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RESEARCH ARTICLE

Comparative Analysis of Transfer Learning, LeafNet, and Modified LeafNet Models for Accurate Rice Leaf Diseases Classification

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ABSTRACT Early detection of plant diseases is essential for effective crop disease management to prevent yield loss. In this study, we developed a methodology for classifying diseases in rice leaves using four deep learning models and a dataset with 2658 images of healthy and diseased rice leaves. Four models, namely LeafNet, Modified LeafNet, MobileNetV2, and Xception, were compared. The Modified LeafNet model involved updates to LeafNet's architectural parameters, whereas transfer learning techniques were applied to the MobileNetV2 and Xception pretrained models. The optimal hyperparameters for training were determined by considering several factors such as batch size, data augmentation, learning rate, and optimizers. The Modified LeafNet model achieved the highest accuracies of 97.44% and 87.76% for the validation and testing datasets, respectively. In comparison, LeafNet obtained 88.92% and 71.84%, Xception obtained 88.64% and 71.95%, and MobileNetV2 obtained 82.10% and 67.68% for the validation and test accuracies on the same datasets, respectively. This study contributes to the development of automated disease classification systems for rice leaves, thereby leading to increased agricultural productivity and sustainability.

INDEX TERMS Deep learning, convolutional neural networks, transfer learning, image classification.

I. INTRODUCTION

Agriculture represents a significant development in the evolution of moderately advanced human civilization. This allows urban living by enabling individuals to generate surplus food through crop cultivation. Large-scale agricultural operations are required for crop production and human consumption. However, crops have repeatedly been decimated by diseases, which have had a profound negative impact on agricultural productivity and the financial performance of the sector [1]. Additionally, tropical and temperate regions of the world have been adversely affected by a range of environmental factors and abrupt changes in climate and atmosphere. Consequently, these environmental factors may have considerable impacts on crop production [2], [3].

Early detection of plant diseases is crucial for healthy food production. Plant disease identification plays a significant role in normal plant ecology research. Owing to their subtle features, farmers sometimes struggle to precisely diagnose signs of plant diseases [4]. According to the report published by the Foreign Agricultural Service of the United States Department of Agriculture (USDA), rice was cultivated over a total area of 163.99 million hectares in the years 2020 and 2021, with an average yield of 4.57 metric tons per hectare and a total production of 502.10 million metric tons. However, there was a 2.16% decrease in production compared to previous years [5]. These statistics represent a decrease in the production of rice fields compared to previous years, with several different diseases considered to be among the factors affecting the growth and productivity of rice crops. If not effectively controlled, these diseases, which can be caused by pathogens such as bacteria, fungi, and viruses, can lead to substantial losses for farmers [6]. Some common rice

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diseases include brown spot, hispa and leaf blast [7]. Effective disease management strategies, such as crop rotation, the use of resistant varieties, and timely application of fungicides, can help to minimize the impact of these diseases on rice production [8].

Chemical pesticides are one of the methods used to control rice diseases [9]. They are applied to paddy fields to kill or prevent the growth of pathogens such as bacteria, fungi, and viruses that cause diseases. Depending on the type and stage of the disease, these chemicals can be applied as foliar sprays, seed treatments, or soil drenches [8]. Chemical pesticides can be effective in controlling rice diseases, but they also have potential negative impacts on the environment and human health [10].

The early identification and diagnosis of rice diseases are crucial for effective disease management. By identifying the disease and its severity at an early stage, farmers can take timely action to control its spread and minimize yield losses. Early diagnosis also allows the use of more targeted and less hazardous control methods, such as cultural practices or the application of less toxic pesticides. Rapid and accurate diagnosis can be achieved through a combination of visual inspection, laboratory tests, and diagnostic tools, such as molecular assays [11]. Some modern diagnostic tools, such as remote sensing and machine learning-based algorithms, can also aid in the early detection of rice diseases [12].

Convolutional neural networks (CNNs) can perform convolutional operations on input data, providing a robust system architecture capable of addressing complex problems. A CNN model consists of an input layer, alternating convolutional and pooling layers, fully-connected layers, and an output layer [13]. By exploiting robust autonomous learning and feature extraction capabilities, this model can automatically extract image features for classification and identification [13]. Feature extraction occurs within the convolutional layers, delivering the output to the fully- connected layer for classification. CNN is one of the most widely used deep learning architectures as it offers substantial model capacity and the ability to handle complex information [13], [14].

In recent years, computer vision techniques have been commonly used in detection and classification problems [15]. These techniques involve the use of image processing algorithms to analyze digital images of plants and identify signs of disease [16]. Computer vision can be used to detect diseases at an early stage before symptoms are visible to the naked eye. Some common computer vision techniques used in plant disease detection include the following:

Image Segmentation is a process of dividing the image into different regions or segments, each having similar characteristics. This can be used to identify and isolate specific parts of the plant, such as leaves, for further analysis [17].

Feature Extraction is the process of extracting relevant information from images, such as texture, color, and shape. These features can then be used to classify images as healthy or diseased [18].

Machine Learning (ML) algorithms, such as support vector machines, can be used to classify images based on extracted features. These algorithms can be trained on a dataset of labelled images of healthy and diseased plants and then used to classify new images of plants [19].

A method known as transfer learning in deep learning uses CNNs trained for a specific task as the foundation for models to be used for other relevant tasks. The weights can be initialized using a network pretrained on large labelled datasets, such as public image datasets, which can save time and effort compared to starting from scratch and initializing the weights arbitrarily. It is recommended to use models that have been pretrained on a substantial dataset, such as ImageNet, before being retrained for tasks defined on the target dataset. The VGGNet, ResNet, Inception V4, DenseNets, and SqueezeNet models, which were developed to categorize plant diseases, rely heavily on transfer learning [20], [21].

Our study focused on the disease classification of rice leaves. We utilized the LeafNet model, which is a CNN-based network proposed by Barré et al. [22], as our base model. LeafNet is a convolutional neural network-based model used to analyze images of plant leaves and classify them into different species.

In this study, we modified the LeafNet model to enhance its ability to classify rice diseases using rice leaf images. The model under study was compared based on important parameters such as batch size, learning rate, precision, recall, F1-score and accuracy. Two optimizers, Adaptive Moment Estimation (Adam) and Root Mean Square Propagation (RMSprop), were used for error minimization. Two pretrained models were selected for comparison. The first model was Xception, which was considered a heavily complex model owing to its size and architecture. The second model was MobileNetV2, which was considered a relatively lightweight model compared to Xception. Transfer Learning was applied to both models to test and examine their abilities and performance using only rice leaf images. The pretrained models had been trained on the ImageNet dataset, which contains a large number of general images. Transfer learning was implemented in this study by employing the pretrained models and freezing their convolutional layers. The fully-connected layers were then trained using the rice leaf image dataset. The hyperparameters were tuned and the performance of the models was evaluated.

The key contributions of this paper are as follows:

(**a**) **Modified LeafNet model**: A convolutional neural network capable of classifying rice leaf diseases from images. The major characteristic of this model is its higher classification accuracy (i.e., validation and testing) compared to that of the LeafNet model on the rice leaf disease dataset.

(**b**) **Transfer Learning**: We employed state-of-the-art models that demonstrated superior performance in classification tasks. In this study, we utilized Xception and MobileNetV2, applying transfer learning to these models by freezing their convolutional layers, using pretrained weights for these frozen layers, and training the fully-connected layers exclusively for the classification of rice leaf diseases.

(**c**)**Explainable Artificial Intelligence (AI):** The intermediate class activation map technique was used to visualize the pixels that most influenced the model's predictions for specific classes.

The remainder of this paper is organized as follows: Section II presents the background study; Section III outlines the data preprocessing methods and introduces the proposed framework; Section IV delves into the evaluation metrics used to assess the experiments conducted; Section V discusses the experimental results and their implications; and Section VI concludes the study and suggests potential directions for future work.

II. RELATED WORKS

With the evolution of artificial intelligence (AI) and deep learning (DL), solutions based on specially designed neural networks have become more accurate and reliable [23]. Neural networks, particularly CNNs, have been used in various applications involving disease diagnosis [24], [25], [26]. The use of computer vision techniques to categorize rice leaf diseases has gained popularity in recent years.

Rice is a widely cultivated crop that serves as a staple food in many parts of the world. Rice leaves are often affected by various diseases and pests that can damage large quantities of rice crops. Recently, finding solutions to improve production in the agricultural industry has become a major concern. Given their exceptional capabilities in extracting and learning image features, CNN models can be used as effective image classifiers to identify plant types and detect diseases.

Bashir et al. [27] presented a study focusing on the classification of rice diseases, specifically brown spot, false smuts and bacterial leaf blight. They used a support vector machine (SVM) classifier and reported 94.16% accuracy, 91.6% recall, and 90.9% precision based on a dataset of 400 images obtained from several sources.

According to Hossain et al. [28], recognizing rice leaf diseases is critical for sustaining the global rice demand for a large population. Nevertheless, rice leaf disease recognition is limited by factors related to the image surroundings and the conditions under which the images are captured. They suggested a unique CNN-based approach to identify diseases in rice leaves by lowering the network parameters. Numerous CNN-based models have been trained to recognize five prevalent rice leaf diseases, using a unique dataset of 4199 images of rice leaves. Prasad et al. [29] suggested the use of an InceptionResNetV2 model in conjunction with a transfer learning strategy to identify diseases in rice leaf images. The dataset was constructed from 5200 images and included three categories of diseases: leaf blast, brown spot, and bacterial blight. Furthermore, Ghosal and Sarkar [30] stated that owing to their lack of experience, farmers find it extremely challenging to identify rice diseases visually. Therefore, they used CNN models for automatic image recognition to solve such issues through deep learning. Since there was no large dataset of rice leaf diseases, they created a limited amount of data and used transfer learning with a deep learning model. The proposed CNN architecture based on the VGG-16 architecture was trained and evaluated using data gathered from the Internet and rice fields. According to Hossain et al. [28], the CNN-based model achieved the best validation accuracy of 97.35% and a training accuracy of 99.78%. The effectiveness of the suggested model was assessed using a collection of separate images of rice leaf disease, with the best accuracy of 97.82% and an area under the curve (AUC) of 0.99. The model proposed by Prasad et al. [29], which was an InceptionResNetV2-based model, achieved a reasonable accuracy of 95.67%. Finally, the VGG16-based model developed by Ghosal and Sarkar [30] achieved an accuracy of 92.46%.

Patil et al. [31] conducted a study in which they utilized the Faster R-CNN approach for the detection of infected regions of rice leaf. Their results showed that they achieved an accuracy of 96.43% using EfficientNet-B0 as the backbone model.

A study was done by Barré et al. [22] to develop an automatic system for identifying plant species using images of leaves. The authors proposed a CNN-based system called LeafNet. The authors used a dataset of leaf images from different plant species to train and test the system. They evaluated the performance of the system using different metrics, such as accuracy, precision, and recall. The results showed that the system achieved high accuracy in identifying different plant species and outperformed traditional machine learning methods.

Similarly, recent studies that utilized the same dataset as ours have employed various approaches. For instance, Zhang [32] proposed a feature extraction methodology for classifying rice leaf diseases, namely healthy, brown spot, hispa, and leaf blast, using an attention-based technique. They utilized a weakly supervised data augmentation network (WS-DAN) and obtained a testing accuracy of 87.60%. Putra et al. [33] proposed a novel methodology known as Hierarchical Transfer Learning (HTL), wherein they utilized pretrained models such as DenseNet, XceptionNet and MobileNet for feature extraction. Subsequently, the models were assembled and fused. The authors employed the MK-II dataset, which consisted of brown spot, hispa, and leaf blast, and achieved a validation accuracy of 91%. On the other hand, Verma et al. [34] proposed a novel approach using a lightweight CNN model for the classification of corn, rice, and wheat diseases. Furthermore, they conducted a comparative analysis with state-of-the-art pretrained models that are commonly used for image classification tasks. However, for the rice classification dataset, the proposed lightweight CNN model achieved an accuracy of 73.02% for four distinct classes: brown spot, hispa, leaf blast and healthy. Additionally, a similar study by Bhowmik et al. [35] proposed an ensemble learning network with VGG16 and the Light GBM model. They used four classes, which were brown spot, healthy, hispa and leaf blast, and achieved an accuracy of 96.49%.

III. PROPOSED FRAMEWORK

The methodology adopted for the classification of diseases from rice leaf images is shown in Fig. 1. The primary aim of this study is to classify rice leaf diseases into four classes: brown spot, leaf blast, hispa and healthy. The main stages of our methodology are dataset preparation, data preprocessing (which involves augmentation of the leaf images in the dataset), training of the model, and model evaluation based on the classification of diseases in the given images.

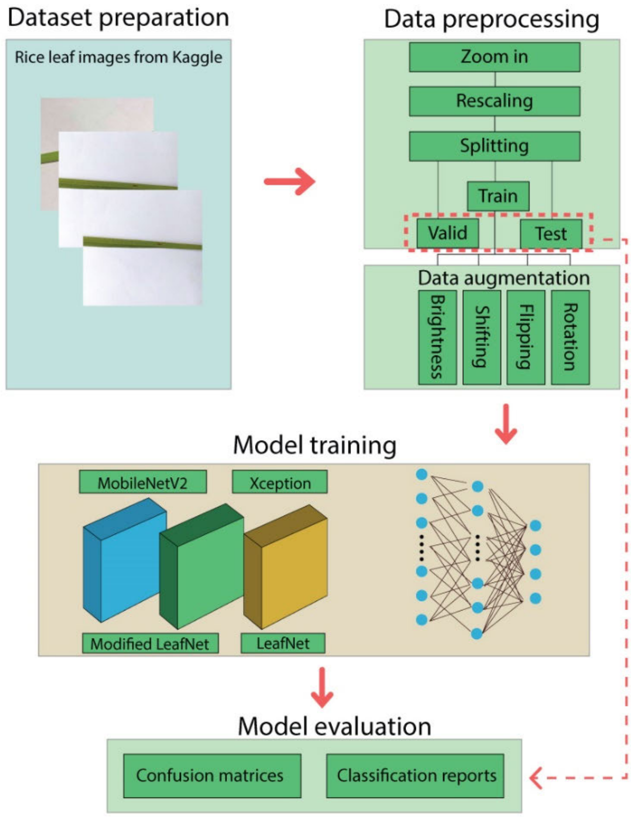


FIGURE 1. Overview of the methodology used in this study.

A. DATASET PREPARATION

In this study, rice leaf images were used to classify rice leaf diseases. The dataset was categorized into four classes: brown spot, leaf blast, hispa and healthy. A total of 2658 labelled images were sourced from publicly accessible datasets available on the Kaggle platform [36], [37]. The collected dataset was further split into training, validation and testing sets.

The training and validation sets were used during model training, and the testing set was kept unseen for the model. Model evaluation was performed on the validation and testing sets. The details of the dataset used in this study are listed in Table 1. Four sample images, one for each class of the dataset, are shown in Fig. 2. Furthermore, the leaf images were in JPEG format when retrieved from the Kaggle platform.

TABLE 1. Data splitting details.

Classes	Train	Valid	Test	Total
Brown Spot	360	90	86	536
Hispa	512	128	113	753
Leaf Blast	361	91	151	603
Healthy	499	125	142	766

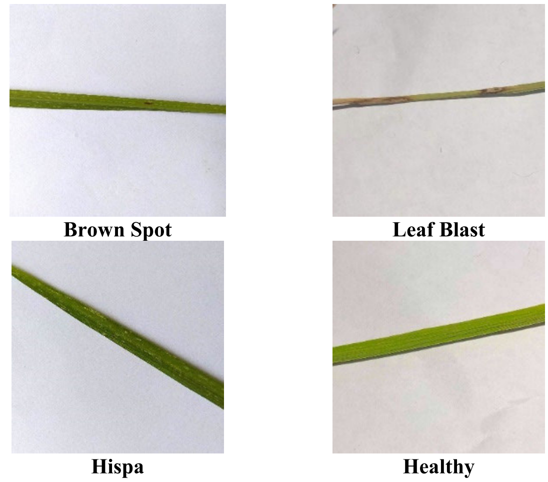


FIGURE 2. Samples of images obtained from the Kaggle platform.

B. DATA PREPROCESSING

The images in the dataset were initially zoomed in to enhance the visibility of spots or infected regions on the rice leaves. In Fig. 3, images from the original dataset are shown along with their zoomed-in versions. Subsequently, these preprocessed images were rescaled and resized. For rescaling, the pixel values of the images were multiplied by a factor of $1/255$, ensuring that each pixel value fell within the range of 0 to 1. This was primarily performed to normalize the dataset to the same scale values.

We recognize the significance of addressing real-world challenges in the detection of rice leaf diseases. One of the anticipated challenges is the diversity of imaging conditions, which can introduce variability and potential artifacts into images. To overcome this, we employed data augmentation techniques to enhance the robustness and real-world applicability of our models. This was done by applying various augmentation techniques to the training images, such as rotating by 30°, horizontal and vertical flipping, adjusting the height and width within a range of 80% to 120%, and modifying the brightness within a range of 80% to 120%.

We conducted rigorous validation and testing to assess the ability of the models to handle potential artifacts or alterations introduced during the preprocessing phase. These preprocessing techniques can be incorporated into the system to facilitate automated processing of real-world unprocessed images before their utilization in disease classification.

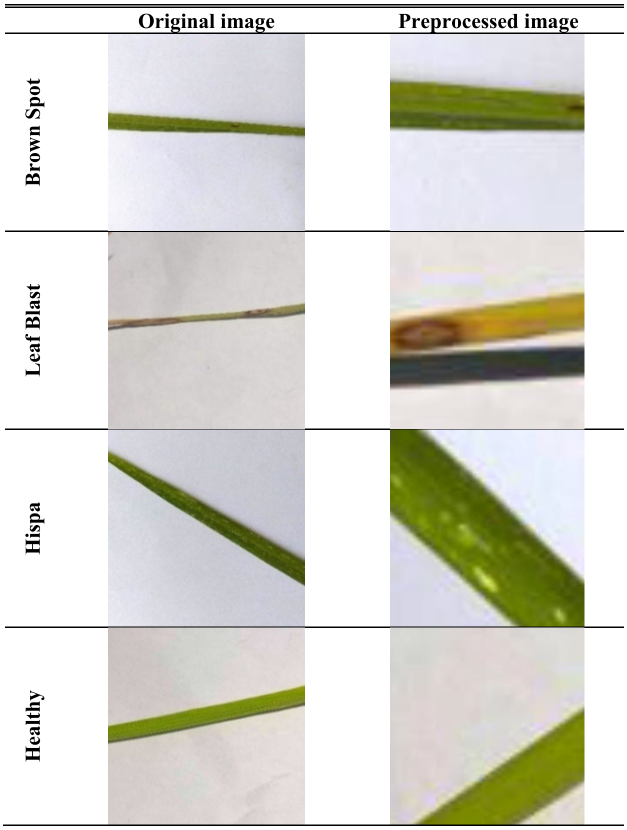


FIGURE 3. Examples of original (left) and preprocessed (right) images used in this study.

C. LEAFNET MODEL

In this study, LeafNet [22] was used as the base model. The LeafNet model contained 11 convolutional layers and three fully-connected layers. The architecture of the LeafNet model is shown in Fig. 4. This model was trained with an input size of 256×256, a max pooling filter of 3×3, and varying kernel filters in each convolutional layer. The first two layers used a filter shape of 9×9 and the next two layers used a filter shape of 5×5. The remaining layers had the same kernel filter shape of 3×3. The fully-connected layers of the model were composed of two dense layers, each with 2048 neurons, and an output layer that employed a Softmax activation function. However, the output layer was mapped to four classes instead of 185 classes for our model.

D. MODIFIED LEAFNET MODEL

To improve the classification of rice leaf diseases, we proposed a modified version of the LeafNet model. The model summary and parameters of each layer in the Modified LeafNet model are listed in Table 2. The architecture of the proposed Modified LeafNet model is illustrated in Fig. 5.

To enhance the performance of the model, we made certain changes to the original LeafNet model architecture. Specifically, we maintained a consistent kernel size of 3×3 across all convolutional layers, as opposed to the original model's utilization of kernel sizes of 9×9, 5×5, and 3×3. Additionally, we employed a 3×3 max-pooling layer. In contrast, the original LeafNet model utilized a 2×2 max-pooling layer. These modifications were crucial for achieving improved results for our specific application. The output layer in the Modified LeafNet model used four neurons representing four different classes, whereas the original LeafNet model contained 185 neurons representing 185 different classes. These changes improved model performance by extracting the important features for better classification.

The input parameters of all the models evaluated in this study are listed in Table 3. Table 4 presents an overall summary of these models.

The process flow structure is shown in Table 5. It describes the steps applied for data preprocessing, model building, hyperparameter tuning, and model evaluation.

Hyperparameter tuning was performed via a grid search method by changing the parameters of batch size, learning rate, and optimizers. After training the model for a specified number of epochs, we saved the best weights in the HDF5 format that were obtained based on the minimum loss value of the validation data. We then utilized this trained weight file to classify rice leaf images on a local machine.

E. PRETRAINED MODELS

The Xception and MobileNetV2 models were selected for this study to demonstrate and compare the differences between the complex and lightweight models. Both models are deep convolutional neural networks with different input sizes and architectures. The input size for the Xception model was $299 \times 299\times3$, whereas that for MobileNetV2 was $224 \times 224\times3$. In this study, a standard input size of $224 \times 224\times3$ was used. Both models were previously trained extensively on an ImageNet dataset for the classification of 1000 subjects. The pretrained models can be imported with weights using the Keras Application Programming Interface (API).

Transfer learning was applied to the MobileNetV2 and Xception models by loading the weights from the previous training on the ImageNet dataset and subsequently freezing the convolutional layers from block1_conv1 (Conv2D) to block14_sepconv2_act (Activation) in the Xception model and from Conv1 (Conv2D) to out_relu (ReLU) layers in the MobileNetV2 model. The original fully-connected layers were removed and replaced with Flatten and Dense layers. The Flatten layer transformed the feature map obtained from the max-pooling layer into a format that can be understood by the Dense layers, which were responsible for classifying the input. The rice leaf dataset was then used to train new fully-connected layers for classification.

Table 6 lists the last few layers of Xception and MobileNetV2 models. By leveraging models pretrained on extensive datasets, transfer learning enables the extraction of useful features without the need for a vast amount of training data. This reduced the computational resources required for training and led to improved performance because the pretrained models typically learned a rich set of features via

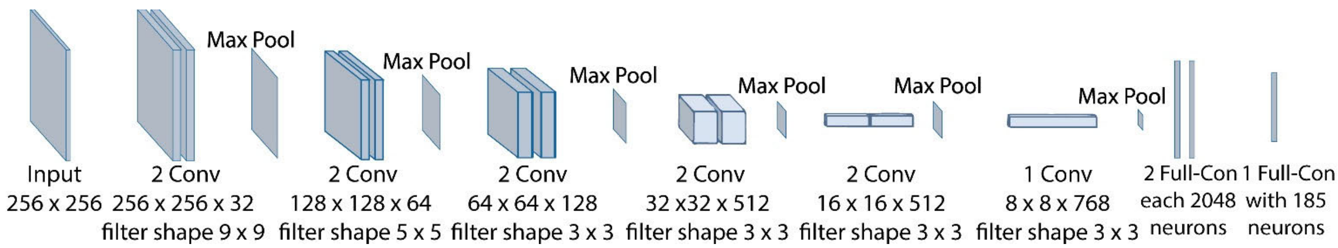


FIGURE 4. Architecture of the original LeafNet model [22].

TABLE 2. Model summary of the modified leafnet model.

Layers	Output Shape	Parameters
conv2d	224,224,32	155
conv2d_1	220,220,32	1,344
conv2d_2	218,218,32	1,344
Max_Pooling2d	109,109,32	0
Batch_Normalization	109,109,32	128
conv2d_3	107,107,64	2,400
conv2d_4	105, 105, 64	4,763
Max_Pooling2d_1	52, 52, 64	0
Batch_Normalization_1	52, 52, 64	256
conv2d_5	50, 50, 128	8,896
conv2d_6	48, 48, 128	17,664
Max_Pooling2d_2	24, 24, 128	0
Batch_Normalization_2	24, 24, 128	512
conv2d_7	22, 22, 256	34,176
conv2d_8	20, 20, 256	68,096
Max_Pooling2d_3	6, 6, 256	0
Batch_Normalization_3	6, 6, 256	1024
Flatten	9216	0
Dense	128	1,179,776
Dense_1	64	8,256
Dense_2	4	260

training on a large-scale dataset. In addition, transfer learning allows the reuse of well-designed architectures such as Xception and MobileNetV2, reducing the need for laborious model design and experimentation.

F. INTERMEDIATE CLASS ACTIVATION MAPS

In a CNN model, visualizing intermediate class activations during the training process provides deeper insight into the feature extraction process, particularly for image-based datasets. The term ''activation'' refers to the output of a layer in the network, with outputs from pooling and convolutional layers referred to as ''feature maps.'' The purpose of visualizing these activations is to display feature maps and to better understand how the network decomposes an input image using learned filters.

The intermediate class activation map (ICAM) is a visual tool used to interpret the decision-making process of a CNN model [38]. It provides a visualization of the extracted features of the important regions of an input image that contribute to the final prediction made by the model [38], [39], [40]. By visualizing these regions, one can gain insights into what the model is focusing on, and whether the model uses appropriate features to make its predictions.

To generate an ICAM, the model was modified to produce intermediate activation of specific layers during the forward pass. These activations were then used to compute a weighted sum of the activations of the last convolutional layer to generate a heatmap representation. The weights used in the sum were obtained by computing the gradient of the output of the model for the activation of the last convolutional layer. The resulting heat map highlighted the regions in the input image that had a significant impact on the prediction of the model.

The ICAM for the LeafNet and modified LeafNet models are shown in Table 7, which depicts the ICAM for both the LeafNet and modified LeafNet models, showcasing the feature extraction process performed by these models. The original image contained the affected area with pale yellow dots on the middle-left side, indicating the leaf blast disease. The images in the subsequent columns reveal the pixels extracted from both models. Notably, the LeafNet model failed to extract the affected pixels from the original image, as is evident in column conv2d_8. In contrast, the Modified LeafNet model successfully extracted the most influential pixels. These extracted features, as revealed by ICAM, highlight the ability of the modified LeafNet to concentrate on the most significant and informative pixels, which forms the foundation for the model's classification process.

G. HYPERPARAMETERS

The performance of the models was influenced by several variables including the optimizer, learning rate, metrics, batch size, and epochs. For the models, the loss function was minimized using the Adam or RMSprop optimizer, with learning rates of 0.001 or 0. 0001. The number of images fed into the model at a given time is referred to as batch size. Two different batch sizes, 16 and 32, were used to evaluate the performance of the models. Table 8 lists the hyperparameters of the models used in the study.

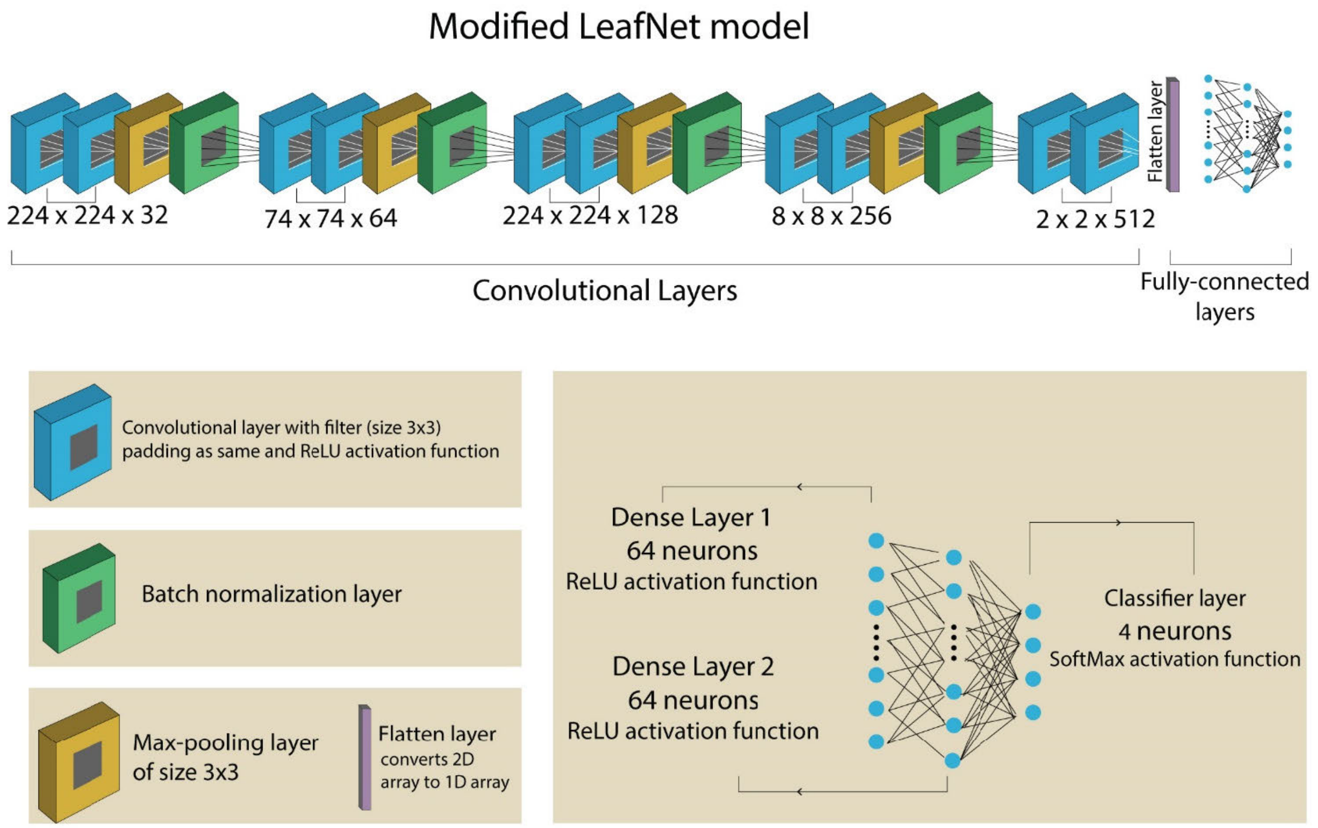


FIGURE 5. Architecture of the Modified LeafNet model.

TABLE 3. Models' parameters used in this study.

Models	Convolutional Layers	Input layer size	Output layer size
LeafNet	11	(224, 224, 3)	(4,1)
Modified LeafNet	10	(224, 224, 3)	(4,1)
MobileNetV2	53	(224, 224, 3)	(4,1)
Xception	71	(299, 299, 3)	(4,1)

TABLE 4. Summary of the models.

Models	Total parameters	Trainable parameters	Non-Trainable parameter	Size (MB)
LeafNet	4,747,236	4,746,254	982	11
Modified LeafNet	1,329,063	1,328,023	960	6
MobileNet V2	6,272,388	4,014,404	2,257,904	14
Xception	27,284,332	6,422,852	20,861,480	88

TABLE 5. Process flow used in this study.

Data Preprocessing			
1:	Importing Libraries		
2:	Importing dataset from device		
3:	Zooming and saving the new pictures		
4:	Train-Valid-Test splitting		
5:	Hyperparameters selection		
6:	Data Augmentation using image data generator library		
Building Models' Architecture			
LeafNet and Modified LeafNet		**MobileNetV2 and Xception**	
1.	Building CNN model from scratch	1:	Importing models from Keras libraries
2:	Adding convolutional and Maxpooling layers	2:	Importing ImageNet weights
3:	Adding Flatten and Dense Layers	3:	Adding Flatten and Dense Layers
4:	Model summary	4:	Model summary
Model Training			
1:	Training the model on the training dataset and validation dataset		
2:	Print the loss and accuracy graphs		
Model Evaluation			
1:	Print confusion metrics on validation and testing dataset		
2:	Print classification report on validation and testing dataset		

H. EXPERIMENTAL SETUP

In this study, experiments were conducted using Google Collaboratory with Python v3.8, TensorFlow v2.9.2, and Keras v2.9.0. The hardware used was an NVIDIA Tesla T4 with driver version 460.32.03.

IV. EVALUATION METRICS

The aforementioned models, namely LeafNet, Modified LeafNet, MobileNetV2 and Xception, were evaluated using the testing and validation datasets. The chosen learning rate was 0.0001 using the Adam optimizer. For the performance

TABLE 6. Summary of last layers in the pretrained models.

Models	Layers	Output Shape	Parameters
Xception	Flatten	100,352	0
	Dense	64	6,422,592
	Dropout	64	0
	Dense_1	4	260
MobileNetV2	Flatten	62,720	0
	Dense	64	4,014,144
	Dropout	64	0
	Dense_1	4	260

comparison of each model, important performance metrics, such as recall, precision, F1-score, and accuracy, were studied. These metrics were obtained using (1), (2), (3) and (4). The 4×4 confusion matrices were used to acquire the values needed to calculate the performance metrics, such as True Positive (TP), True Negative (TN), False Positive (FP), and False Negative (FN). The 4×4 confusion matrix with the appropriate term for each case is presented in Table 9.

A. CONFUSION MATRIX

For a 4×4 confusion matrix, it is often challenging to consider the positive and negative samples. TP and TN terms varied for each class in a 4×4 matrix. Based on the terms used in Table 10, the TP and TN samples for each class are presented in Table 9.

Similarly, FP and FN are crucial parameters of the confusion matrix. Knowing perfect samples is an important part of observing and evaluating a model. FP and FN samples for each class are listed in Table 11.

B. ACCURACY

Accuracy represents the overall ability to correctly classify the TP and TN classes from all images. This can be calculated using (1).

$$\text{Accuracy} = \frac{\text{TP} + \text{TN}}{\text{FP} + \text{TP} + \text{TN} + \text{FN}} \times 100\% \tag{1}$$

C. PRECISION

Precision measures the ratio of TP samples to all positively predicted samples of that class. This can be calculated using (2).

$$\text{Precision} = \frac{\text{TP}}{\text{TP} + \text{FP}} \tag{2}$$

D. RECALL

Recall measures the ratio of TP samples to all positive samples of that class. This can be calculated using (3).

$$\text{Recall} = \frac{\text{TP}}{\text{FN} + \text{TP}} \tag{3}$$

E. F1-SCORE

F1-score is another crucial parameter, and there is a difference between this parameter and accuracy. Accuracy provides the ratio of correctly predicted samples to all samples. However, F1-score is the harmonic mean of precision and recall, which provides a measure of the overall performance of the model in terms of both precision and recall. This can be calculated using (4).

$$\text{F1} - \text{score} = 2 \times \frac{\text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}} \tag{4}$$

V. RESULTS AND DISCUSSIONS

The training performance of the models is shown by the training and validation curves for 400 epochs. The curves for the Modified LeafNet and LeafNet models are illustrated in Fig. 6, while those for the Xception and MobileNetV2 models are depicted in Fig. 7. These curves were obtained using the Adam optimizer and a learning rate of 0.0001 with a batch size of 32. They revealed that the models performed well and had no overfitting or underfitting issues.

The confusion matrices and classification reports for the LeafNet and Modified LeafNet models on the testing dataset are shown in Fig. 8. From these results, we observed that the Modified LeafNet model achieved better accuracy on the testing dataset. It should be noted that the testing dataset was completely unseen by the models. The modified LeafNet model outperformed the LeafNet model, with an accuracy of 97.44% for the validation dataset and 87.76% for the testing dataset. According to the classification report, it can be observed that both models had the most misclassified cases in the leaf blast class.

A comparison of the classification accuracies of the Xception and MobileNetV2 models for rice leaf diseases is presented in Fig. 9, by showing the confusion matrix and classification report for each model. It also provides accuracy, precision, recall, and F1-score and displays the classification accuracy score for each class.

As shown in Fig. 9, the Xception model performed well with a batch size of 32, whereas MobileNetV2 performed well with a batch size of 16. As evident in Fig. 9, models with complex architectures, such as Xception, can learn more. Therefore, a larger batch size accelerates the training process, whereas the MobileNetV2 model has a simpler architecture that requires a smaller batch size to slow down the training process for the model to learn more effectively.

The validation accuracies achieved by the aforementioned models varied, as shown in Fig. 10. The highest accuracy was obtained with the modified LeafNet model, which achieved an accuracy of 97.44% for the classification of rice leaf diseases. However, we observed that the LeafNet, MobileNetV2 and Xception models also demonstrated impressive performance. The LeafNet model achieved an accuracy of 88.92%, whereas the Xception and MobileNetV2 models achieved accuracies of 88.64% and 82.10%, respectively.

TABLE 7. Intermediate class activation map (ICAM).

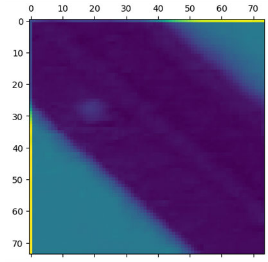
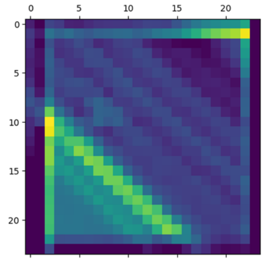
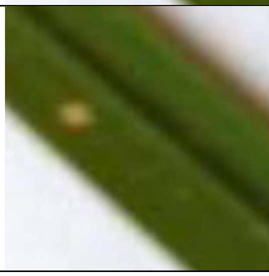
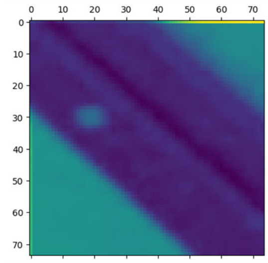
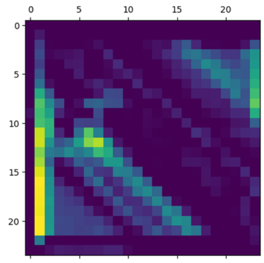
	Original Image	conv2d_2	conv2d_8
LeafNet			
Modified LeafNet			

TABLE 8. Hyperparameters used in this study.

Parameters	Value			
Optimizer	Adam		RMSprop	
Learning Rate	0.001	0.0001	0.001	0.0001
Batch Size	16	32	16	32
Loss	Categorical Cross entropy			
Metrics	Accuracy			
Epochs	400			

TABLE 9. Confusion matrix for four classes.

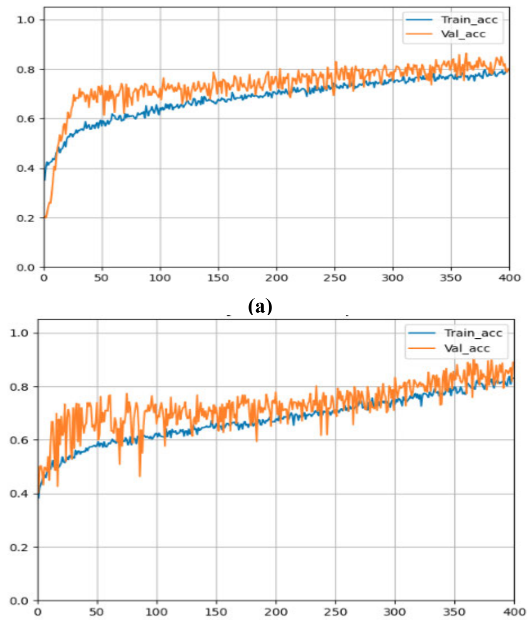
		Predicted Classes			
		Brown Spot	Leaf Blast	Hispa	Healthy
Actual classes	Brown Spot	TP_{BS}	F_{AB}	F_{AC}	F_{AD}
	Leaf Blast	F_{BA}	TP_{LB}	F_{BC}	F_{BD}
	Hispa	F_{CA}	F_{CB}	TP_{HISPA}	F_{CD}
	Healthy	F_{DA}	F_{DB}	F_{DC}	TP_{NORMAL}

TABLE 10. True positive and true negative for four classes.

Class	True Positive (TP)	True Negative (TN)
Brown Spot	TP_{BS}	$TP_{LB} + F_{BC} + F_{BD} + F_{CB} + TP_{HISPA} + F_{CD} + F_{DB} + F_{DC} + TP_{NORMAL}$
Hispa	TP_{LB}	$TP_{BS} + F_{AC} + F_{AD} + F_{CA} + TP_{HISPA} + F_{CD} + F_{DA} + F_{DC} + TP_{NORMAL}$
Leaf Blast	TP_{HISPA}	$TP_{BS} + F_{AB} + F_{AD} + F_{BA} + TP_{LB} + F_{BD} + F_{DA} + F_{DB} + TP_{NORMAL}$
Healthy	TP_{NORMAL}	$TP_{BS} + F_{AB} + F_{AC} + F_{BA} + TP_{LB} + F_{BC} + F_{CA} + F_{CB} + TP_{HISPA}$

TABLE 11. False positive and false negative for four classes.

Class	False Positive (FP)	False Negative (FN)
Brown Spot	$F_{BA} + F_{CA} + F_{DA}$	$F_{AB} + F_{AC} + F_{AD}$
Hispa	$F_{AC} + F_{BC} + F_{DC}$	$F_{CA} + F_{CB} + F_{CD}$
Leaf Blast	$F_{AB} + F_{CB} + F_{DB}$	$F_{BA} + F_{BC} + F_{BD}$
Healthy	$F_{AD} + F_{BD} + F_{CD}$	$F_{DA} + F_{DB} + F_{DC}$



(b)

FIGURE 6. Training and validation curves. (a) LeafNet. (b) Modified LeafNet.

Furthermore, the models were evaluated on the test dataset, which was kept unseen for the models. Consequently, evaluating the models on the test dataset revealed their true performance. As shown in Fig. 10, the modified LeafNet model outperformed the other models, achieving a test accuracy of 87.76%. In comparison, the LeafNet, Xception and

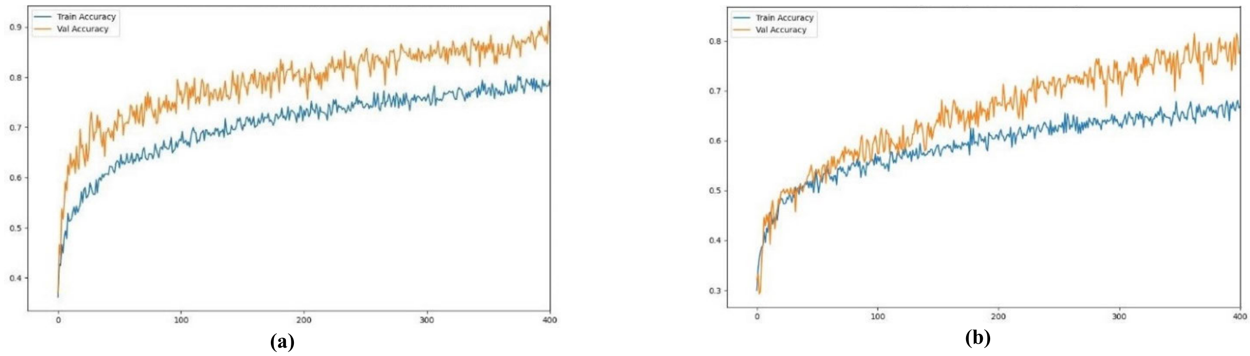


FIGURE 7. Training and validation curves. (a) Xception. (b) MobileNetV2.

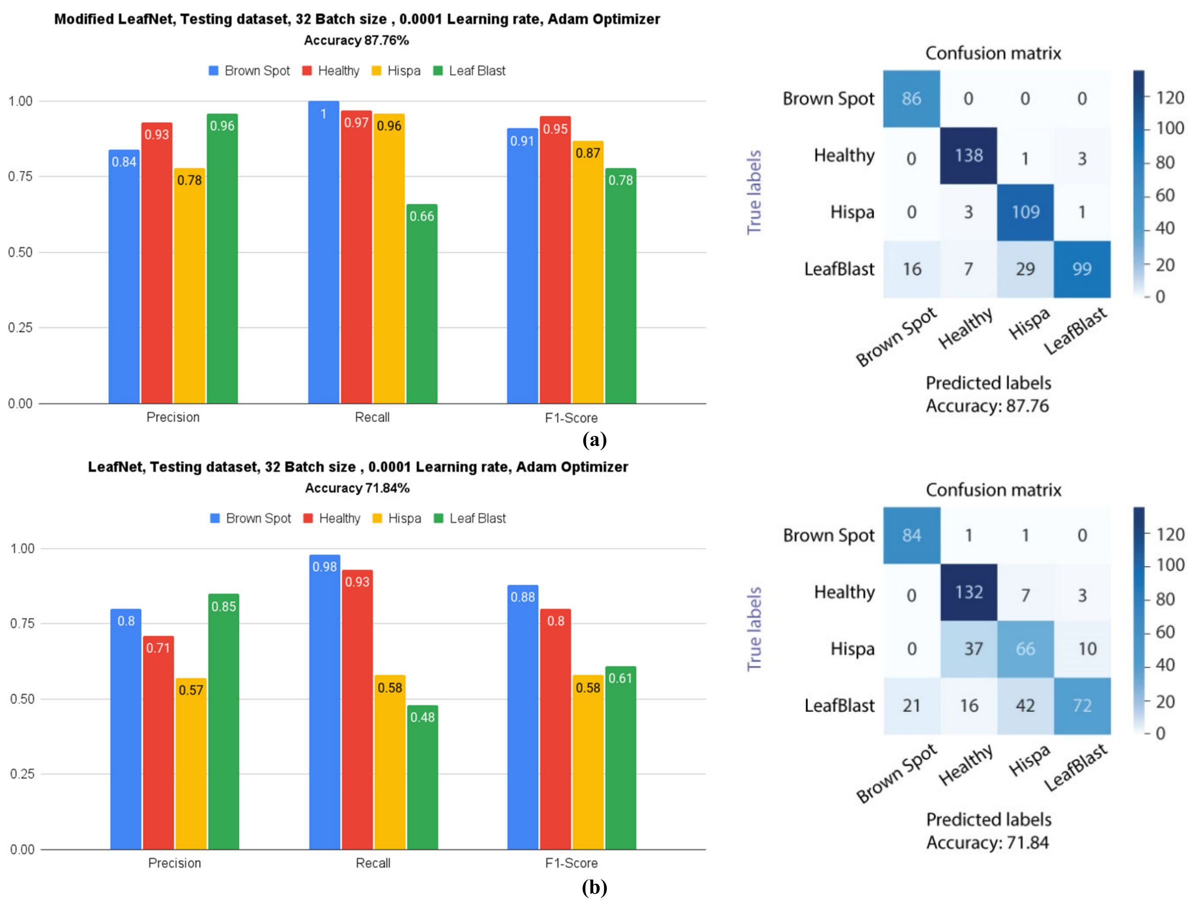


FIGURE 8. Model performance on the testing dataset. (a) Modified LeafNet classification report and confusion matrix. (b) LeafNet classification report and confusion matrix.

MobileNetV2 models achieved test accuracies of 71.84%, 71.95% and 67.68%, respectively.

One possible explanation for the high performance of the Modified LeafNet model is that it was specifically designed for the classification of rice leaf diseases. Therefore, it may have more robust features that are better suited for identifying subtle differences between different types of rice leaf diseases. In addition, the high accuracy of the Modified LeafNet model may be attributed to the large number of parameters it utilizes, which allows it to capture more intricate patterns in the dataset.

In contrast, the MobileNetV2 and Xception models performed reasonably well, even though they were not specifically designed for the classification of rice leaf diseases. The success of these models suggests that transfer learning can be an effective strategy for classifying images of rice leaf diseases, even when the model was trained on different types of images.

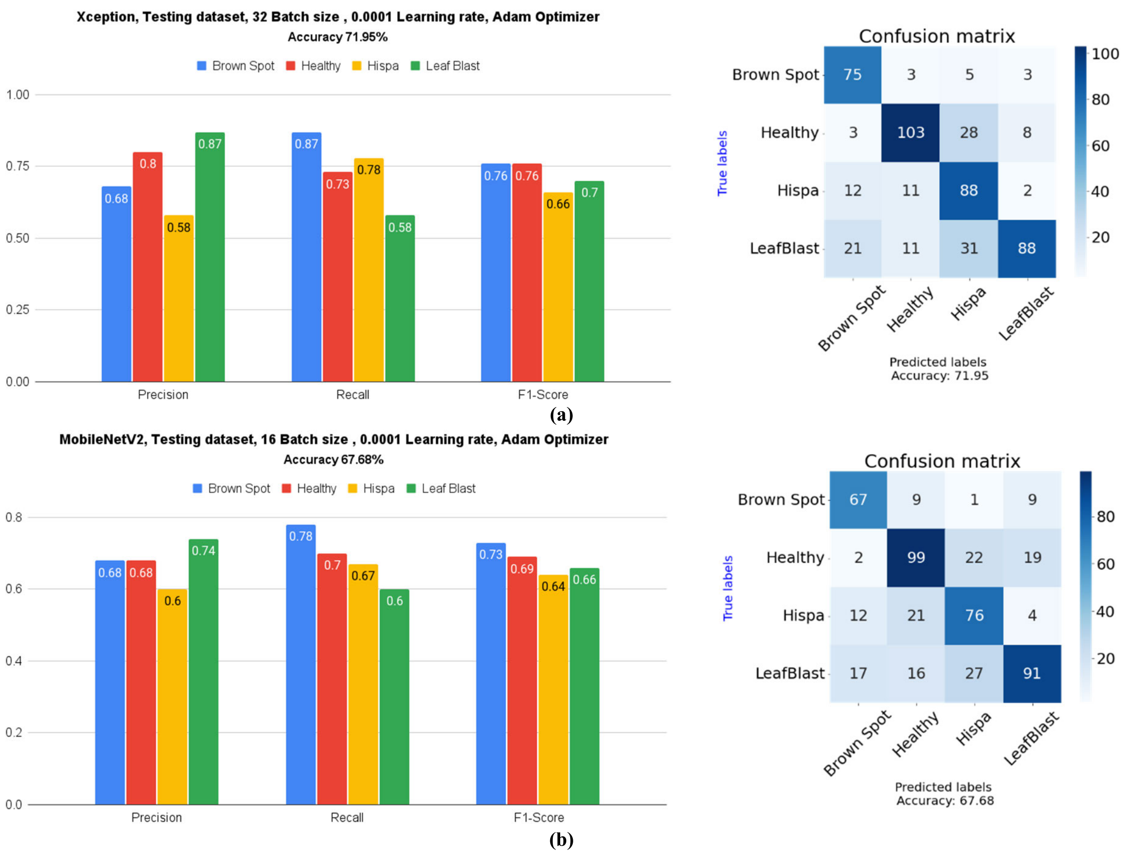


FIGURE 9. **Model performance on the testing dataset. (a) Xception classification report and confusion matrix. (b) MobileNetV2 classification report and confusion matrix.**

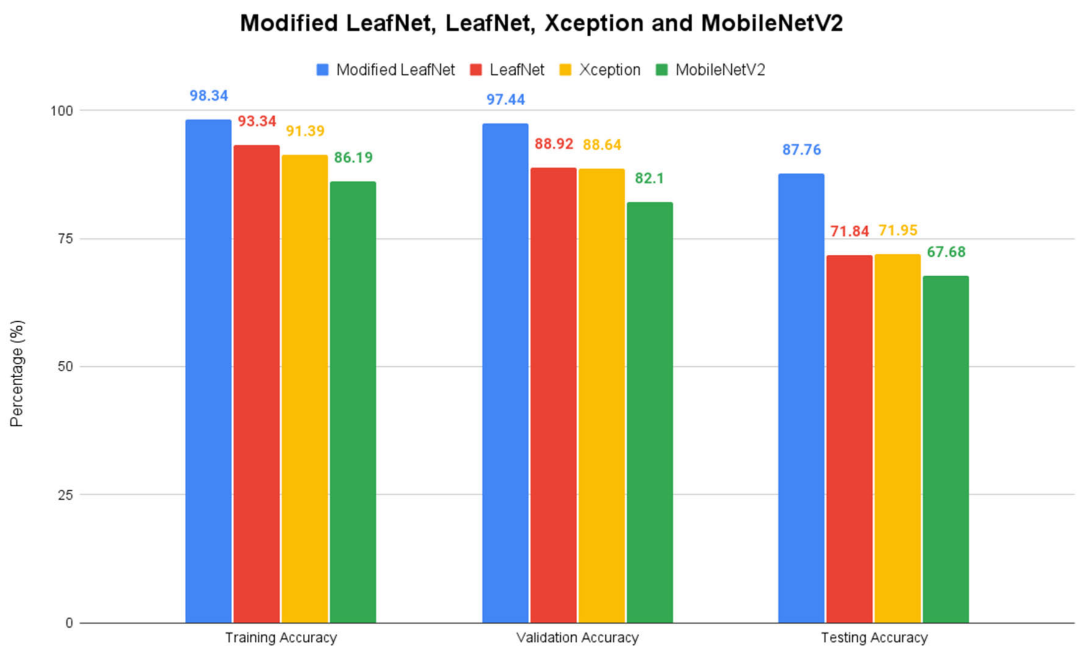


FIGURE 10. **Performance comparison among all four models (all models used a batch size of 32, except MobileNetV2, which used a batch size of 16).**

The main aim of this study was to build a model that could recognize rice leaf diseases. There were some difficulties in detecting rice leaf diseases owing to the imaging conditions. The rice leaves were small, and all images that contained the

TABLE 12. **Comparative analysis of studies with the same dataset.**

Authors	Classes	Algorithm	Accuracy
Zhang [32]	Healthy, Brown Spot, Hispa, and Leaf Blast	WS-DAN	Testing Accuracy: 87.60% Validation Accuracy: N.A.
Putra et al. [33]	Brown Spot, Hispa, and Leaf Blast	HTL	Testing Accuracy: N.A. Validation Accuracy: 91%
Verma et al. [34]	Healthy, Brown Spot, Hispa, and Leaf Blast	Lightweight CNN model	Testing Accuracy: 73.02% Validation Accuracy: N.A.
Bhowmik et al. [35]	Healthy, Brown Spot, Hispa, and Leaf Blast	Ensemble Model (VGG16+Light GBM)	Testing Accuracy: N.A. Validation Accuracy: 96.49%
This study	Healthy, Brown Spot, Hispa, and Leaf Blast	Modified LeafNet model	Testing Accuracy: 87.76% Validation Accuracy: 97.44%

rice leaves had a white background. As the rice leaves in these images were relatively small, it was difficult for the models to detect them. Therefore, all the models initially exhibited low performance owing to the condition of the images. To solve this issue, data preprocessing was applied, in which all images were zoomed in to obtain a clearer view of the rice leaves. In addition, data augmentation was applied to the images in the training set, including horizontal and vertical flips, vertical and horizontal shifts, and rotations. From the experiment, it was observed that the image conditions can affect the model performance, and that image preprocessing should be considered.

CNN deep learning models are suitable for rice leaf disease classification. Transfer learning can be applied to improve model accuracy, as pretrained CNN models were trained on general images, such as the ImageNet dataset. Before applying transfer learning, the last few layers must be correctly replaced to fit the objective of the study, which is the classification of rice leaf diseases. The LeafNet model is a well-built model that generally detects and recognizes leaf types and performs well, based on a study conducted in [22]. In contrast, the Modified LeafNet model used in this study was designed to classify rice leaf diseases. For future researchers planning to study leaf classification, the following three suggestions are recommended. Firstly, use CNN models with transfer learning. Secondly, employ LeafNet as a viable option. Lastly, consider using the Modified LeafNet model, as it can provide improved accuracy when classifying rice leaf diseases.

To facilitate a comparison with previous studies, Table 12 presents a comparative analysis of relevant studies that utilized the same dataset as ours. This table presents the performance of four algorithms from the literature for classifying different rice leaf diseases. All algorithms, except one, were tested on four classes: healthy, brown spot, hispa, and leaf blast. Zhang [32] used the WS-DAN algorithm and reported a testing accuracy of 87.60% for all classes. Putra et al. [33] used the HTL algorithm and reported a validation accuracy of 91% for three classes: brown spot, hispa, and leaf blast. Verma et al. [34] used a lightweight CNN model and reported a testing accuracy of 73.02% for all classes.

Bhowmik et al. [35] used an ensemble model (VGG16 + Light GBM) and reported a validation accuracy of 96.49% for all classes. In contrast, our proposed Modified LeafNet model achieved the highest validation accuracy of 97.44% among all algorithms. These results demonstrate the effectiveness of the Modified LeafNet and ensemble models for the classification of plant leaf diseases.

Overall, our findings suggest that the Modified LeafNet model is the most effective for classifying rice leaf diseases. Additionally, transfer learning can be an effective method for reusing well-designed pretrained models for accurate classification. Future studies should focus on exploring additional deep learning models and image processing techniques to further improve the accuracy of rice leaf disease classification.

VI. CONCLUSION

Rice leaf diseases, such as brown spot, hispa and leaf blast can be classified using the proposed models. The models were trained to identify these diseases using rice leaf images. The Xception and MobileNetV2 models achieved testing accuracy of 71.95% and 67.68%, respectively. The LeafNet model is considered a state-of-the-art model for classifying leaves. Therefore, we studied LeafNet and a modified version of LeafNet to classify rice leaf diseases. Our results showed that the Modified LeafNet model outperformed all models in this study, achieving the best classification accuracy of 97.44% on the validation set and 87.76% on the testing set.

In addition to achieving higher accuracy, the goal should encompass enhancing the dependability and robustness of the model across diverse datasets. Thus, future studies should focus on categorizing images of rice leaf diseases in the presence of complex surroundings and varying lighting conditions. As classification accuracy only provides a partial description of most real-world activities, future work should also place greater emphasis on interpretable CNN models that present features for classifying diseases in ways that are easy to understand. While our study excels in the classification of rice leaf diseases, it is imperative to recognize several limitations that offer valuable insights for future research. The primary limitation pertains to the dataset size and variety. To address this, future work should prioritize the collection of a more extensive dataset that encompasses a wide range of rice leaf diseases. Such an enriched dataset would undoubtedly enhance the robustness and practical utility of the proposed models. Additionally, we acknowledge the significance of model size and inferencing time, particularly for deployment on resource-constrained edge devices. To mitigate this, our future work will explore model optimization techniques, such as quantization and pruning, to reduce the model size, thereby improving the inference speed and enabling the creation of lightweight models. Furthermore, external validation using independent datasets is a crucial avenue for future research. By subjecting our models to diverse real-world scenarios, we can ascertain their performance beyond the confines of our specific dataset, strengthening their credibility and demonstrating their real-world utility. Finally, we are committed to exploring alternative interpretability techniques to enhance the transparency and interpretability of our deep learning models.

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