Explainable Deep Transfer Learning Framework for Rice Leaf Disease Diagnosis and Classification

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***Abstract*—Rice plays a vital role in the food stock. But sometimes this crop leaf falls into disease. And, the amount of food consumed will decrease due to leaf disease. So, discovering the rice leaf disease is necessary to improve rice productivity. Currently, many researchers use deep learning methods to solve this problem. Unfortunately, their research results were less accurate. In this paper, we construct transfer learning models to diagnose and categorize illnesses affecting rice leaves. To further improve the model performance, we construct three ensemble learning models to combine various architectures. In order to bring transparency to the disease diagnostic process, we explore the explainable AI (XAI) problem of the visual object detector and integrate Gradient-weighted Class Activation Mapping (Grad-CAM) into three ensemble models to generate explanations for individual object detections for assessing performance. The results of Ensemble Learning indicate that merging different architectures can be effective in disease diagnosis, as evidenced by their best accuracy of 99.78% which is better than other state-of-the-art works. This research demonstrates that the integration of deep learning and transfer learning models yields improved prediction interpretability and classification accuracy of rice leaf disease. So, we established a dependable method of deep, transfer, and ensemble learning for the diagnosis of diseases affecting rice leaves.**

***Keywords*—Rice leaf; ensemble-learning; explainable AI; disease diagnosis; transfer learning**

I. Introduction

Over half of the world's population depends on rice production as their primary staple, making it essential for global food security [1], [2], [3]. Because it sustains livelihoods, particularly in Asia where it is a significant source of employment and revenue, it has a significant impact on people [4], [5]. Efficient rice cultivation has a crucial role in maintaining and enhancing lives globally by ensuring food stability, economic well-being, and socio-economic development [6].

Finding rice leaf disease is a vital job in agriculture since rice is one of the most important crops in the world and feeds millions of people as a staple diet. Brown spot, leaf blast, and bacterial blight are just a few of the diseases that can severely limit rice crop productivity, resulting in financial losses and food poverty. By using targeted treatments or preventive measures, farmers can take appropriate corrective action to preserve crop health and maximize production. Early and precise detection of these diseases using rice leaf images can assist farmers in doing just that. The scalability and effectiveness of image analysis in rice leaf disease detection make it a valuable tool. Conventional approaches to disease identification are laborious, arbitrary, and prone to mistakes as they frequently depend on the manual inspection of specialists. However, a quick, reliable, and scalable solution is provided by automated detection that makes use of computer vision and machine learning algorithms. Advanced models have demonstrated significant potential in accurately classifying rice leaf illnesses from images. These models include ensemble learning models (e.g. combining VGG16, ResNet50, InceptionV3, and EfficientNet) and deep learning architectures (e.g. CNNs) [7], [8]. By including Explainable AI methods such as Grad-CAM, these models become more visible and users are able to see which leaf portions are responsible for the predictions made by the model [9]. This guarantees that academics and farmers alike can rely on the technology and obtain practical knowledge about the well-being of rice crops, which in turn promotes improved disease control and more environmentally friendly farming methods [10], [11].

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The main goal of rice leaf disease identification using rice leaf images is to create an automated, precise, and effective system that can recognize and categorize illnesses that impact rice harvests. Reduced reliance on costly, time-consuming, and error-prone manual expert inspection is the aim of utilizing sophisticated image processing and machine learning approaches [13], [14], [15]. By early detection of illnesses including bacterial blight, brown spot, and leaf blasts, this method hopes to give farmers the information they need to take preventative measures that can stop the disease's progress and lessen crop loss. Another goal is to provide a scalable solution that can be implemented at various agricultural scales and geographical locations to increase the overall productivity and sustainability of rice growing. The system employs deep learning models [16], [17], [18], such as CNNs, in conjunction with ensemble learning techniques that integrate the capabilities of models like VGG16, ResNet50, and InceptionV3, to achieve a high degree of disease detection accuracy while maintaining resilience in a range of environmental circumstances and image characteristics. The goal also includes improving these models' interpretability by using Explainable AI techniques like Grad-CAM, which let users see the specific regions of the rice leaf that the algorithm targeted for prediction. This openness strengthens farmer confidence in the system and gives them a greater knowledge of the health of their crop [19], which in turn improves disease control procedures and promotes more sustainable agricultural results.

The key contributions of this paper are as follows:

1 We explored the disease of rice leaf images from two datasets using separate deep and transfer learning models.
2 We customized and applied three ensemble learning techniques from deep and transfer learning.
3 We proposed an ensemble learning model with the highest accuracy and lowest data loss rate.
4 We used Explainable AI to evaluate the input image and with the proposed ensemble learning.
5 Finally, we proposed new algorithms for generated ensemble learning algorithms.

The remaining parts of this paper are formatted as follows: Section II explains the previous studies of existing work that were published recently. While Section III describes the research technique used in this work, Section IV provides the experimental results of this work. Section V demonstrates the conclusion and future work of this study.

II. Prior Studies

Many researchers have published solutions for rice leaf disease diagnosis using different types of algorithms such as deep learning, machine learning, ensemble learning, etc. Some recent publications are mentioned here.

S. Ghosal and K. Sarkar et al. [20], proposed a VGG-16-based CNN architecture to detect different rice leaf diseases accurately and they used their own collected dataset containing about 500 images and achieved 92.46% of accuracy. In the paper et al.[21], authors applied several image processing techniques such as RGB to HSV conversion, background subtraction, segmentation, etc., and then implemented an automated system using a deep neural network for rice leaf disease detection and achieved an average accuracy of 92% using their self-collected dataset of 209 images. J. Chen, D. Zhang, Y. A. Nanehkaran, and D. Li et al. [22] proposed a system for the detection of various rice leaf diseases combining DenseNet pre-trained with ImageNet and Inception module on an image dataset collected by Fujian Institute of Subtropical Botany, Xiamen, China and achieved an outstanding accuracy of no less than 94.07% for each type of disease category.

M. A. Islam et al. [23] worked with four types of paddy disease to detect it early and accurately. They applied several deep learning CNN models such as VGG-19, Inception-Resnet-V2, ResNet-101, and Xception and their experimental result shows that Inception-Resnet-V2 performed better with 92.68% accuracy. Several image processing techniques [24] were applied by the authors to extract important features from images that describe the most significant characteristics and then classified the images as rice leaf disease category using XGBoost and SVM algorithms and got about 86.58% accuracy. They created their own dataset for the experiment and used a public dataset for testing. They extract features from images using several image processing techniques [25] and applied CNN models VGG16, ResNet50, and DenseNet121 to detect rice leaf disease accurately and 91.63% accuracy is achieved by the model DenseNet121.

To detect rice leaf disease automatically considering various leaf sizes author applied deep learning-based CNN model ResNet and YOLOv4 [26] on a public dataset of 4960 images and YOLOv4 models show better performance with mAP value 91.14%. In the paper et al. [27], the author applied various CNN techniques for rice leaf disease detection such as VGG16, VGG19, Xception, ResNet, and the 5-layer convolution model, and finally, it is shown that the 5-layer convolution model achieved the highest accuracy 78.2% in compare to other models. CNN models DenseNet121, DenseNet169, MobileNetV2, and VGG16 are employed [28] on the public dataset from Kaggle containing the 5932 images for rice leaf disease detection, and DenseNet169 and moboleNetV2 show the highest performance with 94.30% accuracy. In the paper et al. [29] collected 1500 images from Feni, Bangladesh to detect rice leaf disease and applied CNN model YOLOv5 and achieved 76% mAP value.

A new machine learning approach Nu-SVM model is employed [30] on a Kaggle dataset to detect rice leaf disease and the experimental result shows 52.12% to 53.81% of validation accuracy. In the paper et al. [31], the author employed various filter-based feature transformation techniques for rice leaf disease detection accurately. They used a public rice leaf dataset from Kaggle and it showed that in the experiment the KNN model achieved the highest balance accuracy of 90%. DNet-SVM: XAI is proposed [32] by the authors to detect sugarcane disease detection and they used a public sugarcane dataset from kaggle. DNet-SVM: XAI detects and predicts sugarcane disease early and explains its prediction reason. They also applied another deep learning model such as VGG16, VGG19, and Inception, etc., and compared the result with the proposed model. The proposed model outperformed in comparison to other models. Rice crop disease detection is very important and to detect rice crop disease early author applied the CNN model for detection and LIME to explain its interpretability [33]. The experimental result shows that the proposed models achieved 91.60% accuracy.

Deep learning models VGG16, SqueezeNet, and InceptionV3 were employed in [34] for rice leaf disease detection and the proposed model SqueezeNet achieved the highest accuracy of 93%. P. Kulkarni and S. Shastri at el. [35] proposed a novel deep learning-based CNN model that is applied for the automatic detection of rice leaf disease. They used a public dataset from Kaggle and the author achieved about 95% accuracy in the experiment. In the classification of corn leaf diseases, the proposed VGG16 model augmented with LRP [36] performed better than earlier cutting-edge models. The outcomes of the simulation showed that the model not only produced findings with a high degree of accuracy but also highlighted important areas in the images that were classified. The authors introduce an improved YOLOv8 [37] that combines EIoU loss and α-IoU loss to replace the original Box Loss function and enhance the rice leaf disease detection system's performance. Finally, they compare YOLOv8 performance with YOLOv5 and YOLOv7 and it is shown that their proposed model performed better with 89.90% accuracy.

The limitation of previous studies was less accurate. In most of the publications, they used pretrained models of deep learning and transfer learning to detect and classify rice leaf disease. The use of Explainable AI was rare.

We employed the "Rice Leaf Disease Detection" dataset from Kaggle and some effective deep learning methods such as CNN, VGG-16, and InceptionV3 in our suggested work shown in Table I, which exhibits higher accuracy than earlier studies. Machine learning, deep learning, and advanced image processing techniques have greatly expanded the field of rice leaf disease detection and recognition. These advancements improve prompt intervention and detection accuracy. However, issues like environmental unpredictability and dataset restrictions still exist. In order to enhance sustainable rice cultivation and further improve detection systems, future research should focus on these concerns.

III. Proposed Framework and System Architecture

The proposed working flow diagram of rice leaf disease diagnosis and classification is illustrated in Fig. 1 where data collection to result in findings is described sequentially.

A. Dataset

For experimental implementation, we collected image datasets from different types of online sources. We used two datasets from online. One is "Rice Leafs Disease Dataset"[1]. This data has a total of two different directories as training and validation with 6 classes. The total images contain 2,627 in six classes. The classes are Bacterial Leaf Blight, Brown Spot, Healthy, Leaf Blast, Leaf Scald, and Narrow Brown Spot. Each class has 350 images for training and 88 images for validation.

Another dataset name is "Rice Leaf Diseases Detection"[2]. This dataset is released at the beginning of 2024. This dataset is also divided into two divisions training and validation. Each directory has a total of 10 classes such as bacterial-leaf-blight, brown-spot, healthy, leaf-blast, leaf-scald, narrow-brown-spot, neck-blast, rice-hispa, sheath-blight, and tungro. Each class has a total of 1,385 images for training and 350 for validation. The total dataset has 17, 350 images for both training and validation. Fig. 2 and 3 describe the sample dataset for two different types of images.

[1]https://www.kaggle.com/datasets/dedeikhsandwisaputra/rice-leafs-disease-dataset

[2]https://www.kaggle.com/datasets/loki4514/rice-leaf-diseases-detection

B. Feature Extraction and Image Processing

To remove noise, reduce dimensions, and make it suitable for model training, we change the shape of the images into 224*224 dimensions after converting the grayscale. To extract the features of the images, the Lanczos interpolation method. We later normalized the images by dividing 255.0 between the pixel values of 0 and 1.

Basically, two feature extraction methods were used here [38]. These are: (1) Shaped based technique, and (2) Transform based Technique.

The dataset is labeled using One-hot encoding techniques for each class in two datasets. Data labeling makes it easy to train and validate the model. Based on the unique class name, the images are labeled with a one-hot encoding method in this study [39].

C. Image Preprocessing

As the preprocessing part of the data, we made changes to the images as:

1 Resize of the images into 224*224
2 Set batch size=32 and classmode='categorical' for the multi-class classification.
3 Array conversion with the help of Numpy.
4 Input shape is 224*224*3.

Such preprocessed images are shown in Fig. 4; where six images from six classes are combined into a single form [40].

D. Data Augmentation

We augmented the dataset 1 to increase the number of images [41], [42]. The increased amount of data will increase the detection and training accuracy of the model [43]. If the dataset is vast then augmentation is not needed but dataset 1, has only 2,627 images. That's why, we used the augmentation method for dataset increasing. We set the parameter details in the augmentation part as follows:

rescale=1.0/255.0,

horizontal-flip=True,

zoom-range=0.2,

shear-range=0.2

But dataset-2 has around 17,350 image data. This amount is enough for the model training. However, dataset-2 has satisfactory data, so, it does not need to augment this data [44]. We ignored to augment. The augmented images for dataset 1 are shown in Fig. 5, where six individual images from six classes are merged into a single image.

TABLE I. Comparative Analysis Between Existing Work with Proposed Work

Reference	Dataset	Used Methods	Accuracy	XAI
[20]	Private (500)	CNN, VGG-16	92.46%	No
[21]	Private (209)	DNN, KNN	Avg. 92.6%	No
[22]	Private (500) Fujian Institute of Subtropical Botany, Xiamen, China	DENS-INCEP, VGGNet-19, ResNet-50, DenseNet-201, InceptionV3, VGG19-SVM	94.07%	No
[24]	UCI rice leaf disease dataset	XGBoost, SVM	86.58%	No
[25]	Private (386)	VGG16, ResNet50, DenseNet121	91.63%	No
[26]	Rice Leaf Dataset (4960)	ResNet, YOLOv4	—–	No
[27]	Kaggle Dataset (1600)	VGG16, VGG19, Xception, ResNet, 5-layer Convolution	78.20%	No
[28]	Kaggle Dataset (5932)	DenseNet121, DenseNet169, MobileNetV2, VGG16	74.30%	No
[29]	Private Dataset (1500)	YOLOv5	—–	No
[30]	Rice Leafs Dataset from Kaggle	Nu-SVM	53.81%	No
[31]	Kaggle Dataset	RFC, KNN, LDA, HGBC etc.	90%	No
[32]	Sugarcane (14000) from Kaggle	DNet-SVM, VGG16,VGG19, ResNet, Inception, DenseNet, DNet-SVM	94%	Yes
[33]	Kaggle Dataset	CNN and LIME	90.60%	Yes
[34]	Rice Leaf Dataset	VGG16, SqueezeNet, and InceptionV3	93%	No
[35]	Kaggle Dataset	CNN	95%	No
[36]	Corn Leaf Dataset (4188)	VGG16, LRP	94%	Yes
[37]	Private Dataset (1634)	YOLOv8	89.90%	No
Proposed Work	Rice Leaf Diseases Diagnosis	Deep-transfer learning ensembles	99.78%%	Yes

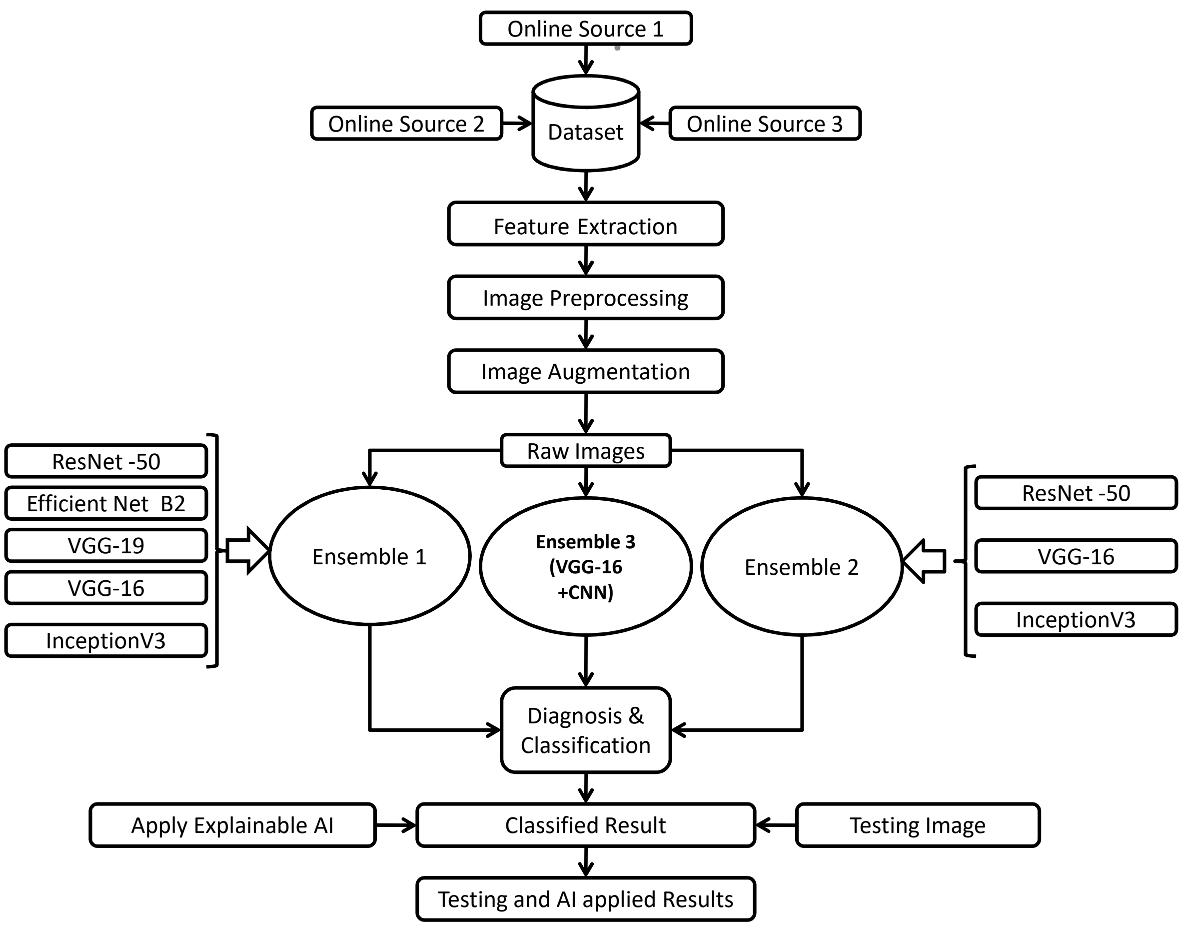

Fig. 1. Proposed system architecture.

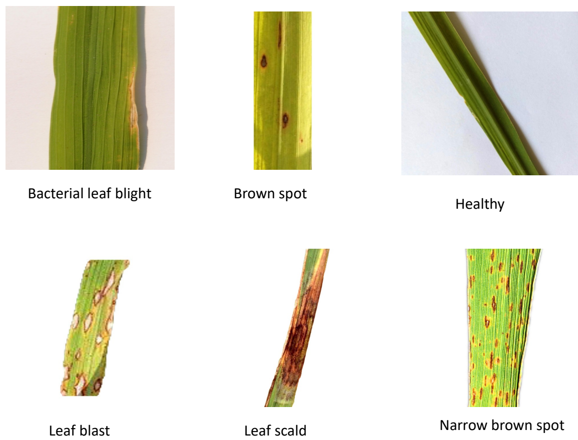

Fig. 2. Dataset-1 sample with six classes.

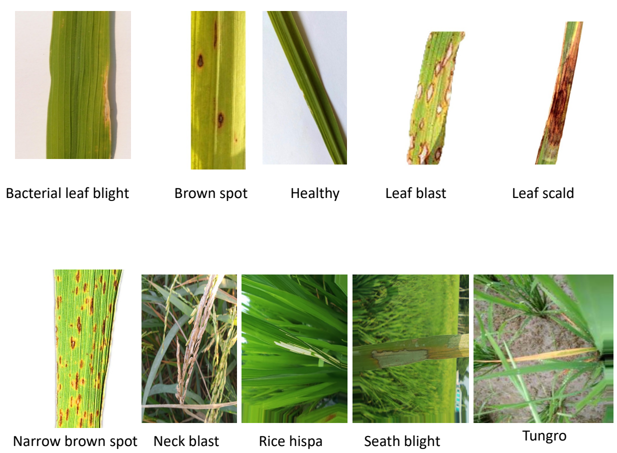

Fig. 3. Dataset-2 sample with 10 classes.

E. Feature Extraction Based on Deep Learning

For model training and validation, we used a deep learning model CNN in this study. This model is suitable for image classification. Preprocessed and augmented images were trained and validated by this model. CNN model is applied to two datasets separately. It is constructed with an input layer, a fully connected layer, some convolutional layers, and max pooling layers [45]. The input layer takes images as input, convolutional layers use a 3*3 filter or kernel for image filtering. The Max pooling layer receives the output from the convolutional layer and processes it. After processing, the output will go through the fully connected layer. The fully connected layer combines the output from the max-pooling layer and makes a single form in the Dense layer. Dense layers flatten the previous layers for making a single form or it is used for combining [46], [16]. The basic organization of the CNN architecture of rice leaf image classification is shown in Fig. 6. CNN model parameter details are shown in Table II.

TABLE II. CNN Model Parameter Details in Every Layer

Layer (type)	Output Shape	Parameter
input-1 (InputLayer)	[(None, 224, 224, 3)]	0
block1-conv1(Conv2D)	(None, 224, 224, 64)	1792
block1-conv2(Conv2D)	(None, 224, 224, 64)	36928
block1-pool(MaxPooling2D)	(None, 112, 112, 64)	0
block2-conv1(Conv2D)	(None, 112, 112, 128)	73856
block2-conv2(Conv2D)	(None, 112, 112, 128)	147584
block2-pool(MaxPooling2D)	(None, 56, 56, 128)	0
block3-conv1(Conv2D)	(None, 56, 56, 256)	295168
block3-conv2(Conv2D)	(None, 56, 56, 256)	590080
block3-conv3(Conv2D)	(None, 56, 56, 256)	590080
block3-pool(MaxPooling2D)	(None, 28, 28, 256)	0
block4-conv1(Conv2D)	(None, 28, 28, 512)	1180160
block4-conv2(Conv2D)	(None, 28, 28, 512)	2359808
block4-conv3(Conv2D)	(None, 28, 28, 512)	2359808
block4-pool(MaxPooling2D)	(None, 14, 14, 512)	0
block5-conv1(Conv2D)	(None, 14, 14, 512)	2359808
block5-conv2(Conv2D)	(None, 14, 14, 512)	2359808
block5-conv3(Conv2D)	(None, 14, 14, 512)	2359808
block5-pool(MaxPooling2D)	(None, 7, 7, 512)	0
flatten(Flatten)	(None, 25088)	0
dense (Dense)	(None, 2)	50178
Total params:	0	14,764,866
Trainable params:	0	50,178
Non-trainable params:	0	14,714,688

F. Feature Extraction Based on Transfer Learning

To implement the proposed work, we used total five transfer learning algorithms such as VGG16, VGG19, ResNet-50, InceptionV3, and EfficientNetV2-M. These models apply to two different datasets separately. For vast datasets, transfer learning models are suitable for the best accurate training and validation. Most of the algorithms work are similar way. However, we described them separately below.

1) VGG16: It is the variants of the deep learning model and updated version of the CNN model. This model has basic 16 layers. That is why, it is called VGG16. It consists of some layers such as the Input layer, Convolution layers, Max-pooling layer, Dense layer, and Output layer [47]. A 3*3 laplacian mask was applied here. The image input shape is 224*224 with RGB Channel. Then input image is processed by convolution and max pooling layer [48], [49]. Finally, layers are combined into a single layer named as dense layer. It produces the final output of the model. During trainable. all layers are frozen. The activation function is “softmax” used here [50]. The parameters for the VGG16 is set as:

optimizer=‘rmsprop’,

loss=‘categorical-crossentropy’,

metrics=[‘accuracy’]

The summary parameter details of VGG16 is illustrated in Table III.

2) VGG19: VGG19 is also a transfer learning model, used for classification. It has basic 19 layers. So, it is called, VGG19 [51]. It can classify a total of 1,000 classes of objects. So, this model is highly applicable to vast datasets. It is the incremental version of VGG16 [52], [53]. We used two separate datasets. The first dataset has 2,627 images. The second dataset has 10 image classes and around 17,350 image data. So, we used

Fig. 4. Preprocessed image sample.

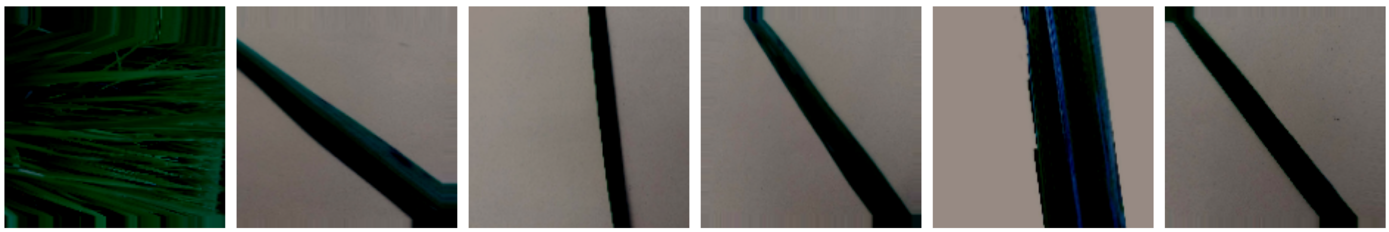

Fig. 5. Augmented images for dataset 1.

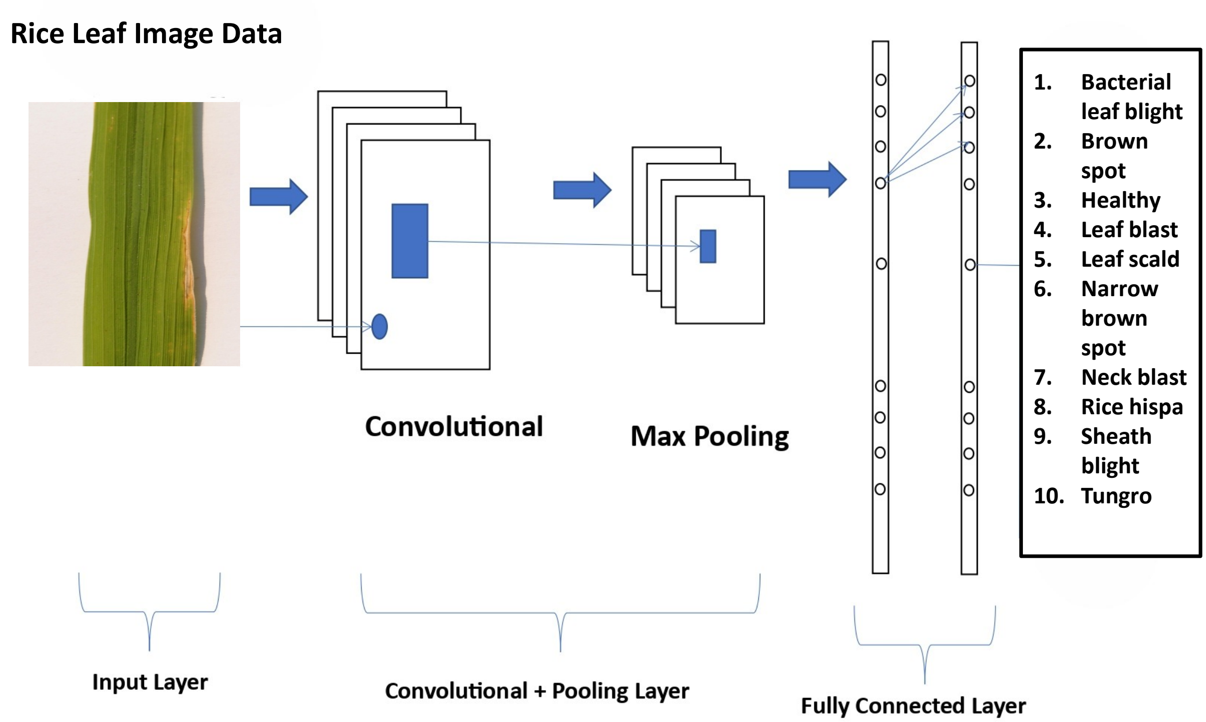

Fig. 6. CNN Architecture for rice leaf disease diagnosis.

TABLE III. VGG16 Model Parameter Details

Layer (type)	Output Shape	Parameter
vgg16	(Functional) (None, 7, 7, 512)	14714688
flatten-1 (Flatten)	(None, 25088)	0
dense-2 (Dense)	(None, 512)	12845568
dropout-1 (Dropout)	(None, 512)	0
dense-3 (Dense)	(None, 10)	5130
Total params:	0	27565386
Trainable params:	0	12850698)
Non-trainable params:	0	14714688

it to get the highest accuracy. This model can classify the object with high accuracy. It takes the input image as 224*224 in standard format. This model consists of some layers. The layers are Convolution, Max pooling, fully connected, input, and dense layer. The dense layer is used to flatten the previous layers and it provides the output image [54]. The parameter details of VGG19 are shown in Table IV.

TABLE IV. VGG19 Model Parameter Details in Every Layer

Layer (type)	Output Shape	Parameter
input-2 (InputLayer)	[(None, 224, 224, 3)]	0
block1-conv1 (Conv2D)	(None, 224, 224, 64)	1792
block1-conv2 (Conv2D)	(None, 224, 224, 64)	36928
block1-pool (MaxPooling2D)	(None, 112, 112, 64)	0
block2-conv1 (Conv2D)	(None, 112, 112, 128)	73856
block2-conv2 (Conv2D)	(None, 112, 112, 128)	147584
block2-pool (MaxPooling2D)	(None, 56, 56, 128)	0
block3-conv1 (Conv2D)	(None, 56, 56, 256)	295168
block3-conv2 (Conv2D)	(None, 56, 56, 256)	590080
block3-conv3 (Conv2D)	(None, 56, 56, 256)	590080
block3-conv4 (Conv2D)	(None, 56, 56, 256)	590080
block3-pool (MaxPooling2D)	(None, 28, 28, 256)	0
block4-conv1 (Conv2D)	(None, 28, 28, 512)	1180160
block4-conv2 (Conv2D)	(None, 28, 28, 512)	2359808
block4-conv3 (Conv2D)	(None, 28, 28, 512)	2359808
block4-conv4 (Conv2D)	(None, 28, 28, 512)	2359808
block4-pool (MaxPooling2D)	(None, 14, 14, 512)	0
block5-conv1 (Conv2D)	(None, 14, 14, 512)	2359808
block5-conv2 (Conv2D)	(None, 14, 14, 512)	2359808
block5-conv3 (Conv2D)	(None, 14, 14, 512)	2359808
block5-conv4 (Conv2D)	(None, 14, 14, 512)	2359808
block5-pool (MaxPooling2D)	(None, 7, 7, 512)	0
flatten-1 (Flatten)	(None, 25088)	0
dense-1 (Dense)	(None, 6)	150534
Total params:	0	20174918
Trainable params:	0	150534
Non-trainable params:	0	20024384

3) InceptionV3: This model is another powerful transfer learning model for image data classification. There are eleven inception modules, two max-pooling layers, five convolutional layers, one average pooling layer, one fully connected layer, and one max-pooling layer in InceptionV3[55]. We used this model for rice leaf disease diagnosis and classification. For two separate datasets, we applied this model. Though it takes more time than other models, it can be classified accurately than other models. The basic parameter details of this algorithm are lengthy. So, we are ignoring the parameter details. It has a total of 48 layers [56].

4) ResNet-50: A deep convolutional neural network (CNN) architecture with 50 layers, ResNet-50 is intended for computer vision and image recognition applications. Recursive learning, also known as "skip connections", was presented, in which the network learns residuals, or the variations between input and output layers [57]. This facilitates more effective training of deeper models by addressing the vanishing gradient issue that arises in very deep networks. Convolutional, pooling, and fully connected layers are the building blocks of ResNet-50, which are arranged in residual blocks [58]. It has achieved state-of-the-art results in several vision tasks and has been widely utilized for transfer learning, having been trained on big datasets such as ImageNet. Reputably, the model strikes a balance between computational efficiency and depth. We used this model for two separate datasets in rice leaf image classification.

5) EfficientNetV2-M: EfficientNetV2-M is a powerful transfer learning algorithm, used for large-scale image data. A member of the EfficientNet family, EfficientNetV2-M is renowned for striking an ideal balance in image recognition tasks between computational efficiency and model performance. By adopting a more sophisticated scaling technique and methodically increasing breadth, depth, and resolution, it improves accuracy and speed over the original EfficientNet. Depthwise separable convolutions and more sophisticated methods such as Fused-MBConv are combined by EfficientNetV2-M to minimize computing expenses without sacrificing precision. Large-scale picture classification tasks are especially well-suited for this model, which offers shorter training periods and smaller model sizes than its predecessors. It is adaptable for a range of computer vision applications because it has been pretrained on big datasets like. However, to classify the rice leaf images, we used this model for two separate datasets. Due to the lengthy of layers, we are ignoring the parameter details of this model [59].

To implement the working process and evaluate the performance, we proposed a new algorithm followed in Algorithm 1.

G. Ensemble Learning

Using the pretrained deep and transfer learning models, we got the disease detection accuracy to be more than 95% but not reach 99.99%. We tried multiple ensembling techniques because it was unknown to us which ensemble would be the proper model for this type of work. So, we used three types of ensemble methods [60], [51]. To improve the training and validation accuracy by more than 95%, sometimes we used some models in a single structure known as ensemble learning. Bagging and Boosting are the commonly used ensemble techniques for image classification [61]. The main purpose of ensemble learning is:

1 improving the training and validation accuracy,
2 decrease the data loss amount,
3 find out the optimum solution of time and space complexity,
4 find out the proper detection, prediction, and diagnosis,
5 increase the system speed, etc.

However, in this study, we ensembled deep learning and transfer learning to find out the above requirements. We made three ensembles from six separate models such as CNN, VGG16, VGG19, InceptionV3, ResNet-50, EfficientNetV2-M [62]. Three ensembles are described below.

Algorithm 1 Proposed Algorithm for Rice Leaf Disease Detection

#Rice Leaf Images used as Dataset
$DataX : Training, Validation, Testing$
$InputImage \leftarrow (256, 64, 3)$
$Algorithms :\leftarrow CNN, InceptionV3, ResNet50, VGG16, VGG19, EfficientNetV2M$
$ITR \leftarrow NumberofIterations$
$ACC \leftarrow Performancematrix$
$ALG \leftarrow Numberofalgorithms$
#Feature Extraction using Deep and Transfer Learning Algorithms
$ML \leftarrow ModelLayer$
$M \leftarrow Epochs$
#Deep and Transfer Learning Model Training:
for 1 to M **do**
  for each ML **do**
    for each Sample in X **do**
      calculate A from X by Conv. Process
    end for
  end for
end for
Ensemble Learning Call
$E1 \leftarrow Ensemblelearning1$
$E2 \leftarrow Ensemblelearning2$
$E3 \leftarrow Ensemblelearnin3$
#Number of Iteration
for 1 to ITR **do**
  1. Train Model with N Number of batch size
  2. Feature Extraction through hidden layers
  3. Forward propagations
  4. Backword propagation for updating weights
  5. Model validation with validation data to check overfitting
end for
Model Evaluation:
1. Evaluate the model with test data
2. Store the model performance in Acc variable

1) *Ensemble Learning-1:* Ensemble Learning-1 is developed from transfer learning models. To make this, we used 5 transfer learning models [63]. They are VGG16, VGG19, InceptionV3, ResNet-50, and EfficientNetV2-M. After bagging them, we got a new model named "Ensemble learning-1". Though it requires more time than other single models, it can classify and diagnose the disease more correctly than other normal models [64], [65]. The basic structure of the newly developed ensemble model-1 is illustrated in Fig. 7 and the parameter list is shown in Table V. Algorithm 2 is the proposed new algorithm for ensemble learning-1 used in this study. It is developed based on the fusion of VGG16, VGG19, ResNet-50, InceptionV3, and EfficientNetV2-M [66], [67].

2) *Ensemble Learning-2:* Another transfer learning combination of the three models is developed into a single structure known as "ensemble learning-2". We made it, after voting the VGG16, Inception V3, and ResNet-50 [68]. This structure is simpler than Ensemble learning-1. Also, it is suitable for high accuracy of the model training and validation. Though its parameter list is vast, hence it can classify the image data and can detect the diagnosis[69]. The basic structure of ensemble-2

Algorithm 2 Proposed Algorithm for Ensemble Learning-1

$ITR \leftarrow NumberofIterations$
$ACC \leftarrow Performancematrix$
$ALG \leftarrow Numberofalgorithms$
#Ensemble Models
$E1 \leftarrow FusionofALG$
$ALG \leftarrow ResNet50, EfficienNetV2M, InceptionV3, VGG16, VGG19$
for 1 to ITR **do**
  1. Preprocess the input features of fusion model
  2. Customize the layers in the model
  3. Freezing the base model
  4. Optimize the parameters in the model
  5. Train the model by dataset
  6. Model validation with validation data to check overfitting.
end for

#Number of Iteration
for 1 to ITR **do**
  1. Train Model with N Number of batch size
  2. Feature Extraction through hidden layers
  3. Forward propagations
  4. Backword propagation for updating weights
  5. Model validation with validation data to check overfitting
end for

is described in Fig. 8 and the parameter list is shown in Table VI. Algorithm-3 describes the combined algorithm proposed for this model. It is the appropriate model in this structure.

3) *Ensemble Learning-3:* Ensemble learning-3 is developed from one deep learning and one transfer learning model. By CNN and VGG16 combinations, ensemble-3 is made [70]. It saves memory and space complexity also. Its structure is simple and easy to implement [71], [72]. The basic structure is shown in Fig. 9 and the parameter list is also shown in Table VII. Algorithm 4 explained the basic working process of this fusion model from deep learning and transfer learning. We proposed the algorithm in this stage for rice leaf disease diagnosis at high accuracy and it is more effective now [73].

IV. RESULT ANALYSIS AND DISCUSSION

In this section, we will discuss different types of algorithm performance applied in our study. Particularly, we will explain training, validation, and testing accuracy for each model as well as loss. Graphical representation also will be described here such as Plot details, Curves [74], Confusion Matrix, Classification report, Correctly classified and misclassified images, AI-based testing image report, etc. After all, a comparison of

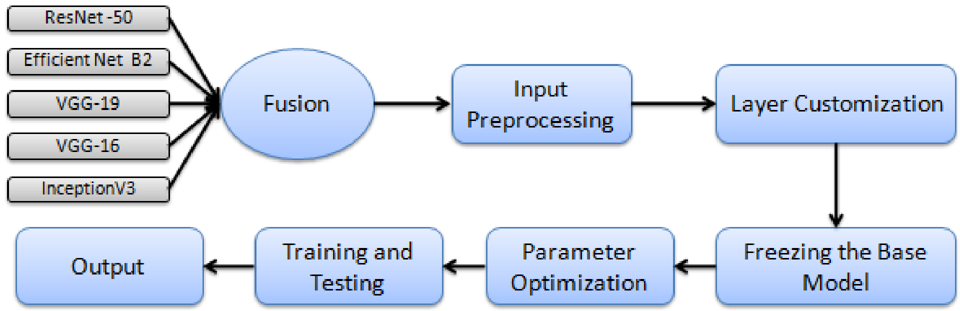

Fig. 7. Basic Architecture of proposed ensemble learning-1 model for rice leaf disease diagnosis.

TABLE V. Ensemble Learning-1 Parameter Details

Layer (type)	Output Shape	Parameter	Connected to
input-2 (InputLayer)	[(None, 224, 224, 3)]	0	[]
preprocess-vgg16 (Lambda)	(None, 224, 224, 3)	0	['input-12[0][0]']
preprocess-inception (Lambda)	(None, 224, 224, 3)	0	['input-12[0][0]']
preprocess-resnet (Lambda)	(None, 224, 224, 3)	0	['input-12[0][0]']
preprocess-vgg19 (Lambda)	(None, 224, 224, 3)	0	['input-12[0][0]']
preprocess-efficientnet (Lambda)	(None, 224, 224, 3)	0	['input-12[0][0]']
vgg16 (Functional)	(None, 512)	14714688	['preprocess-vgg16[0][0]']
inception-v3 (Functional)	(None, 2048)	21802784	['preprocess-inception[0][0]']
resnet50 (Functional)	(None, 2048)	23587712	['preprocess-resnet[0][0]']
vgg19 (Functional)	(None, 512)	20024384	['preprocess-vgg19[0][0]']
efficientnetv2-m (Functional)	(None, 1280)	53150388	['preprocess-efficientnet[0][0]']
concatenate-features (Concatenate)	(None, 6400)	0	[five-models [0][0]]
dense-1 (Dense)	(None, 1024)	6554624	['concatenate-features[0][0]']
dropout-1 (Dropout)	(None, 1024)	0	['dense-1[0][0]']
dense-2 (Dense)	(None, 512)	524800	['dropout-1[0][0]']
dropout-2 (Dropout)	(None, 512)	0	['dense-2[0][0]']
output-layer (Dense)	(None, 6)	3078	['dropout-2[0][0]']
Total params:	140362458	0	0
Trainable params:	7082502	0	0
Non-trainable params:	133279956	0	0

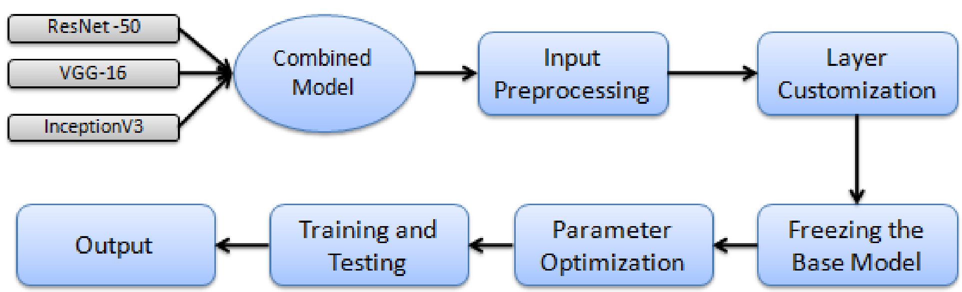

Fig. 8. Basic Architecture of proposed ensemble learning-2 model for rice leaf disease diagnosis.

each model for two datasets will be added for analysis [75], and a comparison table will be created for recently published existing work with the proposed work [76].

A. Transfer Learning Models Performance

In the proposed study, we used five transfer learning models such as VGG16, VGG19, InceptionV3, ResNet-50, and EfficientNetV2-M. The performance of these models is explained below.

1) VGG16: VGG16 is applied for the diagnosis of rice leaf disease from images. However, its structure is not easy and it needs more time due to the deep layers. We got accuracy for training, validation, and testing are 98.94%, 93.97%, and 92.70%, respectively. The training and validation loss amounts were 7.69% and 12.16%, respectively. The training, validation, testing, and loss curves for epochs 50 are shown in Fig. 10. The confusion matrix and classification report are illustrated in Fig. 11 and Table VIII, respectively. The classification report and confusion matrix are generated for 50 epochs and we used two datasets with 0.001 learning rate. To analyze and see the details we just explain for one dataset. For both datasets, we mention the accuracy in the Table XVII below. The ROC curve and Precision-recall curve for dataset-1 are illustrated in Fig.

TABLE VI. ENSEMBLE LEARNING-2 PARAMETER DETAILS

Layer (type)	Output Shape	Parameter	Connected to
input-layer-31 (Input-Layer)	(None, 224, 224,3)	0	-
preprocess-vgg16 (Lambda)	(None, 224, 224,3)	0	input-layer-31[0......]
preprocess-inceptionv3 (Lambda)	(None, 224, 224,3)	0	input-layer-31[0.....]
preprocess-resnet (Lambda)	(None, 224, 224, 3)	0	input-layer-31[0....]
vgg16 (Functional)	(None, 512)	14,714,688	preprocess-vgg16
inceptionv3 (Functional)	(None, 2048)	21,802,784	preprocess-inceptionv3
resnet50 (Functional)	(None, 2048)	23,587,712	preprocess-resnet
concatenate-features (concatenate)	(None, 4608)	0	vgg16[0][0], inceptionv3[0][0...], resnet50[0][0]
dense-1 (Dense)	(None, 1024)	4,719,616	concatenate-features
dropout-1 (Dropout)	(None, 1024)	0	dense-1[0][0]
dense-2 (Dense)	(None, 512)	524,800	dropout-1[0][0]
dropout-2 (Dropout)	(None, 512)	0	dense-2[0][0]
output-layer (Dense)	(None, 6)	3,078	dropout-2[0][0]
Total params:	65,352,678	0	0
Trainable params:	5,247,494	0	0
Non-trainable params:	60,105,184	0	0

TABLE VII. ENSEMBLE LEARNING-3 PARAMETER DETAILS

Layer (type)	Output Shape	Parameter	Connected to
input-9 (InputLayer)	[(None, 224, 224, 3)]	0	[]
input-10 (InputLayer)	[(None, 224, 224, 3)]	0	[]
sequential-3 (Sequential)	(None, 36864)	388416	['input-9[0][0]']
sequential-4 (Sequential)	(None, 25088)	14714688	['input-10[0][0]']
concatenate-2 (Concatenate)	(None, 61952)	0	['sequential-3[0][0]', 'sequential-4[0][0]']
dense (Dense)	(None, 512)	31719936	['concatenate-2[0][0]']
dropout (Dropout)	(None, 512)	0	['dense[0][0]']
dense-1 (Dense)	(None, 6)	3078	['dropout[0][0]']
Total params:	46826118	0	0
Trainable params:	32111430	0	0
Non-trainable params:	14714688	0	0

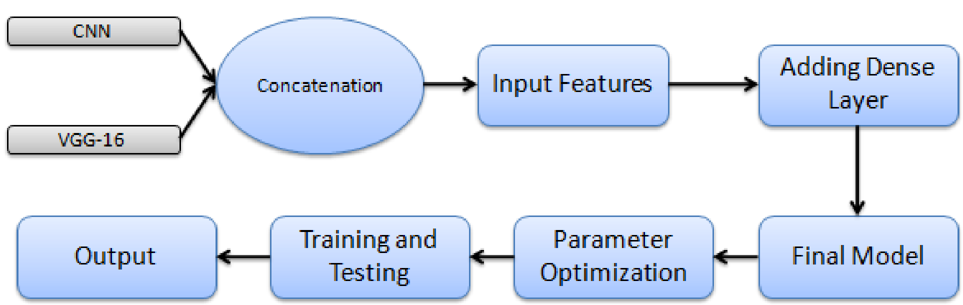

Fig. 9. Basic Architecture of proposed ensemble learning-3 model for rice leaf disease diagnosis.

12 and 13, respectively. It is generated for six class dataset. For the epochs, 50 VGG16 generated these curves.

TABLE VIII. CLASSIFICATION REPORT OF VGG16 MODEL

Class-Name	Precision	Recall	F1-Score	Support
bacterial-leaf-blight	0.96	1.00	0.98	53
brown-spot	0.93	0.86	0.89	63
healthy	0.87	0.91	0.89	44
leaf-blast	0.82	0.85	0.84	55
leaf-scald	0.98	1.00	0.99	42
narrow-brown-spot	1.00	0.97	0.98	58
accuracy	0	0	0.93	315
macro avg	0.93	0.93	0.93	315
weighted avg	0.93	0.93	0.93	315

Though the applied VGG16 model produces around 98.94% training accuracy, it also has some amount of loss. In some cases, it is misclassified and does not properly diagnose the disease. This misclassified rate is rare. However, it was not 100% perfect. But in most of the cases, the model was correctly classified. Some misclassified and correctly classified images are shown in Fig. 14 and 15, respectively. We will ignore the misclassified and correctly classified images for other used models due to vast images and page length.

2) VGG19: VGG19 is used for rice leaf disease diagnosis and classification. Though it requires more time for completion, it can classify and detect the diagnosis more correctly. It has more layers in structure, so it needs time to run. However, after applying this model we got the training, validation, and testing accuracy of 100%, 92.38%, and 92.38%, respectively. The training and validation loss amounts are 7% and 6%, respectively. The learning rate was 0.001 for 50 epochs. The accuracy and loss curve is shown in Fig. 16.

Fig. 17 and 18 describe the ROC and Precision-recall

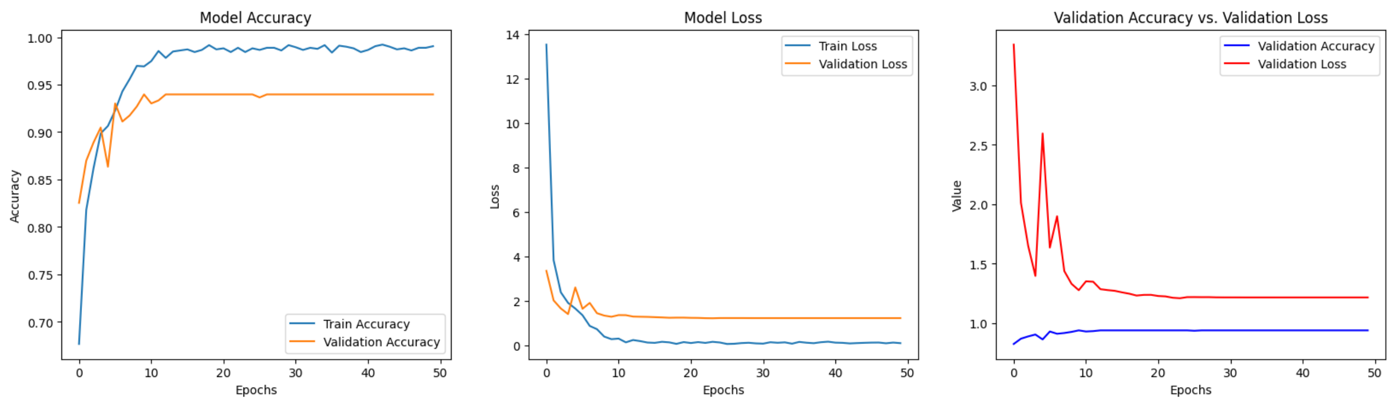

Fig. 10. The training, validation, testing and loss curve of VGG16 model.

Algorithm 3 Proposed Algorithm for Ensemble Learning-2

$ITR \leftarrow NumberofIterations$
$ACC \leftarrow Performancematrix$
$ALG \leftarrow Numberofalgorithms$
#Model Combined
#Extract features using Models combined
$E2 \leftarrow ALG$
for 1 to M **do**
  for each E2 **do**
    for each Sample in X **do**
      calculate A from X by Conv. Process
    end for
  end for
end for
#Number of Iteration
for 1 to ITR **do**
  1. Train Model with N Number of batch size
  2. Feature Extraction through hidden layers
  3. Forward propagations
  4. Backword propagation for updating weights
  5. Model validation with validation data to check overfitting
end for

Algorithm 4 Proposed Algorithm for Ensemble Learning-3

$ITR \leftarrow NumberofIterations$
$ACC \leftarrow Performancematrix$
$ALG \leftarrow Numberofalgorithms$
#Fusion Models
#Extrac features using fusion models
$E3 \leftarrow ALG$
for 1 to M **do**
  for each E3 **do**
    for each Sample in X **do**
      calculate A from X by Conv. Process
    end for
  end for
end for
#Number of Iteration
for 1 to ITR **do**
  1. Train Model with N Number of batch size
  2. Feature Extraction through hidden layers
  3. Forward propagations
  4. Backword propagation for updating weights
  5. Model validation with validation data to check overfitting
end for

curves for the VGG19 Model. Fig. 19 explains the confusion matrix of the VGG19 model. The figures are generated based on data training and validation for 50 epochs using VGG19 Transfer learning models. It is for dataset-1 and we ignore dataset-2. Table IX illustrates the confusion matrix for this model.

3) InceptionV3: Another transfer learning model InceptionV3 is applied in our study for disease diagnosis of rice leaf images. It needs more time due to the increased amount of layers. However, this model classified the images more accurately. The model training, validation, and testing accuracy

TABLE IX. Classification Report of VGG19 Model

Class-Name	Precision	Recall	F1-Score	Support
bacterial-leaf-blight	0.93	98	0.95	53
brown-spot	0.91	0.92	0.91	63
healthy	0.91	0.93	0.92	44
leaf-blast	0.85	0.84	0.84	55
leaf-scald	1.00	0.95	0.98	42
narrow-brown-spot	0.96	0.93	0.95	58
accuracy	0	0	0.92	315
macro avg	0.93	0.93	0.93	315
weighted avg	0.92	0.92	0.92	315

are 100%, 93%, and 93%, respectively. The accuracy and loss plots are shown in Fig. 22. This model epoch was 50 and the

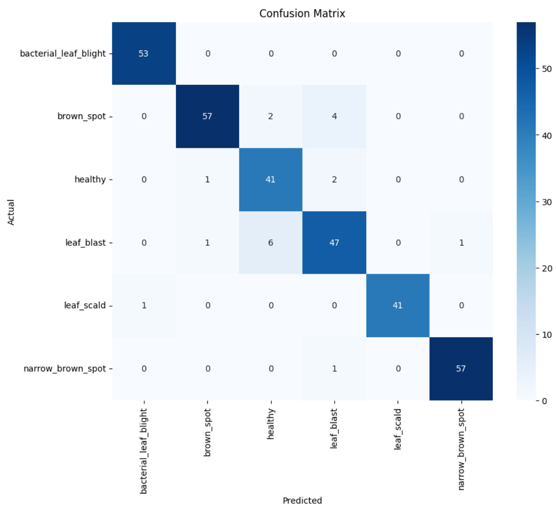

Fig. 11. Confusion matrix for VGG16 model.

curves are generated from the model based on training and validation of the dataset. We used two different datasets but only the dataset-1 curve is explained here due to the lengthy.

Fig. 20 describes the confusion matrix of the InceptionV3 model. The classification report is illustrated in Table X.

TABLE X. CLASSIFICATION REPORT OF INCEPTIONV3 MODEL

Class-Name	Precision	Recall	F1-Score	Support
bacterial-leaf-blight	1.00	98	0.99	53
brown-spot	0.93	0.87	0.90	63
healthy	0.81	0.89	0.85	44
leaf-blast	0.85	0.85	0.85	55
leaf-scald	1.00	1.00	1.00	42
narrow-brown-spot	0.98	1.00	0.99	58
accuracy	0	0	0.92	315
macro avg	0.93	0.93	0.93	315
weighted avg	0.93	0.93	0.93	315

4) *ResNet-50:* It is also a transfer learning deep layer-based model and it is suitable for image classification and disease detection. ResNet has different types of versions such as ReNet 50, ResNet 152, etc. In this study, we used ResNet-50 for Rice Leaf Disease Diagnosis and classification. In this research, this model was applied with 100% training, 96% validation, and 95/25% testing accuracy. The training loss was 5% and the validation loss was 1%. The confusion matrix of ResNet-50 is explained in Fig. 21. The classification report is shown in Table XI. The ROC and Precision-recall curve are explained in Fig. 23 and 24 for 50 epochs in dataset-1.

TABLE XI. CLASSIFICATION REPORT OF RESNET-50 MODEL

Class-Name	Precision	Recall	F1-Score	Support
bacterial-leaf-blight	0.98	0.96	0.97	53
brown-spot	0.92	0.94	0.93	63
healthy	0.98	0.91	0.94	44
leaf-blast	0.91	0.91	0.91	55
leaf-scald	0.93	1.00	0.97	42
narrow-brown-spot	1.00	1.00	1.00	58
accuracy	0	0	0.95	315
macro avg	0.95	0.95	0.95	315
weighted avg	0.95	0.95	0.95	315

5) *EfficientNetV2-M:* This is another transfer learning model. It is normally used for large data image processing and classification. This model requires more time and needs also memory due to its long hidden layer. However, it can detect and classify accurately. We used this model for two datasets and got 99.64% training accuracy, 99.56% validation accuracy, and 97.98% testing accuracy. The data loss amount for training is 2% and 4% for validation. The learning rate was 0.001. The confusion matrix of this model is described in Fig. 25 and the classification report is explained in Table XII.

TABLE XII. CLASSIFICATION REPORT OF EFFICIENTNET V2M MODEL

Class-Name	Precision	Recall	F1-Score	Support
bacterial-leaf-blight	0.93	0.98	0.95	53
brown-spot	0.91	0.92	0.91	63
healthy	0.91	0.93	0.92	44
leaf-blast	0.85	0.84	0.84	55
leaf-scald	1.00	0.95	0.98	42
narrow-brown-spot	0.96	0.93	0.95	58
accuracy	0	0	0.92	315
macro avg	0.93	0.93	0.93	315
weighted avg	0.92	0.92	0.92	315

B. Deep Learning Model Performance

To implement the proposed work, we used a deep learning model named Convolutional Neural Network (CNN). This model is suitable for image classification and detection. For rice leaf disease diagnosis and classification, we used it. CNN model architecture is easy and simple to use. After applying this to two separate datasets, we have 99.34% training accuracy, 87.62% validation accuracy, and 90% testing accuracy. The data loss was 3% for training and 5% for validation. The classification report is explained in Table XIII.

TABLE XIII. CLASSIFICATION REPORT OF CNN MODEL

Class-Name	Precision	Recall	F1-Score	Support
bacterial-leaf-blight	0.96	0.98	0.97	53
brown-spot	0.88	0.84	0.86	63
healthy	0.72	0.89	0.80	44
leaf-blast	0.79	0.67	0.73	55
leaf-scald	0.93	0.95	0.94	42
narrow-brown-spot	0.96	0.95	0.96	58
accuracy	0	0	0.88	315
macro avg	0.88	0.88	0.88	315
weighted avg	0.88	0.88	0.88	315

TABLE XIV. CLASSIFICATION REPORT OF ENSEMBLE LEARNING-1

Class-Name	Precision	Recall	F1-Score	Support
bacterial-leaf-blight	1.00	1.00	1.00	53
brown-spot	0.98	0.98	0.99	63
healthy	0.99	0.99	0.99	44
leaf-blast	1.00	1.00	1.00	55
leaf-scald	1.00	1.00	1.00	42
narrow-brown-spot	0.99	0.99	0.99	58
accuracy	0	0	0.99	315
macro avg	0.99	0.99	0.99	315
weighted avg	0.99	0.99	0.99	315

C. Ensemble Learning Performance

In this study, to reduce the data loss and increase the model accuracy, testing accuracy, and validation accuracy we used three ensemble learning. These methods were generated from

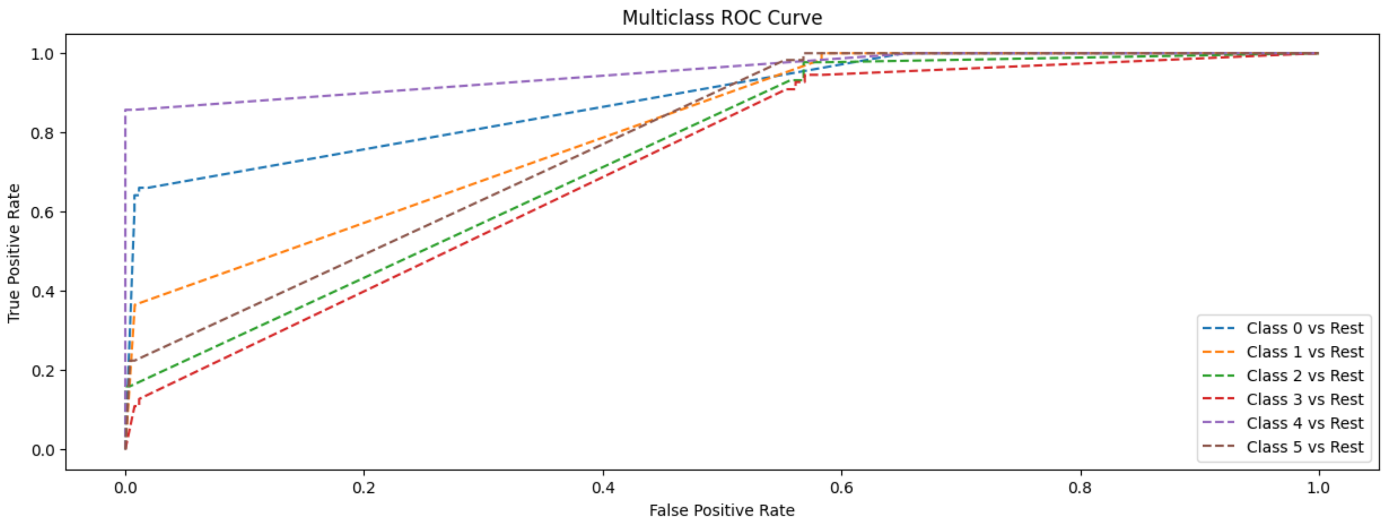

Fig. 12. ROC Curve for VGG16 model.

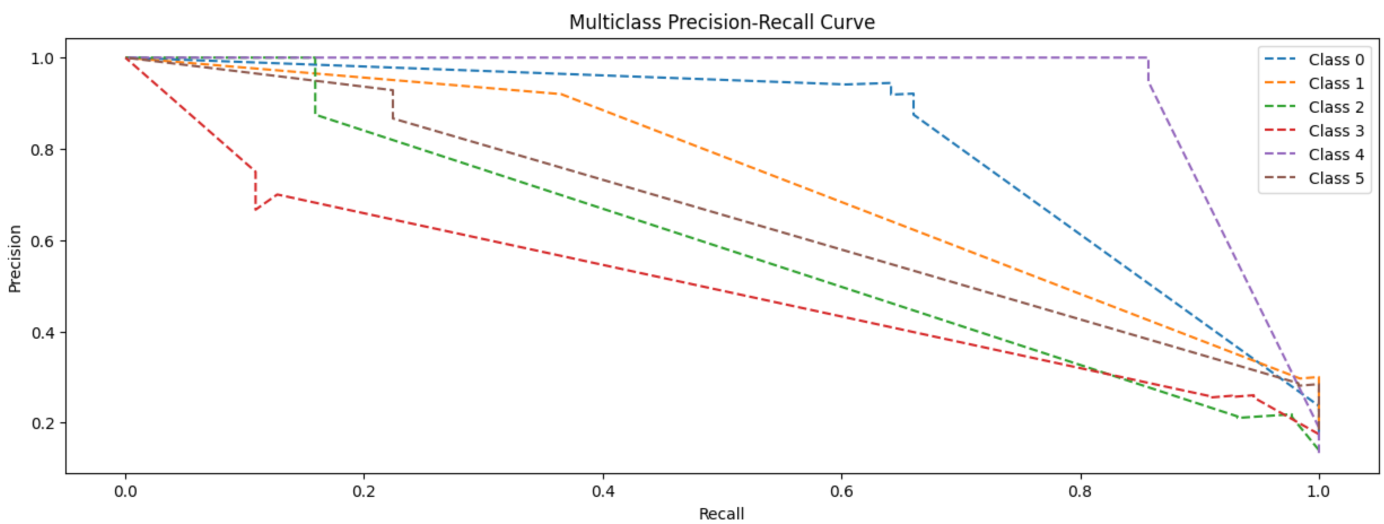

Fig. 13. Precision-recall curve for VGG16 model.

TABLE XV. CLASSIFICATION REPORT OF ENSEMBLE LEARNING-2

Class-Name	Precision	Recall	F1-Score	Support
bacterial-leaf-blight	1.00	1.00	1.00	53
brown-spot	0.99	0.99	0.99	63
healthy	0.99	0.99	0.99	44
leaf-blast	1.00	1.00	1.00	55
leaf-scald	1.00	1.00	1.00	42
narrow-brown-spot	0.99	0.99	0.99	58
accuracy	0	0	0.99	315
macro avg	0.99	0.99	0.99	315
weighted avg	0.99	0.99	0.99	315

TABLE XVI. CLASSIFICATION REPORT OF ENSEMBLE LEARNING-3

Class-Name	Precision	Recall	F1-Score	Support
bacterial-leaf-blight	1.00	0.98	0.99	53
brown-spot	0.87	0.84	0.85	63
healthy	0.72	0.86	0.78	44
leaf-blast	0.78	0.73	0.75	55
leaf-scald	0.98	0.9	0.98	42
narrow-brown-spot	0.98	0.95	0.96	58
accuracy	0	0	0.89	315
macro avg	0.89	0.89	0.89	315
weighted avg	0.89	0.89	0.89	315

deep learning and transfer learning models. We will explore the performance of these ensemble learning models and will propose a new algorithm for the work.

1) Ensemble learning-1 result: fusion of some transfer learning models created this new model for rice leaf disease diagnosis and classified them accurately. Fusion of VGG16, VGG19, InceptionV3, ResNet-50 and EfficientNetV2-M generated ensemble learning-1 named new model and we got 99.14% for training accuracy, 98.98% validation accuracy, and 99% testing accuracy. The data loss was 2% for training, 4% for validation and 3% for testing. The classification report for this model is shown in Table XIV. Fig. 26 describes the model

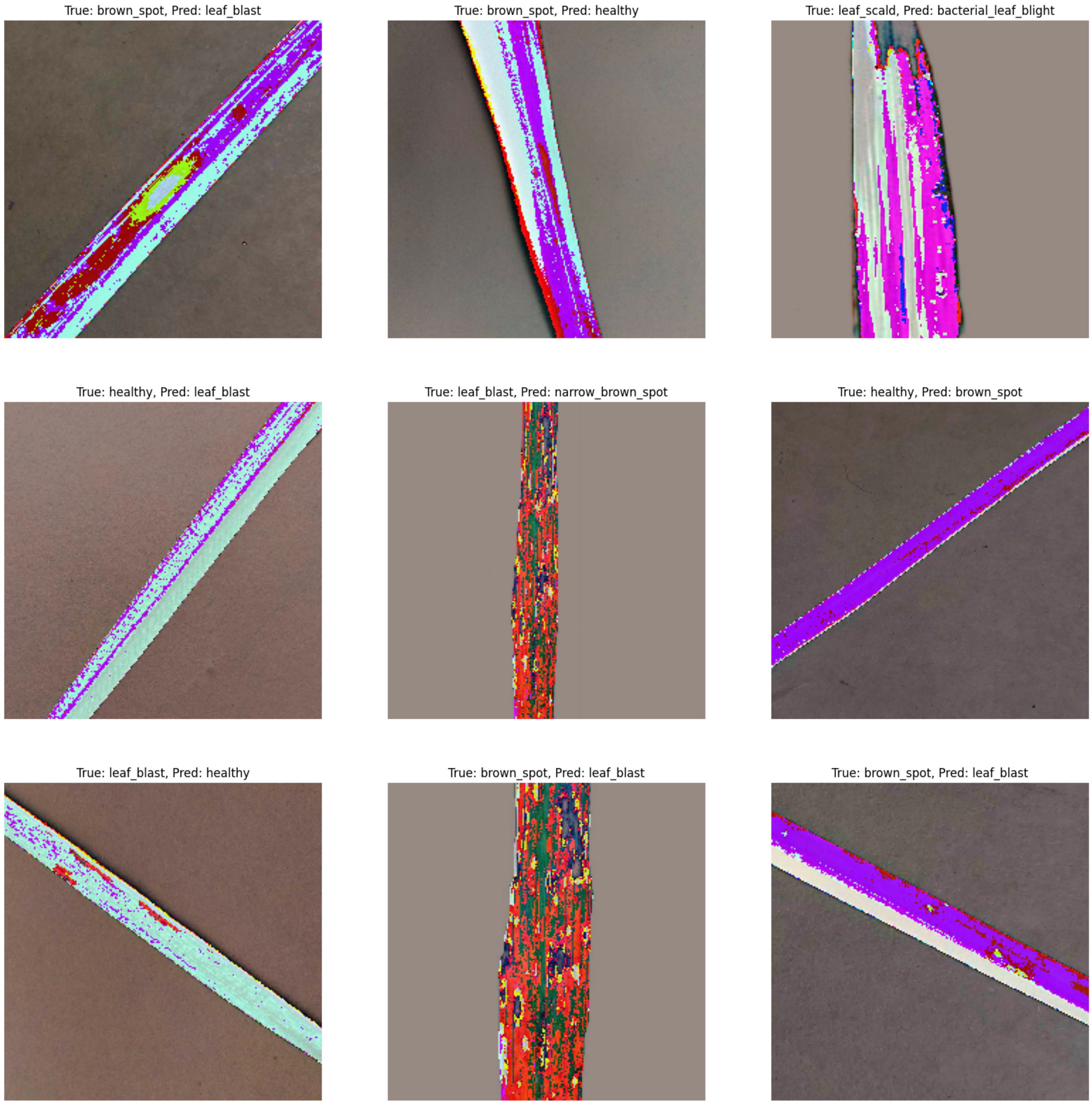

Fig. 14. Misclassified images by VGG16 model.

accuracy, loss, and validation accuracy of ensemble learning-1. This is done for dataset-1 with 50 epochs and not mentioned for dataset-2. Dataset-2 accuracy and loss are most similar to dataset-1.

We got 99.14% accuracy using this technique.

2) *Ensemble learning-2 result:* Ensemble Learning-2 is generated after combining ResNet-50, VGG16, and InceptionV3. We can say that this is the hybrid version of the transfer learning model for large-scale image classification. Though this technique needs more time for data training and validation, it works accurately. We used it to find out the disease of rice leaves from leaf images. The training accuracy was 99.78%, validation accuracy 98.83%, and testing accuracy 97.89%. The classification report is illustrated in Table XV. Confusion Matrix of Ensemble learning-2 is shown in Fig. 27. Fig. 28 represent the model accuracy, model loss, and validation accuracy-loss of ensemble learning-2. Algorithm-2 represents the proposed algorithm for ensemble learning-2

Fig. 15. Correctly classified images by VGG16 model.

in this study. We developed and used this algorithm. This may combination-variant of VGG16, ResNet-50, and InceptionV3.

3) Ensemble learning-3 result: We ensembled one deep learning model named CNN and one transfer learning model named VGG16 and generated a new model named ensemble learning-3. We may consider this new model as a variant of the deep-transfer learning model. It is suitable for detection and classification of large image datasets. We used this new variant for two datasets. But dataset-1 got 99.36% training accuracy, 90.57% validation accuracy, and 92% testing accuracy. But in dataset-2, the training accuracy was 97%, validation accuracy was 95% and testing accuracy was 90%. Fig. 29 represent the accuracy and loss of the ensemble learning-3. Algorithm 3 is the proposed algorithm for ensemble learning-3. We developed it based on this new model. Fig. 30 illustrates the confusion matrix for ensemble learning-3. Table XVI represents the classification report for ensemble learning-3.

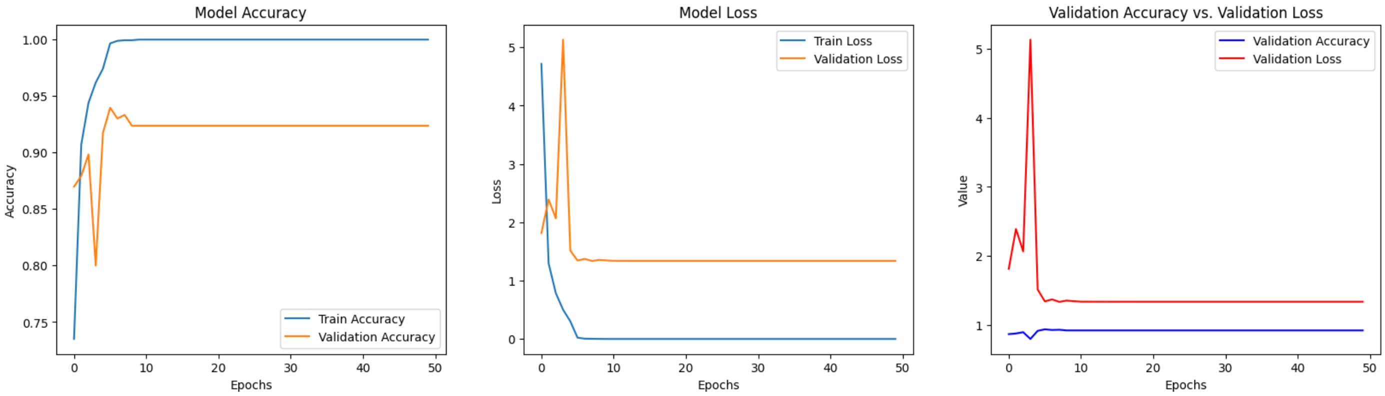

Fig. 16. Accuracy and loss curve for VGG19 model.

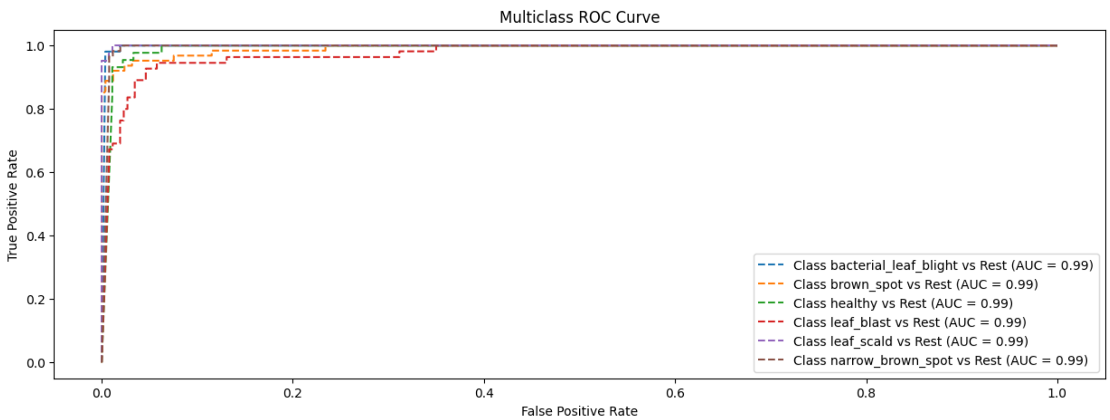

Fig. 17. ROC Curve for VGG19 model.

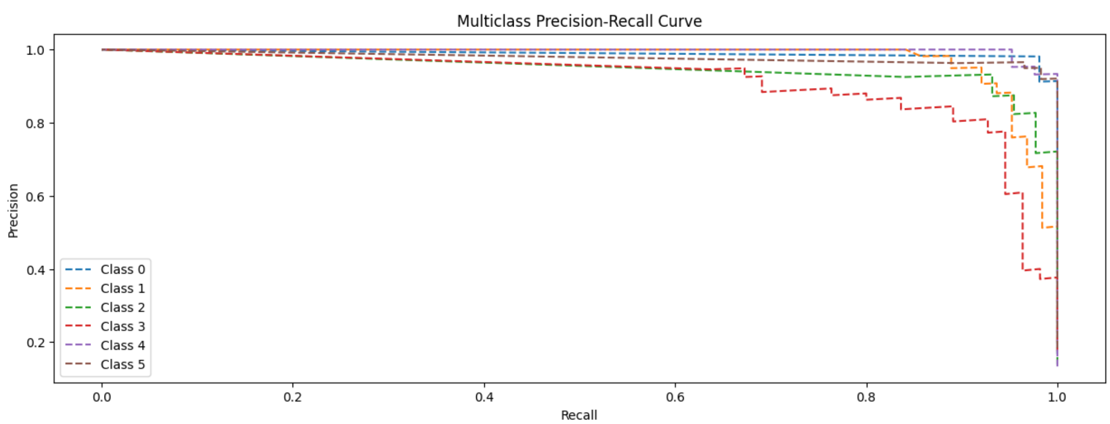

Fig. 18. Precision-recall curve for VGG19 model.

D. Explainable AI "Grad-CAM" for Ensemble Learning-1, 2 and 3

The objective of this work was to increase the interpretability and reliability of image classification using three different ensemble learning models. Combining five strong architectures (VGG16, VGG19, ResNet50, InceptionV3, and EfficientNetV2-M) and leveraging their own strengths, the first ensemble, Ensemble Learning-1, is a formidable combination. Combining the depth of ResNet50, the multi-scale feature extraction of InceptionV3, and the simplicity of VGG16, the second model, Ensemble Learning-2, streamlines these three models. To balance task-specific learning with general feature extraction, the third model, Ensemble Learning-3, combines two deep learning models: CNN and VGG16. The image classification tasks were used to train each ensemble model, and Explainable AI (XAI) techniques like Grad-CAM were

TABLE XVII. Comparative Analysis of Used Model in Dataset-1 and 2

Algorithm	Dataset-1			Dataset-2		
	train	vali:	test	train	vali:	test
VGG16	98.94%	93.97%	92.70%	97.94%	96.78%	95%
VGG19	100%	92.38%	92.38%	99.99%	97%	96%
InceptionV3	100%	93%	93%	92%	95%	94%
ResNet-50	100%	96%	95.25%	99.99%	97%	98%
EfficienNet	99.64%	99.56%	97.98%	98.98%	98.90%	96.98%
CNN	99.34%	87.62%	90%	96.87%	93.78%	94.67%
Ensemble 1	99.14%	98.98%	99%	97.98%	97%	97%
Ensemble 2	99.78%	98.83%	97.89%	96.99%	99%	96%
Ensemble 3	99.36%	90.57%	92%	98.99%	98%	99.98%

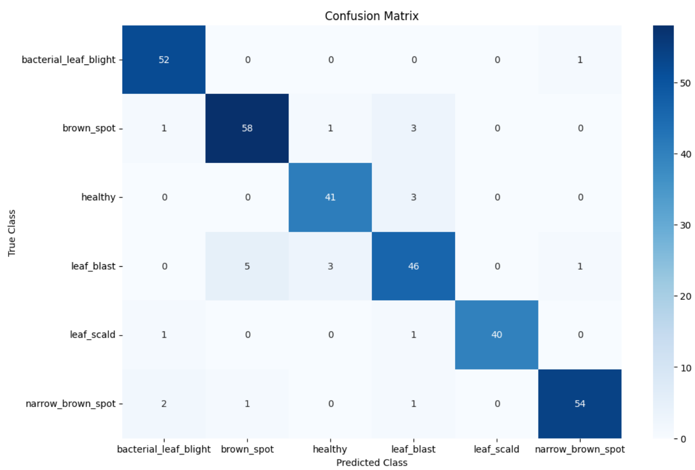

Fig. 19. Confusion matrix for VGG19 model.

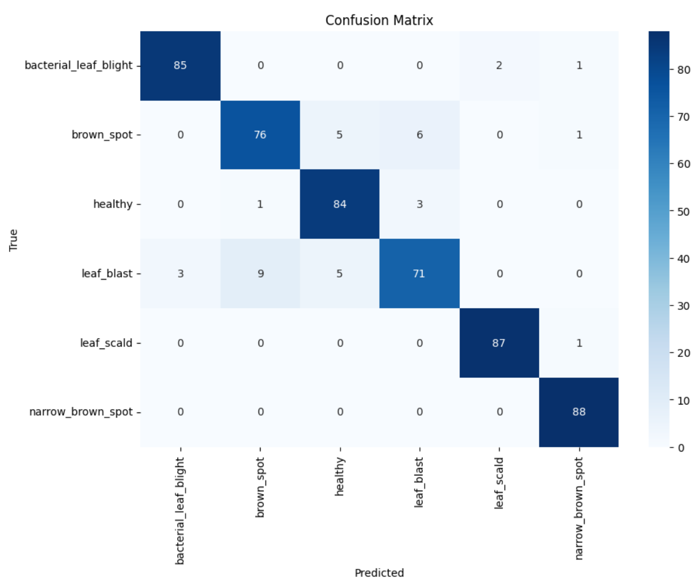

Fig. 20. Confusion matrix for inceptionV3 model.

used to assess interpretability [77], [78]. We evaluated a picture from the "Brown-spot" class to assess the model. Heat maps showing how the model recognized the disease were created using Grad-CAM. The models were able to identify the "Brown-spot" in the input image in every instance, demonstrating the effectiveness of combining XAI and ensemble

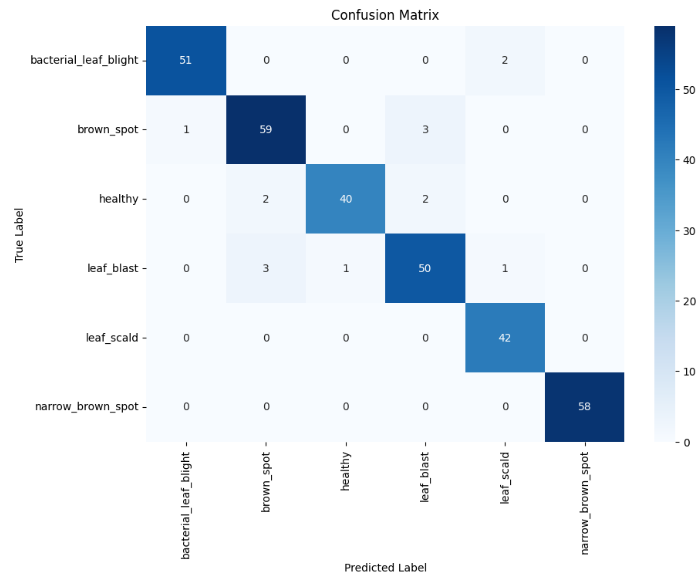

Fig. 21. Confusion matrix for ResNet-50 model.

learning [79]. The XAI-based assessments for models 1, 2, and 3 of ensemble learning are shown in Fig. 31, 32, and 33, respectively. The model predictions perform better and are more transparent using this technique.

E. Discussion

The integration of deep learning and transfer learning models presents a highly efficient approach for the practical diagnosis and categorization of rice leaf disease [80], [49]. Accurately detecting illnesses in rice leaves is critical for crop health and yield maintenance [81], [82]. Models like as VGG16, VGG19, ResNet50, InceptionV3, and EfficientNetV2-M do this [83]. Ensemble Learning-1 demonstrated an accuracy of 99.78% in classification as a result of the integration of these models into ensemble learning structures [84], [85]. Through early disease detection and substantial crop loss prevention, this technique makes it possible to process rice leaf pictures in an effective manner [86], [87].

Moreover, the diagnosis process gains interpretability with the incorporation of Explainable AI (XAI) tools such as Grad-CAM [88]. XAI makes it easier to see which areas of the rice leaf the model concentrates on in order to identify diseases, giving agronomists and farmers more reliable and transparent information [89]. For practical application in agriculture,

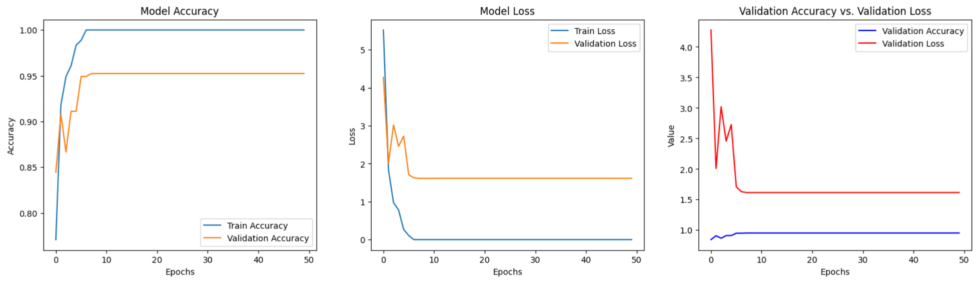

Fig. 22. Accuracy and loss curve for InceptionV3 model.

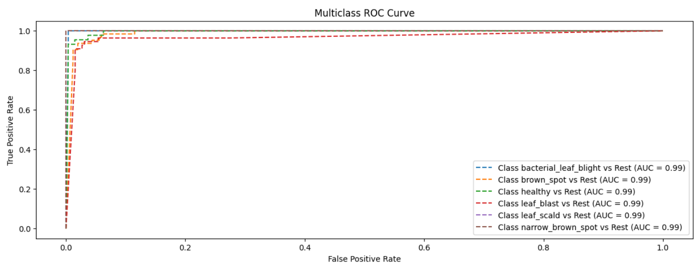

Fig. 23. ROC Curve for ResNet-50 model.

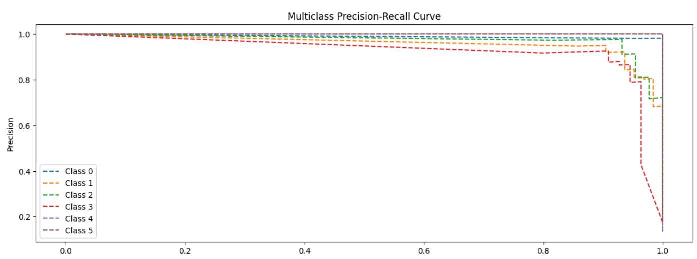

Fig. 24. Precision-recall curve for ResNet-50 model.

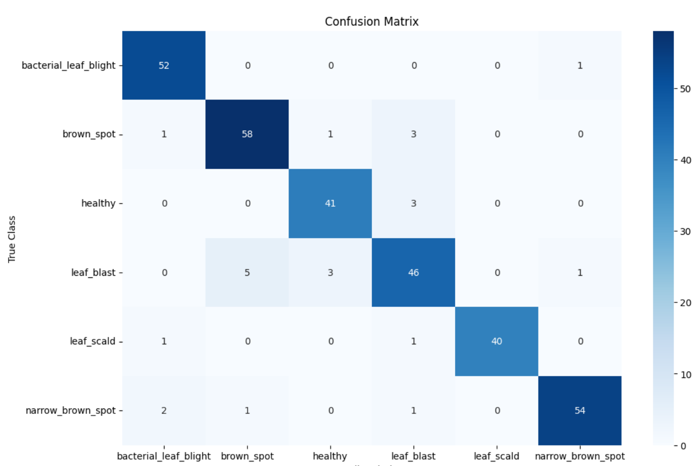

Fig. 25. Confusion matrix for EfficientNetV2-M.

where decision-making depends on the capacity to comprehend the reasoning behind a model's predictions, this transparency is crucial [90]. Rice producers can implement preventive measures earlier and improve crop management and agricultural sustainability by utilizing these AI-driven techniques [91].

Individual models like ResNet50, VGG19, VGG16, and InceptionV3 demonstrated their strong capacity to classify diseases correctly, achieving perfect accuracy (100%), when comparing the performance of individual and ensemble learning models for rice leaf disease detection [92]. Nonetheless, the accuracy of 99.78% was slightly lower but still outstanding when using ensemble learning models, especially Ensemble Learning-1 (which combined VGG16, VGG19, ResNet50, InceptionV3, and EfficientNetV2-M). By utilizing numerous architectures, ensemble models provide the advantage of lowering data loss and enhancing overall robustness despite the slight decrease[23]. The results of the ensembles indicate that adding more diverse models leads to higher generalization and performance, as Ensemble Learning-1 outperformed Ensemble Learning-2 (VGG16, InceptionV3, ResNet50) and Ensemble Learning-3 (VGG16 and CNN).

Furthermore, the incorporation of Explainable AI (XAI) methods, like Grad-CAM, significantly increased the value by offering visual insights into the models' disease detection processes and improving forecast transparency [86]. This is especially significant for agricultural applications because practical usage of the model depends on the user's ability to understand its decisions. As a result, while individual models are very accurate, ensemble learning with XAI balances high accuracy, interpretability, and minimal data loss, making it a more useful and trustworthy method for diagnosing rice leaf disease [93]. To see the comparative analysis of proposed work with other researchers, see Table I; where we got the highest accuracy than other recently published papers. Table XVII represents the comparison of used methods for dataset-1 and dataset-2. The biases of training, validation, and testing accuracy are different in dataset-1 and 2 due to the image characteristics or features.

V. Conclusion and Future Work

This study's findings demonstrate the value of integrating deep learning and transfer learning models to accurately diagnose and classify illnesses affecting rice leaves. Combining different architectures improves accuracy and reliability. The ensemble learning models performed well, with Ensemble Learning attaining the maximum accuracy of 99.78%. Several models, including ResNet50, VGG19, VGG16, and InceptionV3, demonstrated 100% accuracy, demonstrating their efficacy in the identification of diseases. This strategy is useful for

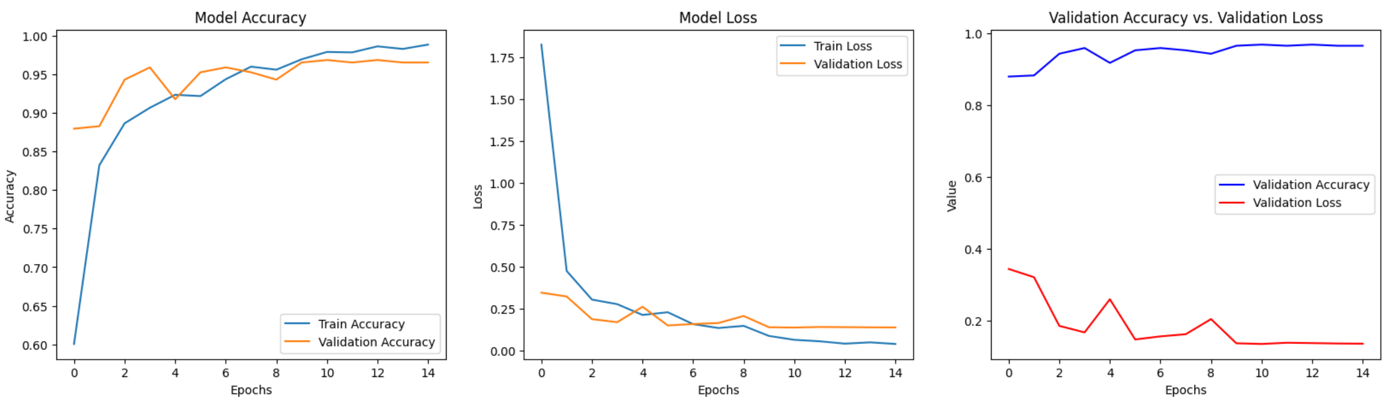

Fig. 26. Model accuracy, loss and validation for ensemble Learning-1.

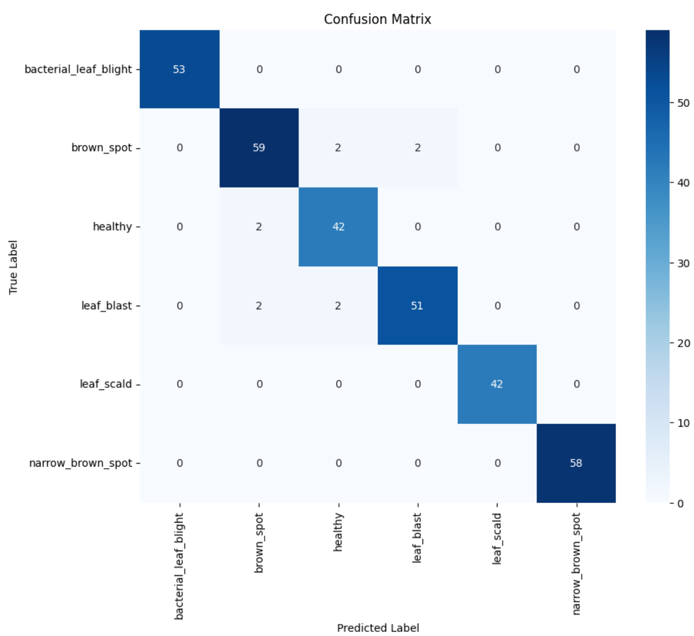

Fig. 27. Confusion matrix for ensemble Learning-2.

real-world applications in agricultural disease control since Explainable AI (XAI) approaches like Grad-CAM also increase the predictability and transparency of the models. We intend to improve performance even further by refining the suggested ensemble learning approach in further work. Furthermore, we hope to investigate the possibility of incorporating real-time data for ongoing observation and early disease diagnosis, as well as to expand this methodology to other crop diseases. Including more extensive and varied datasets may also contribute to improving the models' resilience. The ultimate objective is to create an all-inclusive, field-deployable automated system for diagnosing crop diseases in order to promote sustainable agriculture.

Data Availability

The used datasets are open-access and referenced in this manuscript.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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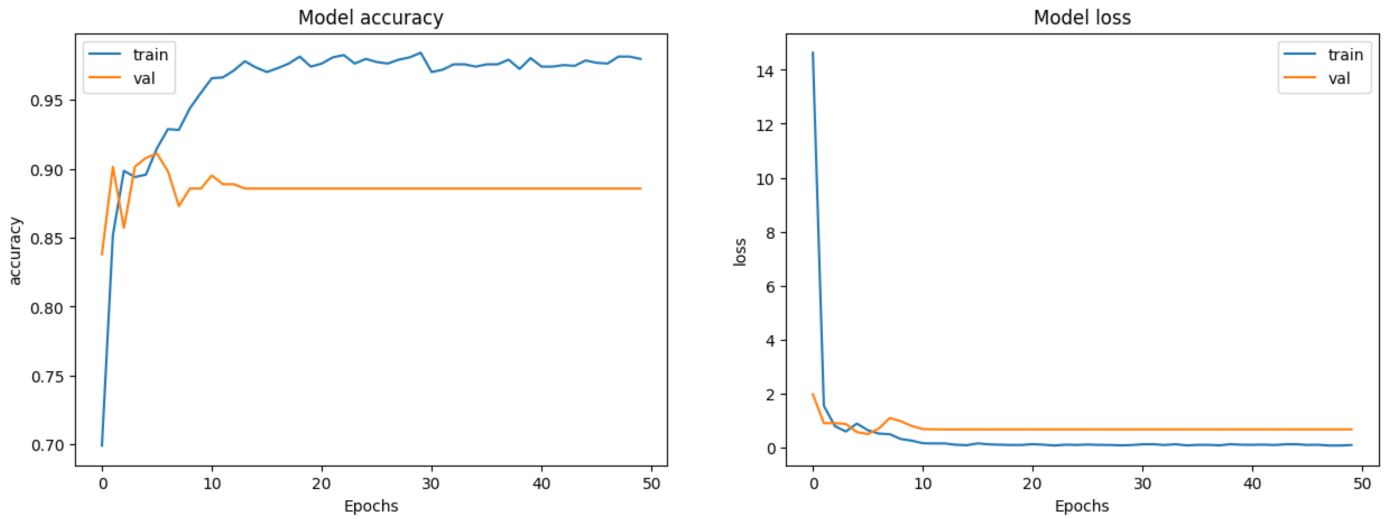

Fig. 28. Model accuracy and loss curve for ensemble Learning-2.

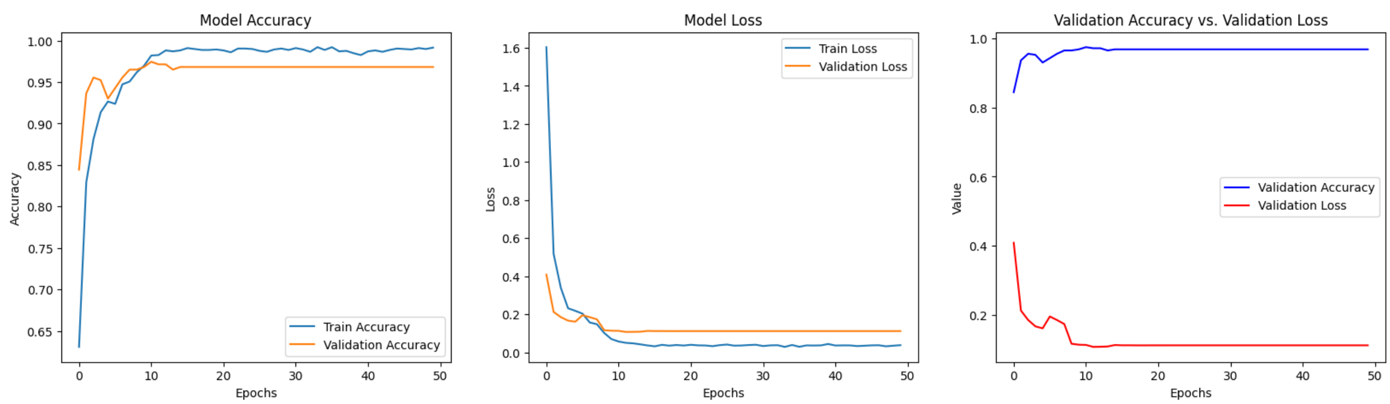

Fig. 29. Accuracy, loss and validation plot for ensemble Learning-3.

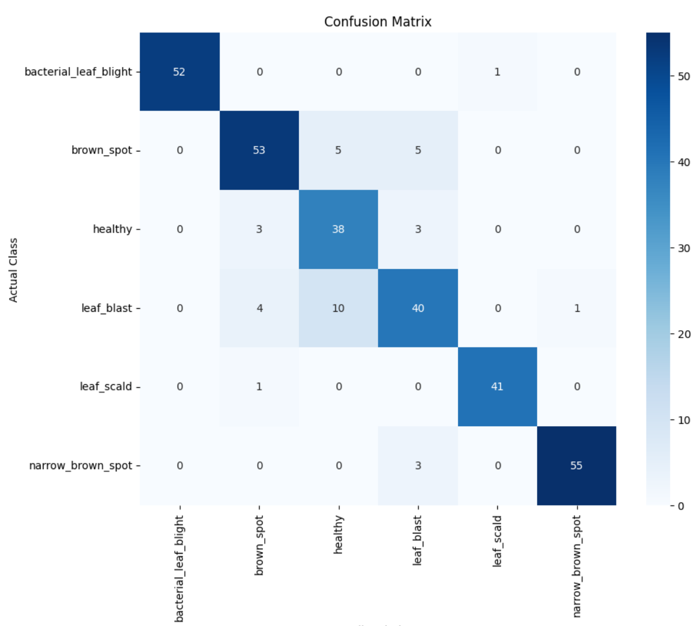

Fig. 30. Confusion matrix for ensemble Learning-3.

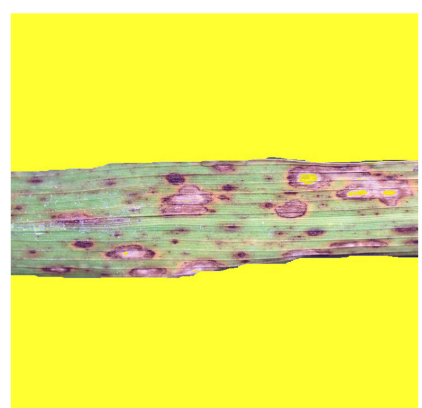

Fig. 31. Explainable AI tested image 1 for ensemble learning-2.

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Fig. 32. Explainable AI tested image 2 for ensemble Learning-2.

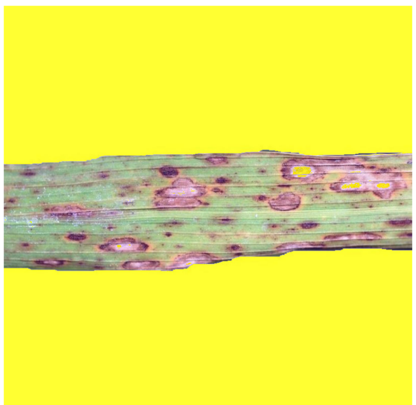

Fig. 33. Explainable AI tested image 3 for ensemble Learning-2.

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