Paddy Leaf Disease Detection Using Fine-tuned EfficientNetB4 Convolutional Neural Network

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***Abstract*: Agriculture serves as the primary source of income and livelihood in numerous countries. Within this context, various food crops play a crucial role, with rice standing out as a major staple, particularly in Asian countries. However, rice cultivation faces challenges from different diseases at various stages, impacting both quality and growth. Identifying these diseases can be challenging through time-intensive traditional methods and manual visual inspection due to similar symptoms among different ailments. Hence, the development and integration of automated systems proves to be highly beneficial in timely disease detection, enabling farmers to prevent crop damage at an early stage to produce quality yields. Over the past few years researchers have explored diverse techniques employing image processing, machine learning, and deep learning methods to develop efficient automated systems. Hence, this paper focuses on fine-tuning several state-of-art deep learning based state-of-art Convolutional neural networks for early prediction of different rice crop diseases i.e. paddy leaf diseases. This work also provides a comparative analysis of the techniques employed using accuracy, precision, recall and F-score metrics with fine-tuned EfficientNetB4 model achieving the best F-score of about 99.7%.**

Keywords: Paddy Leaf Detection, Bacterial Blight, Brown Spot, Tungro, Deep Learning, Mobilenet, DenseNet, XceptionNet, InceptionNet, EfficientNet.

I. Introduction

Agriculture serves as a primary income of source in several countries. Despite farmers adapting their cultivation practices to environmental conditions, they encounter numerous challenges such as plant diseases, natural disasters, and water shortages. Timely precautions can mitigate the impact of these issues, especially with the provision of technical assistance. Offering farmers technical support can effectively address specific problems, ultimately enhancing food productivity and quality without the need for expert intervention. Data science and machine learning play crucial roles in precision agriculture, disease detection, and bio-informatics, offering solutions to a range of challenges. Automated systems, including machine learning, image processing, deep learning, and feature selection or extraction, contribute to these advancements.

Taking a global perspective on different crops, rice emerges as a staple for over half of the world's population, significantly affecting income and food quality. Various diseases detrimentally impact rice crops with majorly following four having the worst impact.

i) Blast: Rice blast, caused by the fungus Magnaporthe oryzae, is a devastating disease that can affect all parts of the rice plant, from the leaves to the grains. The telltale signs of rice blast are oval-shaped lesions with a white or gray center and a reddish-brown border.

ii) Brown Spot: Brown spot is a fungal disease that manifests as small, dark brown lesions with a yellow halo on the leaves of rice plants. It can affect the entire plant, leading to reduced photosynthesis and yield loss.

iii) Tungro: Rice, the backbone of diets across Asia, faces a formidable adversary in the form of tungro virus. This stealthy menace, spread by the green leafhopper, leaves its mark on infected rice plants in the form of stunted growth, reduced tillering, and a disheartening yellowing of leaves.

iv) Bacterial leaf blight: a stealthy bacterial invader, wreaks havoc on rice plants, particularly targeting their leaves. The first signs of this infection are water-soaked lesions that transform into ominous brown spots, gradually causing the leaves to wither and blight.

Timely disease detection of these diseases is pivotal in implementing preventive measures and reducing the risk of widespread crop damage. Traditional methods relying on the naked eye and manual intervention are inadequate for correct disease identification. Extensive literature highlights the effectiveness of image processing in plant disease detection, with researchers employing machine learning and deep learning approaches.

Hence, the primary objective of this work is to use state-of-art deep learning methods relying on Convolutional neural networks (CNN) for paddy leaf disease detection, aiming for accurate and early identification of diseases in rice plant leaves. By analyzing paddy leaf images through modern techniques like MobileNet, EfficientNet, DenseNet etc., the goal is to automate the efficient detection process, providing farmers with timely insights to enhance crop management and improve overall agricultural productivity.

II. LITERATURE SURVEY

Nikhit et al. [1] introduced smart farming, incorporating sensors and machine learning for addressing the agricultural industry's challenges, leading to significant losses in crop yield caused due to several plant leaf diseases. This study compared Support vector machines (SVM), K-Nearest Neighbor (KNN), and Convolutional neural network (CNN) models for detecting eight leaf diseases with CNN model achieving a remarkable 96% accuracy on a soybean leaf disease dataset, surpassing KNN and SVM with accuracies of 64 percent and 76 percent, respectively.

Pothen et al. [2] addressed plant diseases, especially those affecting rice leaves as they are a significant challenge for farmers, impacting food production and causing economic losses. They proposed methods that outlined strategies for classifying rice leaf diseases, involving image segmentation and feature extraction using Local Binary Patterns (LBP) and Histogram of Oriented Gradients (HOG) followed by disease classification by using Support Vector Machines (SVM). The method achieved an impressive 94.6% accuracy with polynomial Kernel SVM and HOG.

Duth et al. [3] studied and introduced a semi-automated method for quickly categorizing rice plants as infected or unaffected by common leaf diseases (Leaf-Blast, Brown-Spot, and Hispa). Utilizing visual characteristics like texture, shape, and color, the SVM classifier efficiently identifies the type of paddy leaf disease, offering a more accurate solution than manual detection. Later, Vijayakumar et al. [4] provided a study that for rice leaf disease detection and compared methods like Convolutional Neural Networks (CNN), data augmentation with CNN, and Generative Adversarial Network (GAN) with CNN for efficiently identifying diseases in rice plant leaves.

Sethy et al. [5] proposed using deep CNNs to identify rice leaf diseases from 5932 on-field images. Comparing more than ten transfer learned CNN models and deep features classification based on SVM approach, where the latter showed superior classification performance. Smaller CNN models like ResNet101 were also examined based on accuracy, sensitivity, specificity, false positive rate, F1 Score, and training time. Statistical analysis favors ResNet50's deep feature plus SVM model, achieving an impressive F1 score of 98.3%

Sudhesh et al. [6] addressed rice leaf disease identification using deep learning with a novel Dynamic Mode Decomposition (DMD) and attention-driven pre-processing. Testing with four disease categories revealed DenseNet121's efficacy while DMD pre-processing boosted XceptionNet's accuracy. Achieving a 94.33% accuracy in on-field images, the proposed method outperformed other models, demonstrating superior performance in terms of several statistical methods.

Almasoud et al. [7] emphasized the use of deep learning methods in a smart computer program for early identification of diseases in paddy leaves. Through rigorous data preparation and performance comparisons, their work proved to be effective, showcasing its potential to significantly contribution to crop quality preservation and increased productivity in agriculture.

Gautam et al. [8] experimented with smart programs to detect diseases in paddy plants. They prepared leaf images, focused on vital areas, and fine-tuned the programs to enhance disease detection, specifically targeting fungal and bacterial infections. Their work demonstrated superior accuracy at 96.4 in identifying diseases in paddy leaves. Later Petchiammal et al. [9] introduced the PaddyNet model, comprising of 17 layers, to enhance accuracy in identifying diseases. Analyzing 16,225 paddy leaf images across 13 classes, the study affirmed PaddyNet's effectiveness, achieving an impressive 98.99% accuracy in classifying disease images.

Rajendran et al. [10] also developed a custom CNN model and trained it on a diseased rice leaf image dataset to capture unique features associated with specific diseases, akin to human intelligence. Later, Ramesh et al. [11] presented an innovative approach for automated disease recognition in paddy plant leaves, aiming to reduce manual efforts by farmers. The method, named "Recognition and Classification of Paddy Leaf Diseases using Optimized Deep Neural Network with Jaya Algorithm," captured rice plant leaf images and employed techniques like HSV conversion, binary image extraction, and clustering for background removal and disease segmentation. The disease classification using the proposed Optimized Deep Neural Network with Jaya Optimization Algorithm (DNN_JOA) achieved notable accuracies, such as 98.9% for blast and 95.78% for bacterial blight, surpassing alternative methods like ANN, DAE, and DNN.

Upadhyay et al. [12] introduced a study that used transfer learning techniques, specifically DenseNet201 model to detect diseases like blast, bacterial leaf blight, and tungro in rice crops. The dataset comprises 240 images across three classes, and DenseNet model was proven to achieve a superior accuracy of 96.09% compared to other existing models.

Nalini et al. [13] utilized IoT and networking for crop management. Their study introduced a DNN model for identifying paddy leaf diseases, optimizing with a crow search algorithm (CSA). The DNN-CSA simplifies statistical learning, ensuring high classification accuracy. Paddy leaf image preprocessing involved K-means clustering to extract disease-indicative areas. Experimental verification demonstrates the superiority of the proposed DNN-CSA model over a support vector machine in terms of classification accuracy.

Haridasan et al. [14] used efficienta computer vision approaches, combining image processing, machine learning, and deep learning to identify diseases like bacterial leaf blight, false smut, brown leaf spot, rice blast, and sheath rot in Indian rice fields. Achieving an accuracy of 91%, this strategy suggested remedies post-disease recognition, aiding timely and effective measures for agriculture-related individuals and organizations. Based on the recent literatures highlighted in recent years [15-16], the proposed work fine-tunes the state-of-art CNN based deep neural networks for identifying disease in paddy leaves for timely control and boosted rice yield.

III. METHODOLOGY

A. Dataset and Features Description:

For the purpose of this study we employed standard paddy leaf (https://data.mendeley.com/datasets/fwcj7stb8r/1) dataset having paddy leaf images, including both healthy and diseased leaves. The dataset contains 5932 images of paddy leaf diseases distributed across four disease classes namely Bacterial Blight, Blast, Brown spot and Tungro as presented in Table - 1. The dataset ensures that the images collected are diverse and representative of the variations in paddy leaf diseases. Fig – 1 represents the sample leaf disease images from the dataset.

TABLE – 2: NO. OF IMAGES FROM EACH CLASS OF DISEASE WITH SPLITUP MENTIONED FOR TRAINING, VALIDATION AND TESTING SAMPLES

Diseases	Training	Validation	Testing
Bacterial Blight	950	316	316
Blast	864	288	288
Brown spot	960	320	320
Tungro	784	261	261

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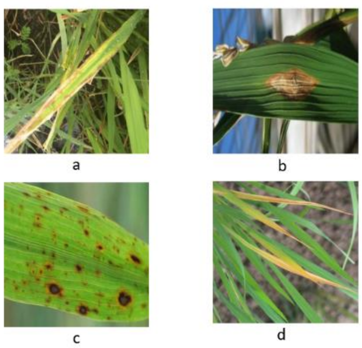

Fig – 1 Leaf Diseases of (a) Bacterial Blight (b) Blast (c) BrownSpot (d) Tungro

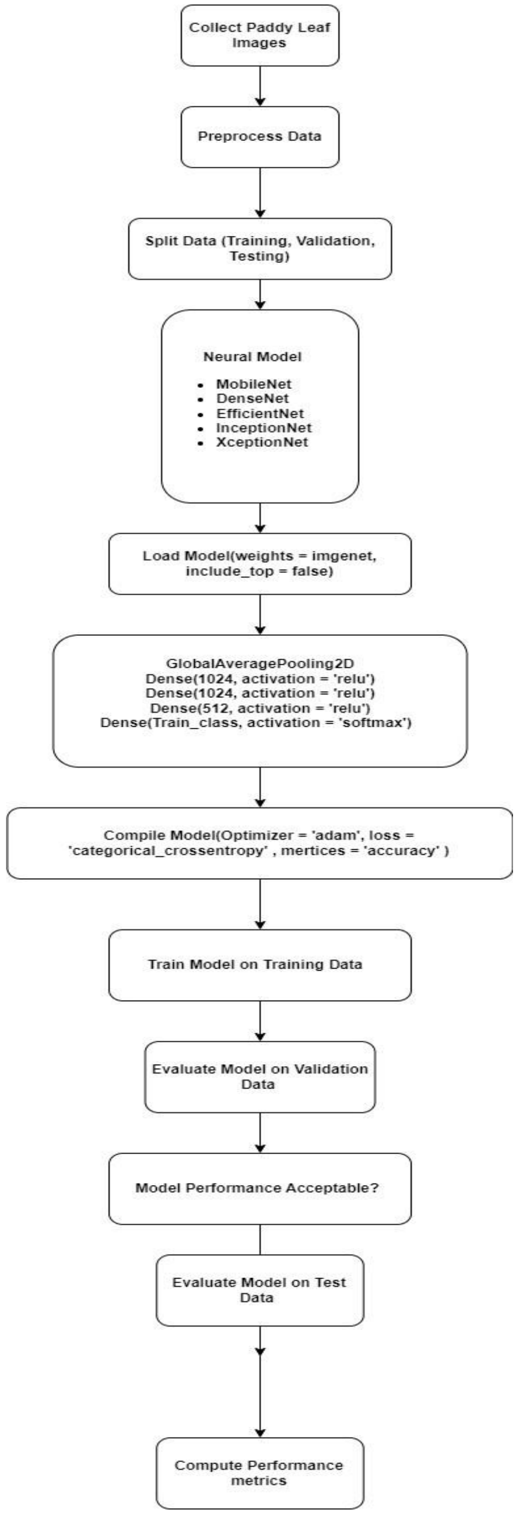

Fig – 2 System architecture for proposed methodology

B. System Architecture

Fig – 2 presents the over-all system architecture of the proposed system. Initially, the paddy leaf dataset is collected and is subjected to various pre-processing tasks. The images in the dataset ae resized to a common image size of 224 x 224 pixels. The images are then subjected to data augmentation techniques involving zoom_range = 0.15, width_shift_range = 0.2 and shear_range = 0.15. The

dataset is split into training, validation and testing sets ina ratio of 60:40:40. Freeze the layers of the base model and add custom layers on top for fine-tuning.
Once the training dataset is ready, the proposed architecture attempts to fine-tune the Convolutional neural network based EfficientNetB4 model for paddy leaf disease detection.

EfficientNetB4 employs compound scaling, simultaneously adjusting depth, width, and resolution for a balanced model. It features repeated blocks with depth-wise separable convolutions, batch normalization, and Swish activation functions. The model is larger and more powerful due to higher scaling factors. The model uses inverted residuals with skip connections to reduce the memory requirements as it is restricted by size of the bottleneck tensors, concluding with global average pooling for parameter reduction. The Swish activation function adopted by the model often utilizes for enhanced performance, and dropout may be incorporated to prevent over-fitting during training.

Fine-tuning of the pre-trained EfficientNetB4 model on Paddy leaf dataset is achieved by adding pooling and few dense layers at the tail end of the model. The Efficient NetB4 model is loaded and its top layer is removed from the model. Then the model is augmented by adding a Global average pooling (GAP) layer to reduce spatial dimensions. This GAP layer is followed by three dense layers having 1024, 1024 and 512 neurons. These layers use Rectified Linear Unit (ReLU) activation function for faster computations. The final output layer consists of 4 neurons and utilizes the Softmax activation for multi-class classification. Use the base model with pre-trained weights. The output layer uses the categorical cross entropy loss for error back-propagation with accuracy performance metric.

C. Pilot Study

Comparisons of the proposed methodology against the state-of-art Convolutional neural network has been done by fine-tuning different state-of-art CNN models namely, MobileNetV3, InceptionV3, XceptionNet and DenseNet201 model on Paddy Leaf disease detection dataset. These models have also been fine-tuned using the similar steps as presented in Fig – 2.
These models have been chosen keeping in mind the unique characteristics of each model which have been discussed in detail in the following sub-sections.

MobileNetV3 model:
MobileNetV3, a lighter CNN model developed for mobile and edge devices, utilizes the depth-wise separable convolution, consisting of depth-wise and point-wise convolutions. Depth-wise convolution reduces parameters by conducting a single 3x3 convolution for each input channel independently. Pointwise convolution integrates information across output channels using 1x1 convolutions. MobileNetV2 introduces inverted residuals with linear bottlenecks, enhancing gradient flow through skip connections. Unlike traditional convolutions, linear bottlenecks use a linear activation function for information preservation. Global average pooling is employed at the network's end, reducing parameters and allowing variable-sized inputs. Two hyperparameters, width multiplier and resolution multiplier, offer flexibility in balancing model size and accuracy by adjusting channel count and input resolution.

DenseNet201 model:
Layers within each block in this architecture optimizes information flow and learning by reusing features from all previous layers. The management of channels and dimensions between dense blocks involves batch normalization, 1x1 convolutions, and average pooling. The inclusion of 1x1 convolutions within dense blocks aids in reducing input channels, enhancing computational efficiency. The network's strength lies in its robust feature propagation and gradient flow, enabling the learning of complex representations. The model's large size allows it to capture intricate patterns and effectively handle challenging tasks. Fully connected layers at the end are replaced to reduce parameters. Additionally, dropout is employed during training to randomly drop connections and prevent over-fitting.
InceptionNetV3:
InceptionNet's innovation lies in inception modules, combining parallel convolutional branches with diverse filter sizes to capture features across scales. 1x1 convolutions reduce dimensionality, while max-pooling operations capture spatial hierarchies. GoogLeNet introduces auxiliary classifiers to address vanishing gradients. InceptionNetV3 uses global average pooling instead of traditional fully connected layers, promoting feature reuse and information flow through stacked inception modules. The architecture concludes with a softmax activation for classification probabilities.

XceptionNet:
XceptionNet efficiently captures hierarchical features using iterated separable convolution blocks. The network comprises an entry flow with conventional and separable convolutions, incorporating skip connections for smooth information flow. The middle flow extracts intricate patterns with separable convolutions, while the exit flow reduces spatial dimensions with global average pooling and utilizes skip connections. XceptionNet replaces traditional fully connected layers with standard convolutions followed by global average pooling, applying batch normalization and ReLU activation. The architecture concludes with a softmax layer for multi-class classification.

IV. Experimentation and Results

Once the model is created, the dataset is split into training, validation and testing sets in the ratio of 60:20:20. To train the model on the training dataset we are using the fit_generator method. We have used number of epochs = 40 for training the model on Paddy leaf dataset. The steps for each epoch is decided based on the ratio of Number of images in Train or Validation class to the Batch size. The model is equipped with Adam optimizer and uses categorical cross entropy loss function. Evaluate the trained model on the test dataset to assess its generalization performance. Table 2 presents the parameter settings for the model training in detail.

TABLE – 2: PARAMETER SETTING FOR VARIOUS CNN MODELS

Training:Validation:Testing	60:20:20
Batch_size	32
Image height and width	224 x 224
Activation Function	ReLU, Softmax(Output Layer)
Optimizer	Adam
Loss function	catogrical_crossentropy
Metrics	Accuracy
steps_for_each_epoch	Number of Images/Batch_size

Once trained, the performance of the model is tested on the test dataset using metrics such as accuracy, precision, recall, and F1 score. A confusion matrix is generated to understand the model's performance on each class.

TABLE - 3 LOSS AND ACCURACY VALUES OBTAINED BY DIFFERENT MODELS AT THE END OF THE 40TH EPOCH

Models	Loss		
	Train	Validation	Test
MobileNet	0.0736	0.0921	0.0807
DenseNet201	0.0623	0.0679	0.1933
EfficientNetB4	0.0499	0.0312	0.0097
InceptionNetV3	0.4271	0.5634	0.569
XceptionNet	0.4271	0.5406	0.4237

Models	Accuracy		
	Train	Validation	Test
MobileNet	0.9653	0.9582	0.9764
DenseNet201	0.9751	0.976	0.9494
EfficientNetB4	0.9858	0.9914	0.9975
InceptionNetV3	0.8185	0.7702	0.817
XceptionNet	0.8254	0.7885	0.8727

From Table 3, we can deduce that amongst the deep learning models evaluated on the test set, EfficientNetB4 stands out as the best performer with the lowest test loss of 0.0097. Lower loss values indicate that the model is better at minimizing the difference between its predictions and the actual target values. In comparison, other models like MobileNet (0.0807), Xception Net (0.4237), DenseNet201 (0.1933), and Inception NetV3 (0.569) have relatively higher test losses. While loss is a crucial metric, the choice of the best model may also depend on other considerations such as computational efficiency, model size, and the specific requirements of the task at hand.

Among the evaluated deep learning models, EfficientNetB4 model also demonstrates the highest performance with an accuracy of 99.75% on the test set, indicating its effectiveness in making correct predictions. Following closely, XceptionNet achieves an accuracy of 87.27%, while MobileNet performs at 97.64%, DenseNet201 at 94.94%, and InceptionNetV3 at 81.70%. Accuracy is a key metric for classification tasks, representing the percentage of correct predictions. However, the selection of the best model may also hinge on other considerations such as computational efficiency, interpretability, and alignment with specific task requirements. In this context, EfficientNetB4 emerges as the top performer in accurately classifying the test data.

Fig – 3 provides a graphical representation of the models, (a) MobileNetV3 (b) DenseNet201 (c) InceptionNetV3 (d) XceptionNet and (e) EfficientNetB4 model learning using loss values over the number of epochs. We can a analyze that EfficientNetB4 model performs well in terms of training and validation loss. It is because the Oscillations of training and testing are stable and the difference between the training and validation is less.

Also Convergence of the training loss between the training and validation is low. So EfficientNetB4 performs well.

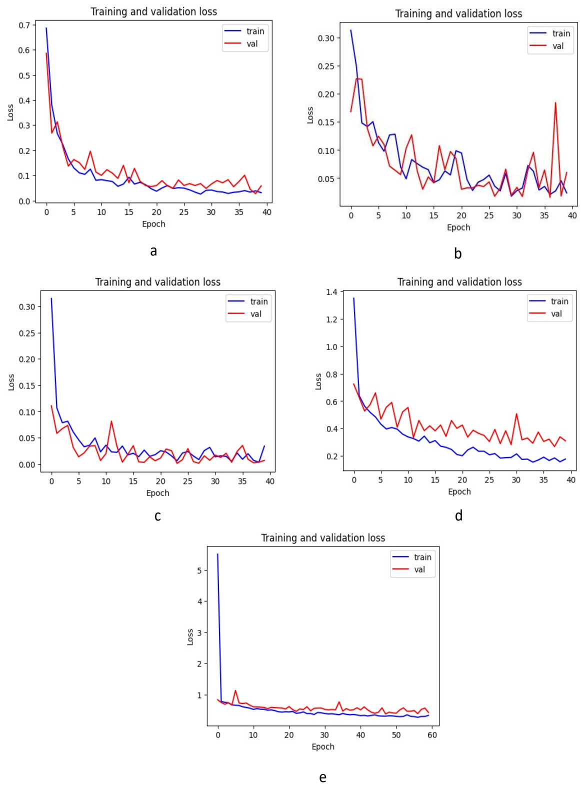

Fig – 3 Training and Validation Loss of (a) MobileNet (b) DenseNet201 (c) InceptionNetV3(d) XceptionNet (e) EfficientNetB4

TABLE - 4 COMPARATIVE PERFORMANCE EVALUATION OF DIFFERENT MODELS ON TEST DATASET

Models	Precision	Recall	F1
MobileNetV3	0.9777	0.9756	0.9764
DenseNet201	0.9498	0.9523	0.9491
XceptionNet	0.8906	0.8707	0.8736
InceptionNetV3	0.8201	0.8147	0.8736
EfficientNetB4	**0.9974**	**0.9975**	**0.9974**

From Table - 4, it can be analyzed that F1 score of the fine-tuned EfficientNetB4 model is the highest at 99.74% on test dataset with exceptional and a balanced Precision and Recall values at 99.74% and 99.75%. While the MobileNetV3 model has also performed well with F1 score of 0.9764 followed by the DenseNet201 model.

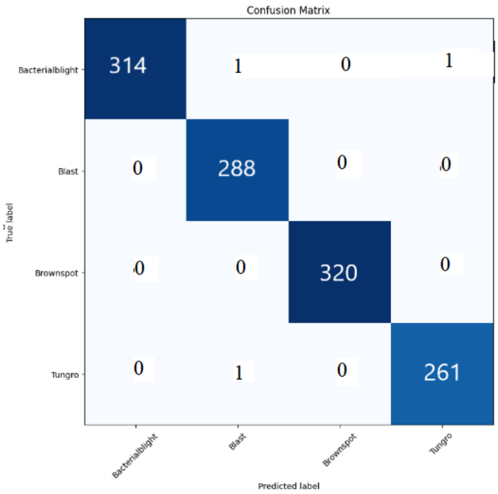

Fig – 4: Classification report obtained for EfficientNetB4 model

The confusion matrix that presents the class-wise classification report for the fine-tuned EfficientNetB4 model claims that the proposed model has performed extremely well in distinguishing diseases of all four kinds. Especially the proposed method obtained perfect classification for 'Blast' and 'Brownspot' diseases with no False positives and False negatives.

V. CONCLUSION

In summary, the integration of various deep learning models, including MobileNetV3, EfficientNetB4, DenseNet201, InceptionNetV3, and XceptionNet, has significantly advanced paddy leaf disease detection. Among these, EfficientNetB4 stands out for its remarkable balance between accuracy and computational efficiency. As a standout performer, EfficientNetB4 proves crucial for practical applications in agriculture, offering precise disease identification while optimizing resources. Looking forward, the ongoing evolution of these models, particularly the efficiency-driven capabilities of EfficientNetB4, holds great promise for enhancing disease management in agriculture and ensuring global food security. Each program has its own special way of doing this, making them useful for different situations in paddy fields. This technology is exciting because it gives farmers and researchers powerful tools to figure out if there are diseases in their crops early on. By catching problems sooner, farmers can take action to protect their crops and make sure they grow well. It's like having a high-tech helper in the field, making farming smarter and more efficient. As these technologies keep getting better, they'll likely play a big part in making sure we have enough food for everyone in the world.

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