Harnessing Deep Learning for Timely Detection and Classification of Rice Leaf Diseases

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Abstract
This research presents a comprehensive study on the application of deep learning techniques for the detection and classification of rice leaf diseases. The objective of this study was to develop an accurate and reliable model for automated disease diagnosis, which can aid in early detection and effective management of rice crop diseases. The research employed a dataset consisting of 2,627 images of six different rice leaf diseases, namely Bacterial Leaf Blight, Brown Spot, Healthy, Leaf Blast, Leaf Scald, and Narrow Brown Spot. The dataset was collected from Kaggle.com and underwent rigorous preprocessing steps to enhance the quality and suitability for training the models. Two transfer learning models, namely VGG19 and MobileNetV2, were selected and trained using the preprocessed dataset. The models were fine-tuned by freezing the pre-trained layers and adding additional layers for classification. The performance of each model was evaluated using various metrics, including accuracy, precision, recall, and F1 score. The results demonstrated the effectiveness of the proposed approach in accurately diagnosing rice leaf diseases. The MobileNetV2 model achieved an overall accuracy of 92.4%, outperforming the VGG19 model, which achieved an accuracy of 90.5%.

Keyword: Rice leaf disease detection, deep learning, computer vision, crop management, sustainable agriculture.

I. INTRODUCTION

Rice is one of the most important staple crops worldwide, serving as a primary food source for a significant portion of the global population. According to the "Food and Agriculture Organization" (FAO) [1], more over half of all humans use rice as their main source of calories. Providing sustenance to over 3.5 billion people. In many developing countries, rice accounts for a significant proportion of daily calorie intake, often exceeding 70% in some regions. However, rice crops are vulnerable to a wide range of illnesses, which may result in substantial production losses and have a deleterious impact on the food security and the economic stability. Timely and accurate detection of rice leaf diseases plays a crucial role in mitigating these challenges and ensuring sustainable crop management. According to Strange RN and Scott PR, plant disease is a significant threat to global food security, resulting in 10-16% losses in the worldwide harvest of crops annually [2, 3]. Traditional methods for rice leaf disease detection, such as visual inspection and manual symptom identification, are labor-intensive, time-consuming, and subjective. These approaches rely on human expertise and are prone to errors, resulting in delayed detection and inadequate disease management. As a consequence, there is a pressing need for automated and reliable systems that can efficiently detect and classify rice leaf diseases. The branch of the machine learning known as deep learning has shown great success in many application areas, such as computer vision & pattern recognition. Convolutional Neural Networks (CNNs) are a type of deep learning algorithm that have been particularly successful in image classification tasks [4]. By leveraging deep neural networks, deep learning models can automatically learn intricate patterns and representations from large-scale datasets, enabling accurate and efficient disease detection. Artificial Neural

Networks is an information processing paradigm inspired by how biological nervous systems function [5]. Applying deep learning techniques to rice leaf disease detection holds immense potential to overcome the limitations of the traditional methods and revolutionize crop management practices.

The purpose of this research is to create a cutting-edge, deep-learning-based system for identifying and categorizing rice leaf diseases. This study aims to enhance the precision, speed, and scalability of the rice leaf disease detection by making use of cutting-edge deep learning architectures and massive datasets. The proposed system will contribute to timely disease identification, enabling farmers and agronomists to take proactive measures for disease management, reduce yield losses, and improve crop productivity..

A. Pre-Trained Models for Image Classification

In the vast realm of transfer learning for image classification, numerous pre-trained models and expansive datasets have garnered widespread acclaim. These models have exhibited remarkable prowess across various computer vision tasks, leveraging extensive training on colossal datasets like ImageNet. Let's embark on an exploration of some renowned pre-trained models and the datasets that have shaped them.

Mobile Net: The widely used MobileNetV2 CNN architecture [6] was developed to perform picture categorization jobs quickly and accurately. It was introduced as an improvement over its predecessor, MobileNetV1, with the goal of achieving higher accuracy while maintaining low computational complexity and model size. Due to its exceptional performance on a wide range of computer vision applications, MobileNetV2 has attracted a lot of interest and been widely adopted. MobileNetV2's main selling point is the way it uses depthwise separable convolutions to strike a healthy equilibrium between accuracy & efficiency. Unlike traditional convolutions that operate on the entire input volume, depthwise separable convolutions decompose the convolutions into separate spatial and channel-wise convolutions. The amount of calculations and parameters in a model are greatly reduced as a result of this partitioning, making the model easier to implement and run more quickly.

VGG (Visual Geometry Group): The illustrious VGG network, crafted by the ingenious minds at the Visual Geometry Group housed within the venerable University of Oxford [7], stands as a prevailing pre-trained model in the domain of image classification. VGG comprises profound convolutional layers, offering diverse iterations like VGG16 and VGG19, each distinguished by its unique depth. These models undergo rigorous training on the expansive ImageNet dataset, encompassing countless labeled images spanning a staggering array of 1,000 object categories. Renowned for their elegant simplicity and exemplary feature representation, VGG models have become a favored choice for transfer learning endeavors.

ResNet (Residual Network): ResNet, aptly named as the Residual Network, revolutionized the landscape of pre-trained models by introducing the revolutionary concept of residual learning. These ResNet architectures ingeniously incorporate skip connections or shortcuts, enabling the training of substantially deeper neural networks. ResNet models, exemplified by ResNet50, ResNet101, and ResNet152, have attained the pinnacle of performance in image classification tasks [8]. Training on extensive datasets like ImageNet empowers these models to capture exceptionally discriminative visual features and representations, cementing their dominance in the field.

II. RELATED WORK

[9] Ahmed, Kawcher, et al (2019) describes a method that uses machine learning techniques to identify illnesses in rice leaf samples. Bacterial leaf blight, Leaf smut, and Brown spot infections are the primary targets of this investigation. As input, the system needs high-quality pictures of diseased rice leaves on a white backdrop. Among the many phases in the process is pre-processing the dataset in order to get it ready for training. The author then used a number of machine learning methods, including "K-Nearest Neighbors" (KNN), Naive Bayes, Decision Tree (J48), and Logistic Regression, to train dataset. After analyzing the results of various methods, the author concluded that the Decision Tree algorithm yielded the highest accuracy (almost 97%) when used with 10-fold cross-validation. This shows that the characteristics collected from the input photos were sufficient for the "Decision Tree algorithm" to successfully detect rice leaf diseases in a test dataset.

[10] This work Ramesh, S., and D. Vydeki (2018) describes a machine learning approach for the automated recognition of the rice plant disease signs. Images of healthy and diseased leaves are used in the suggested method. Both normal and diseased rice leaf regions are used to collect features. The research uses a dataset of 300 photos, split evenly between a training set and an evaluation set. The photos are processed using the suggested approach, which then assigns a health status to each leaf. During the

simulated training phase, an accuracy for the blast-infected photographs was 99% and for the normal images it was 100%. The accuracy is 90% overall infected photos and 86% for the healthy ones, according to testing phase results.

[11] The author Ghosal, Shreya, and Kamal Sarkar (2020) addresses the difficulty that rice farmers have in making correct diagnoses of plant diseases. This research looks at a potential solution by investigating automatic picture detection of rice leaf diseases using Deep Learning methods, in particular "Convolutional Neural Network" (CNN) models. Since there aren't many publicly accessible picture databases of rice leaf diseases, the authors compiled their own, though tiny, one. To get over this restriction, they use Transfer Learning to build their CNN off of the already-trained VGG-16 model. Using data gathered from both rice fields and also the internet, the model is developed and put through its paces. The suggested CNN architecture is 92.46 percent accurate in spotting illnesses in rice leaves. Despite the scarcity of available datasets, this method highlights the promise of Deep Learning & CNN models for precise disease diagnosis in rice fields.

[12] Ramesh, S., and D. Vydeki (2019) suggests a method of employing the machine learning algorithm to identify cases of rice blast illness. In order to efficiently increase rice agricultural output, it is necessary to detect the illness at the early stage of crop cultivation. The process includes taking pictures of paddy field and using eight characteristics to determine whether or not the leaves are healthy. "K-Nearest Neighbors (KNN)" and "Artificial Neural Network" (ANN) are the two machine learning techniques used in the suggested categorization strategy. A confusion matrix is used to evaluate the effectiveness of various methods. The KNN-based classification system obtains the accuracy of 85% for the blast-affected leaf photos and 86% for the normal leaf images, according to the simulation findings. Using the "ANN-based classification mechanism" increases accuracy to 99.9% and 100%, respectively.

[13] Kiratiratanapruk, Kantip, et al. (20200 explores how the "convolutional neural networks" (CNNs) might be used to spot and diagnose illnesses in photographs of rice leaves. Focusing on six main rice diseases—blast, brown spot, bacterial leaf blight, bacterial leaf streak, narrow brown spot, and rice ragged stunt viral disease—this investigation provides new information about these conditions. In this study, we examine the detection accuracy of many popular pre-trained models, such as Faster R-CNN, YOLOv3, RetinaNet, and Mask RCNN. The research makes use of an image library of rice diseases collected from unaltered photos of real rice fields. The models are trained and evaluated using a dataset of 6,330 photos. The experiments show that YOLOv3 has the highest performance for detecting and classifying rice leaf illnesses, with the "mean average precision" (mAP) of 79.19%. Precision scores of 70.96%, 75.92%, and 36.11% are achieved using Faster R-CNN, Mask R-CNN, and RetinaNet, respectively.

III. METHODOLGY

The proposed model architecture has been illustrated in Fig.1

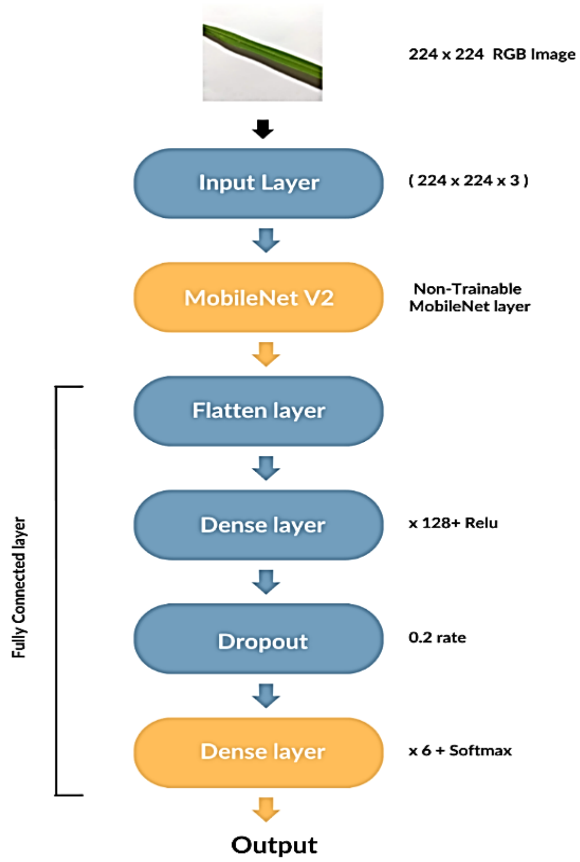

Figure 1 Model Architecture

A. Dataset

A rice leaf disease dataset was collected from Kaggle.com, a popular platform for sharing and discovering datasets. The dataset comprises a total of 2,627 images, which were obtained from the train and validation folders. These images represent six different types of rice leaf diseases, as well as healthy rice leaves. The following diseases are included in the dataset:

Healthy: The healthy class represents images of disease-free rice leaves. These images serve as a reference for comparison and provide a baseline for distinguishing healthy leaves from diseased ones.

Bacterial Leaf Blight: Rice plants are susceptible to a bacterial disease known as the bacterial leaf blight. Significant yield losses may occur due to the "bacterium Xanthomonas oryzae pv. oryzae", which causes this disease.

Brown Spot: Rice fields also often fall victim to brown spot. Small brown spots, ranging in shape from round to oval, appear on the leaves as a result of the "fungus Cochliobolus miyabeanus".

Leaf Blast: The "fungus Magnaporthe oryzae" is responsible for the damaging illness known as Leaf Blast. Rice leaves develop tiny, round spots that are gray in the middle and brown around the edges.

Leaf Scald: The bacteria "Xanthomonas oryzae pv. Oryzicola" is accountable for the occurrence of leaf scald. It causes chlorotic lesions on the leaves, which become long and thin and ultimately brown.

Narrow Brown Spot: Narrow Brown Spot is a disease caused by the bacterium Acidovorax avenae subsp. avenae. It results in the appearance of brownish, narrow, streak-like lesions on the rice leaves.

The dataset was curated and organized into separate folders based on the disease category. This structure facilitates easy access to the images and enables the training and evaluation of the deep learning models for rice leaf disease detection.

Figure 2 Dataset Sample

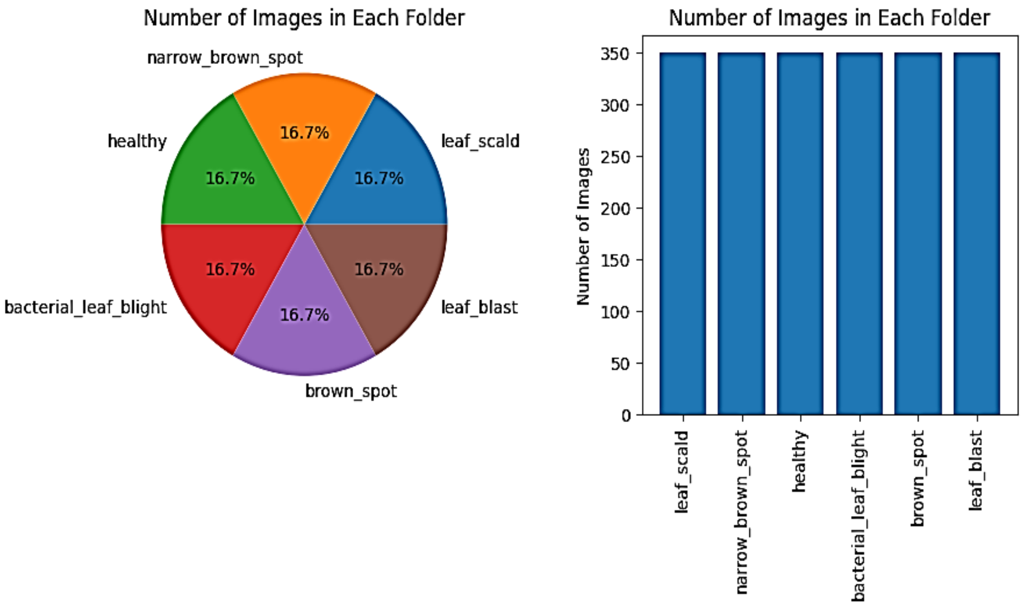

Figure 3 Data Distribution

This dataset served as a valuable resource for training and evaluating the deep learning models developed in this research, enabling accurate and effective rice leaf disease detection.

B. Image Pre-Processing

To ensure the compatibility and standardization of the dataset for effective classification, a series of preprocessing steps were applied. These steps encompass image transformation, data augmentation, and batch processing, all aimed at enhancing the quality and diversity of the dataset while maintaining its integrity. There are several reasons why data augmentation is an important step when training a machine learning model. [14]. Data preprocessing is a critical step in preparing the dataset for model training and evaluation Data Augmentation prevents overftting by modifying limited datasets to possess the characteristics of data [15]. In this research, several preprocessing techniques were applied to the rice leaf disease dataset to enhance the learning capabilities of the deep learning models. The following is a technical explanation of the data preprocessing techniques used and the rationale behind their application:

Batch Size and Image Dimensions: The batch_size parameter was set to 64, determining the number of images processed in each training iteration. This batch-wise processing improves the efficiency of the training process and allows for parallel computation. The target_size parameter was set to (height, width) = (224, 224) to resize the input images to a consistent size. Resizing the images ensures that they have a uniform shape, making them compatible with the input dimensions expected by the deep learning models.

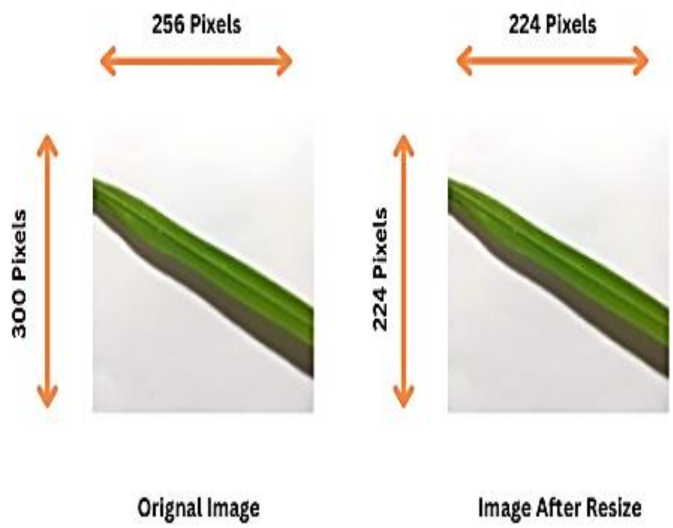

Figure 4 Image Resize

Image Decoding: Image decoding involves converting the images from their original formats, such as JPEG or PNG, into numerical data that can be processed by machine learning algorithms. This enables further processing and analysis of the image data.

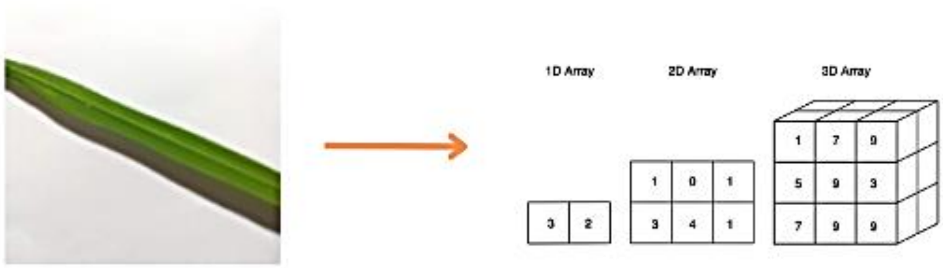

Figure 5 Image Decoding

Image Rescaling: With the help of "Image Data Generator's rescale" argument, we were able to convert the pictures' pixel values to an interval between 0 and 1. This normalization technique ensures that the input data falls within a standardized range and helps the models converge faster during training.

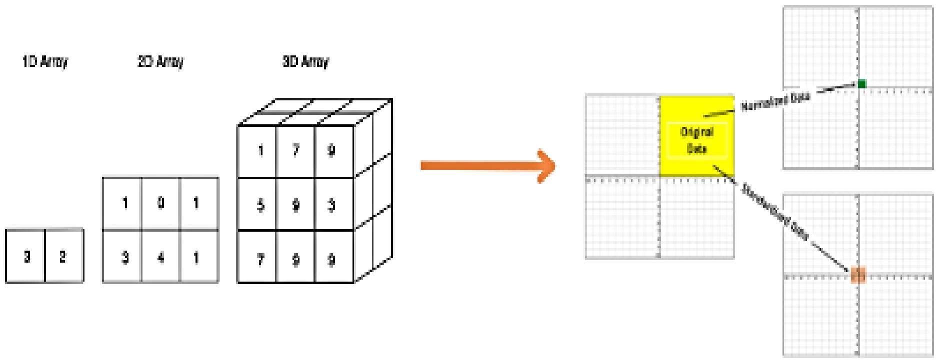

Figure 6 Image Rescale

Augmentation: Data augmentation was employed to artificially expand the dataset and improve the models' generalization ability. Augmentation techniques introduce the variations to existing images, simulating real-world scenarios and increasing the robustness of the models. The augmentation techniques used in this research include shear range, zoom range, rotation range, horizontal flip, and vertical flip. These transformations introduce diverse perspectives of the leaf images, enabling the models to learn and recognize disease patterns from various angles and orientations. Data augmentation has been shown to produce promising ways to increase the accuracy of classification task. [16].

The data preprocessing techniques employed in this research are crucial for enhancing the models' performance and robustness. Normalizing the pixel values, applying data augmentation, and organizing the dataset in a structured manner improve the models' ability to learn and generalize from the data. By incorporating these techniques, the models can effectively identify and classify rice leaf diseases, even in the presence of variations and noise commonly encountered in real-world scenarios.

C. Method

In this research, a methodology combining deep learning and transfer learning techniques was employed for the detection and classification of rice leaf diseases. The collected dataset underwent pre-processing steps, including resizing the images to a uniform size of 224x224 pixels and applying augmentation techniques such as shear range, zoom range, rotation range, and horizontal/vertical flips. Two popular transfer learning models, VGG19 and MobileNetV2, were selected and trained using the preprocessed dataset. The models were fine-tuned by modifying the fully connected layers, and a dense output layer was added to accommodate the six disease classes. The models were trained using the augmented dataset, optimized with the Adam optimizer, and evaluated using metrics such as accuracy, precision, recall, and F1 score. The experiments were implemented using Python programming language and deep learning libraries including TensorFlow, Keras, NumPy, and scikit-learn. The methodology allowed for the accurate detection and classification of rice leaf diseases, paving the way for improved disease management strategies in agriculture.

The proposed model architecture in this study is based on MobileNetV2, a pre-trained deep learning model. The MobileNetV2 model is added as the base model and frozen to leverage the learned features from the ImageNet dataset. Additional layers, including Flatten, Dense, and Dropout, are added to capture complex patterns and mitigate overfitting. The final Dense layer performs multi-class classification. The model is compiled with the Adam optimizer and categorical cross-entropy loss function. The accuracy metric is used for evaluation. By utilizing MobileNetV2 and fine-tuning the model, this research aims to accurately detect and classify rice leaf diseases based on discriminative features learned from the pre-trained weights.

IV. RESULTS AND DISCUSSION

The proposed research conducted an extensive evaluation of two deep learning models, VGG19 and MobileNetV2, for the detection and classification of rice leaf diseases. The results showcased the performance of each model, evaluated in terms of accuracy, precision, recall, and F1 score. After training the MobileNetV2 model for 20 epochs, it achieved an accuracy of 92.4%.

This indicates that 92.4% of the predictions made by the model were correct. The model also exhibited a recall, precision, and F1 score of 92%, indicating its ability to correctly identify positive samples. The F1 score, which considers both precision and recall, was also high at 92%. On the other hand, the VGG19 model achieved an accuracy of 90.5%. This indicates that 90.5% of the predictions made by the model were correct. Similar to the MobileNetV2 model, the VGG19 model demonstrated a recall, precision, and F1 score of 91%, suggesting its ability to correctly identify positive samples. The F1 score for the VGG19 model was 90%.

These findings demonstrate that both models are useful for disease classification in rice leaves. Accuracy, precision, recall, and F1 score were all marginally better for MobileNetV2 model than for VGG19 model

Figure 7 MobileNetV2 Predictions on test dat

Table 1 Proposed Model results

Disease	Precision	Recall	F1 Score	Accuracy
		MobileNetV2		
Bacterial Leaf Blight	0.97	1	0.98	0.92
Brown Spot	0.9	0.8	0.84	0.92
Healthy	0.88	0.95	0.91	0.92
Leaf Blast	0.81	0.81	0.81	0.92
Leaf Scald	1	1	1	0.92
Narrow Brown Spot	1	0.99	0.99	0.92
		VGG19		
Bacterial Leaf Blight	0.99	0.98	0.98	0.91
Brown Spot	0.83	0.8	0.81	0.91
Healthy	0.79	0.93	0.85	0.91
Leaf Blast	0.86	0.76	0.81	0.91
Leaf Scald	0.98	0.99	0.98	0.91
Narrow Brown Spot	1	0.98	0.99	0.91

These results demonstrate the performance of the MobileNetV2 and VGG19 models in terms of accuracy, recall, precision, and F1 score for rice leaf disease detection. The MobileNetV2 model achieved higher accuracy and slightly better performance across all metrics compared to the VGG19 model.

Here are visual results of proposed mode –

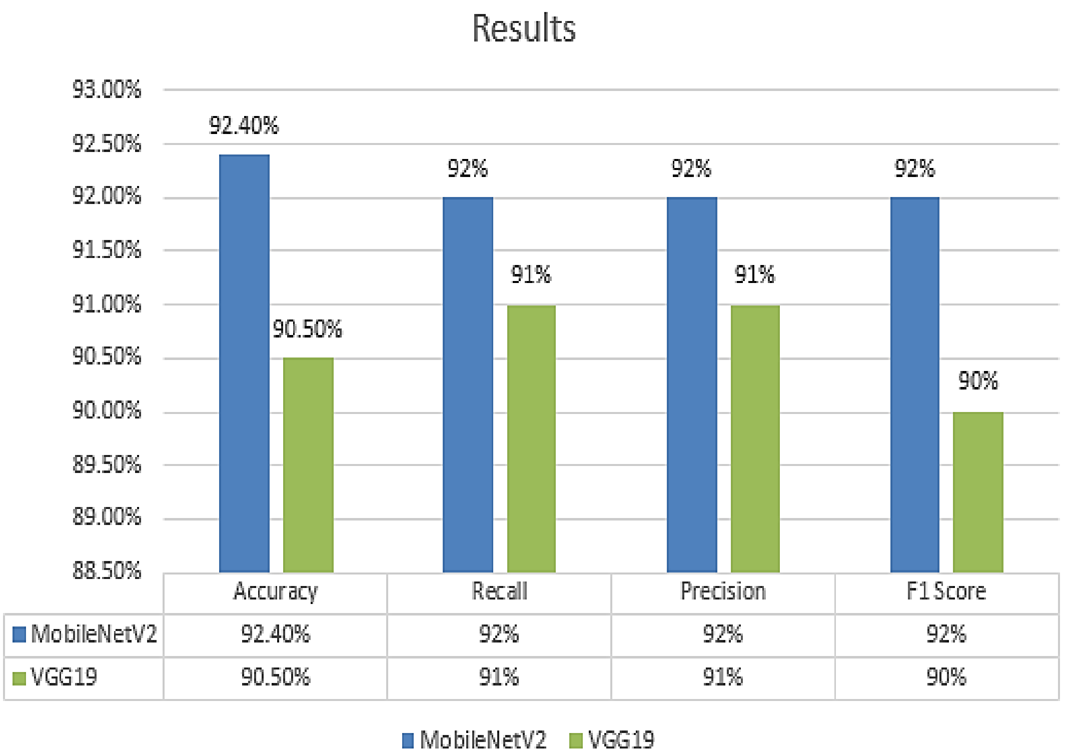

Figure 8 Results

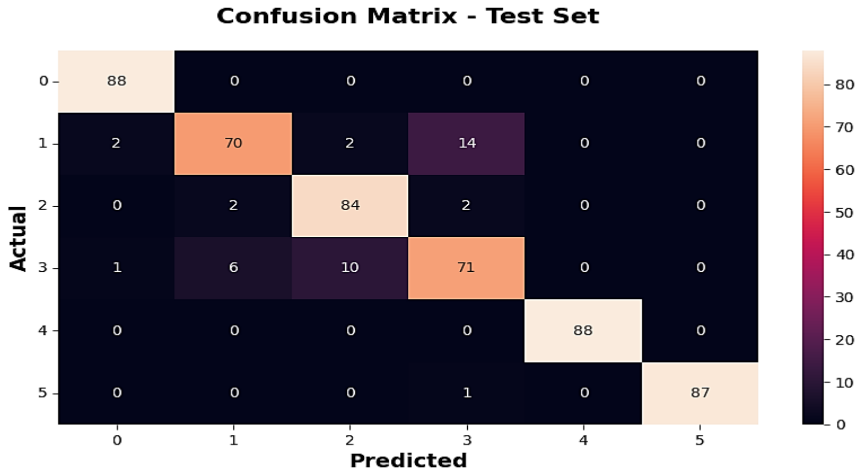

Figure 9 Confusion Matrix of MobileNetV2 on test data

The confusion matrix analysis reveals several insights about the model's performance. It accurately predicted all instances of the "bacterial leaf blight" and "leaf scald" classes, demonstrating high accuracy. However, there were misclassifications in the "brown spot" class, with 2 instances incorrectly labelled as "healthy" and 14 instances misclassified as "leaf blast." Similarly, the model faced challenges in accurately predicting the "leaf blast" class, with 6 instances misclassified as "brown spot" and 10 instances misclassified as "healthy." Nevertheless, it achieved a good performance in identifying the "healthy" class, with 84 instances correctly classified and only a few misclassifications. Additionally, the model accurately predicted all instances of the "narrow brown spot" class, with only 1 misclassification as "leaf blast.".

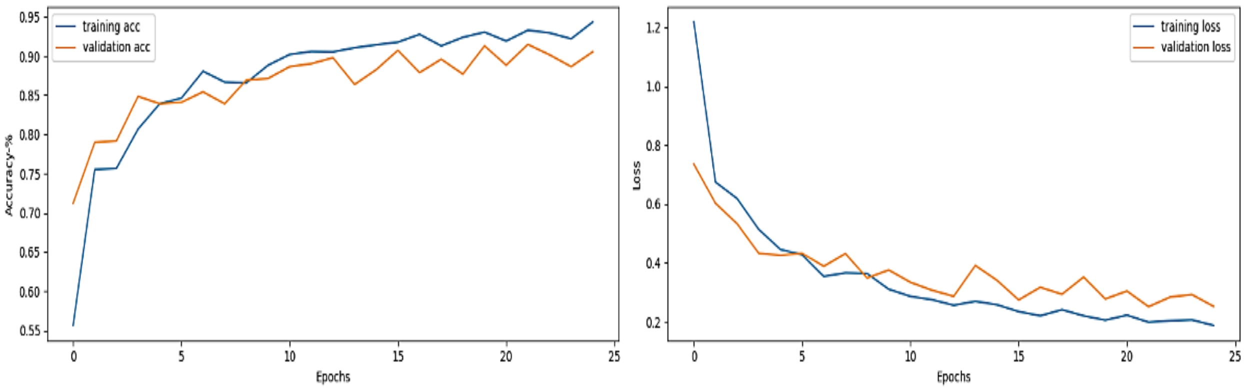

Figure 10 Training curve of MobileNetV2

The MobileNetV2 model, the graph demonstrates that the accuracy starts at a lower value of approximately 0.55% and shows a steady increase over the 25 epochs of training. As the model continues to train, the accuracy gradually improves and reaches. Around 0.92%. This suggests that the MobileNetV2 model is also learning from the training data and achieving higher accuracy with each epoch

Table 2 Comparison with existing studies

Model	Accuracy
MobileNetV2 (Proposed Model)	92.4%
VGG19	90.5%
Random Forest (Existing Work) [17]	69.44%

Our proposed model, MobileNetV2, outperforms the best performing model from the base paper, which is Random Forest. MobileNetV2 achieved an accuracy of 92.4% and demonstrated high precision, recall, and F1 scores across all classes, indicating its ability to accurately classify instances and identify instances of each class. In contrast, the Random Forest model had an accuracy of 69.44% and lower precision and recall values, suggesting it had more difficulty accurately classifying instances and correctly identifying instances of each class.

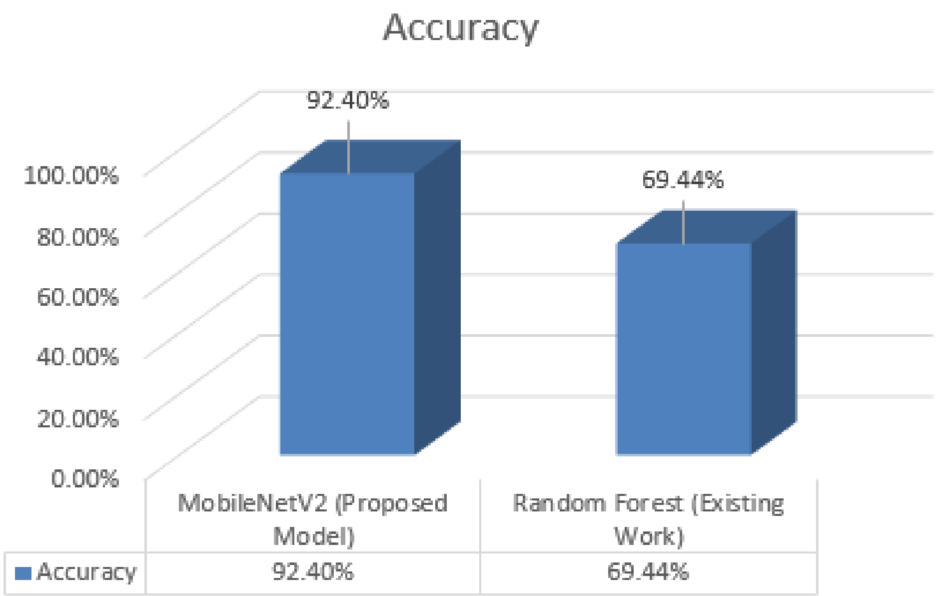

Figure 11 Graph result of proposed work

V. CONCLUSION

The findings of this research highlight the effectiveness of deep learning models, specifically MobileNetV2, in accurately detecting and classifying rice leaf diseases. The achieved high accuracy rates indicate the potential of these models as valuable tools for assisting farmers in disease management and crop protection. The superior performance of MobileNetV2 can be attributed to its efficient architecture and the utilization of pre-trained weights from the ImageNet dataset, which capture relevant visual features. Furthermore, the research demonstrates the significance of transfer learning, where pre-trained models are adapted to new tasks with limited training data. The ability to leverage pre-existing knowledge and generalize well to unseen samples contributes to the success of the proposed approach. However, there are limitations to consider. The performance of the models may vary depending on the dataset quality, diversity of disease instances, and the presence of confounding factors.

Future work should focus on expanding the dataset to encompass a wider range of rice leaf diseases and including images of healthy rice leaves under varying environmental conditions. Fine-tuning the models with additional data and exploring different architectures may lead to further improvements in accuracy and robustness.

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