease classification, are inherently limited by their inability to focus on critical image areas without additional mechanisms. The introduction of attention mechanisms helps, but traditional CNNs still face challenges in extracting the most relevant features. Kernel attention techniques and grouped convolution operations, as employed by Wang Chunshan, offer improvements but can be complex and computationally expensive.

III. PROPOSED METHODOLOGY

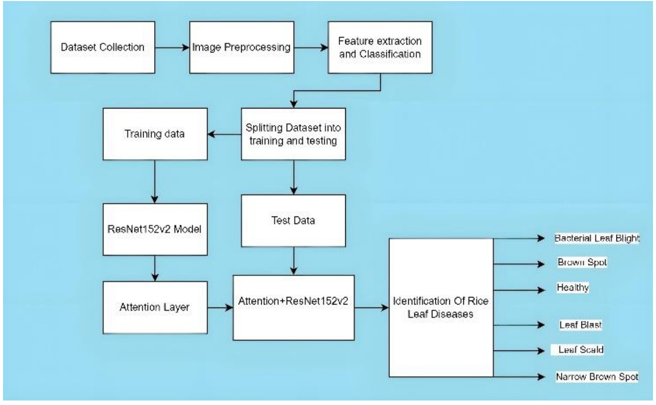

Fig. 1. Block diagram of the proposed work

Fig. 1 represents the workflow of the entire proposed work. The image shows the process of identifying rice leaf diseases using deep learning. The process starts with collecting a dataset of images of rice leaves with different diseases. The images are then preprocessed to remove noise and enhance the features. The features are then extracted from the images using a deep learning model. The features are then used to classify the images into different diseases.

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. (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.

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

The provided Fig. 2 showcases a collection of rice leaf samples, each labeled with its corresponding health status or disease type. The samples are organized in a grid format, demonstrating a variety of visual symptoms associated with each disease. Brown spots appear as dark lesions on the leaf surface, while bacterial leaf blight manifests as streaks or patches of discoloration. Narrow brown spots are characterized by elongated, narrow lesions. Leaf scald displays a burnt appearance with dried, brown edges, and leaf blast is indicated by more severe necrosis and decay. Healthy leaves are uniform in color and free of any visible damage or discoloration. This diverse dataset is essential for training and testing machine learning models aimed at accurately diagnosing and distinguishing between different rice leaf diseases.

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 labelled 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.

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.

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.

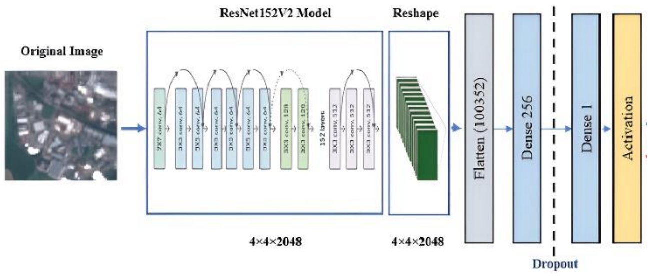

Fig. 3. ResNet 152v2 Model Architecture [17]

Fig. 3 illustrates the workflow of the ResNet152V2 model for image recognition. Starting with the original image, it passes through multiple convolutional layers of the ResNet152V2 architecture, is reshaped, flattened, and then processed through dense layers with dropout regularization, culminating in an activation function to produce the final output.

- **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.

- **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.

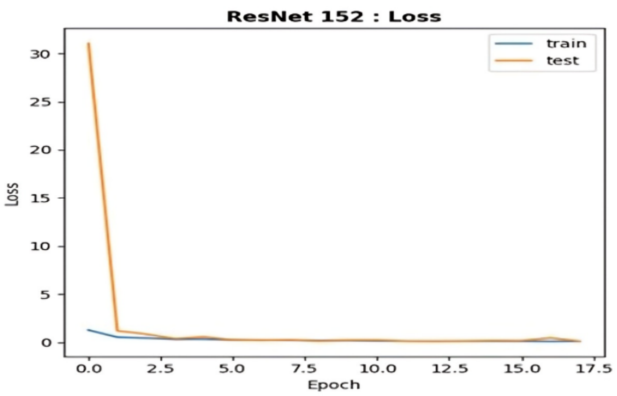

Fig. 4. Loss curve for ResNet 152v2 Model

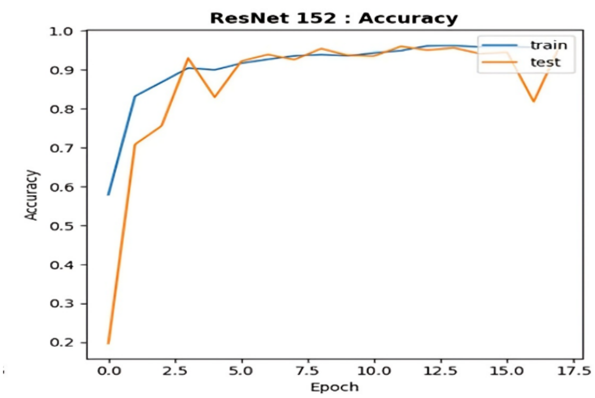

Fig. 5. Accuracy curve for ResNet 152v2 Model

Fig. 4 and Fig. 5 illustrates the loss and accuracy curves for both training and testing datasets over 18 epochs using the ResNet 152V2 model respectively. A sharp decline in loss is observed in the initial epochs, stabilizing near zero, indicating effective learning and minimal overfitting throughout the training process. Initially, accuracy rapidly increases for both datasets, with the training accuracy slightly outperforming the testing accuracy throughout the epochs. The model achieves high accuracy, demonstrating effective learning and generalization.

IV. RESULTS AND DISCUSSION

The performance of the ResNet-152v2 architecture in identifying rice leaf diseases can be assessed using various metrics. The study's evaluation criteria, such as the F1 score, precision, accuracy and recall, are aligned with the research goals and key areas of interest. The precision, recall, accuracy and F1 score were computed using specific evaluation matrices to gauge the model's effectiveness.

Recall Value: The percentage of accurately identified positive samples to actual positive samples is known as the recall rate. The formula is given as follows in equation (1).

$$Recall = \frac{TP}{TP+FN} \quad (1)$$

Precision Value: Precision is defined as the ratio of the number of positive samples classified correctly to the total number of positive samples produced by the classifier as illustrated in equation (2).

$$Precision = \frac{TP}{TP+FP} \quad (2)$$

F-1 value: It refers to the harmonic average of precision rate and recall rate as illustrated in equation (3).

$$F1 - Score = 2 \times \frac{(Precision \times Recall)}{(Precision + Recall)} \quad (3)$$

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).

TABLE II. MODEL PERFORMANCE METRICS

Models	*Accuracy*	*Precision*	*Recall*	*F1-Score*
ResNet50	0.447	0.377	0.447	0.393
Vgg19	0.273	0.18	0.27	0.212
Vgg16	0.167	0.027	0.167	0.0476
AlexNet	0.313	0.289	0.312	0.265
ResNet152v2	0.964	0.9644	0.964	0.9633

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

Fig. 6. Accuracy Value Graph

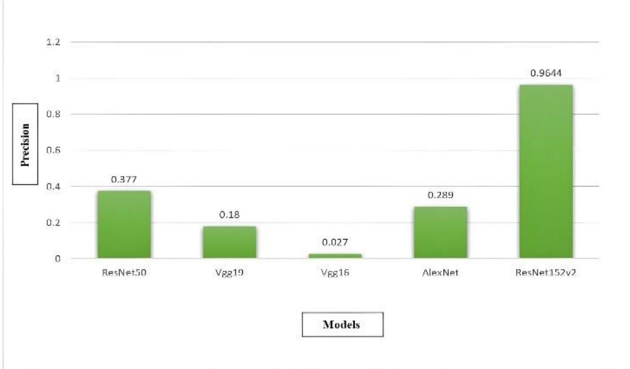

Fig. 7. Precision Value Graph

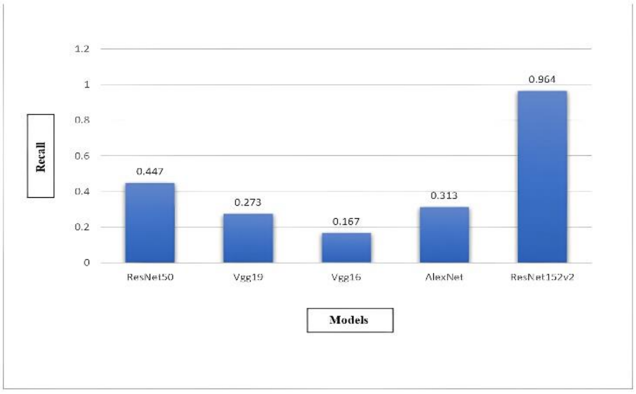

Fig. 8. Recall Value Graph

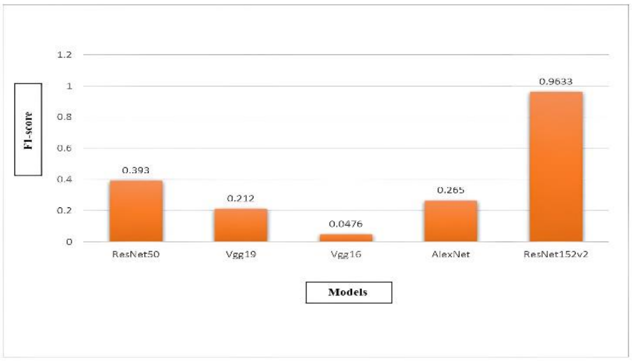

Fig. 9. F1-score Value Graph

The suggested approach can serve as a standard for upcoming research on rice disease classifica-tion 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 in-dicates a novel and effective solution for rice disease classification, contributing to the devel-opment 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 6, 7, 8 and 9 depict the accuracy, precision, recall value, and F1-score of various models, respectively. These figures graphically represent the data presented in Table 2.

TABLE III. COMPARISON TABLE OF RESNET152v2, RESNET50, VGG16, VGG19, ALEXNET

Sensitivity score of various models	***Bacterial Leaf Blight***	***Brown Spot***	***Healthy***	***Leaf Blast***	***Leaf Scald***	***Narrow Brown Spot***
ResNet 152v2	0.989	0.8409	0.997	0.966	0.989	0.988
ResNet50	0.443	0.189	0.761	0.238	0.556	0.682
VGG16	0.001	0.043	0.001	0.112	0.098	0.054
VGG19	0.132	0.213	0.254	0.287	0.318	0.264
AlexNet	0.43	0.387	0.476	0.298	0.416	0.216

Table 3 represents the sensitivity scores of five models- ResNet152v2, ResNet50, Vgg16, Vgg19, and AlexNet -in identifying six rice leaf diseases: Bacterial Leaf Blight, Brown Spot, Healthy, Leaf Blast, Leaf Scald, and Narrow Brown Spot. ResNet152v2 consistently shows the highest sensitivity across all diseases, whereas Vgg16 often has the lowest sensitivity.

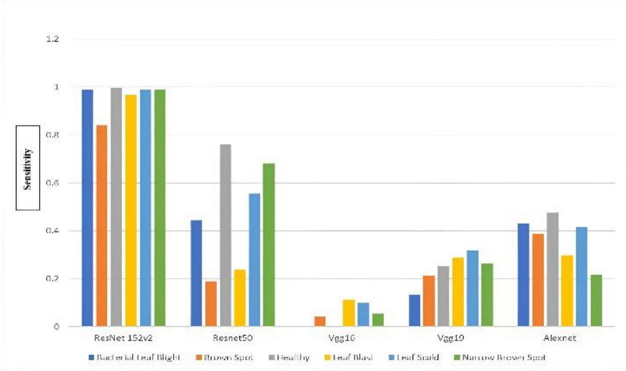

Fig. 10. Sensitivity of Various Models for Different Leaf Diseases

Fig. 10 provides a graphical representation of the data presented in Table 3.

V. CONCLUSION

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 straight-forward 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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