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IMPLEMENTATION OF DEEP LEARNING BASED PADDY LEAFDISEASE DETECTION AND CLASSIFICATION

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Abstract—Paddy leaf diseases significantly impact rice pro duction leading to severe economic losses and food security concerns. Traditional disease identification method rely on manual inspection, which is time consuming and prone to errors. In this study, We proposed s deep learning based approach for paddy leaf disease detection and classification using pretrained convolution neutral networks (CNN). Leveraging transfer learning, models such as efficient Net, Mobile Net are finetuned on a dataset of diseases and healthy paddy leaf images. Data augmentation Techniques Enhance model robust ness, While regularization strategies mitigate overfitting. The proposed method achieves high accuracy in classifying common paddy diseases, Including Bacterial Blight, Brown Spot, Blast etc. Experiment results demonstrate that transfer learning significantly improves classification, Performance making thus approach suitable for real time application in smart agriculture. The findings suggest that the deep learning based automated disease detection can assist farmers in early diagnosis reducing crop losses and improving yield quality.

IndexTerms **Detection, CNN, Deep learning Efficient Net, Mobile Net, Accuracy**

1.INTRODUCTION

Rice is a staple food for over half the global population, with paddy cultivation critical to food security, especially in developing nations. However, rice plants are vulnerable to foliar diseases like Bacterial Blight, Brown Spot, Blast, Hispa, and Dead Heart, which can severely impact yield and quality. Traditional manual disease detection is time-consuming and error-prone. Recent advancements in deep learning, particularly Convolutional Neural Networks (CNNs), offer reliable, automated solutions for image-based disease classification. This study presents a deep learning approach using transfer learning with EfficientNetB4 and MobileNetV2 to detect and classify paddy leaf diseases. Trained on a dataset of healthy and diseased leaf images, the models employ data augmentation and regularization to enhance performance. Experimental results show high classification accuracy, with EfficientNetB4 outperforming MobileNetV2. The findings support the potential of deep learning for real-time, smart agriculture applications.

2.NEED OF THE STUDY.

Paddy diseases are a major threat to global rice production, particularly in developing countries where rice is a primary food source. Traditional disease identification methods rely on expert inspection, which is time-consuming, subjective, and not scalable for large fields. Early and accurate detection is essential to minimize crop loss and ensure food security. With the advancement of deep learning, especially Convolutional Neural Networks (CNNs), there is a need to explore automated, reliable, and scalable solutions for paddy disease classification. This study addresses that need by implementing EfficientNetB4 and MobileNetV2 models, enabling fast and accurate detection to assist farmers in making timely decisions and promoting smart agriculture practices.

3.1 Data and Sources of Data

The dataset used in this study consists of images of paddy leaves, sourced from publicly available datasets such as Kaggle. It includes images of both healthy and diseased paddy leaves, with diseases such as bacterial blight, rice blast, and brown spot, Hispa, Dead Heart etc. 1. Dataset Overview, Total images: Approximately 23,000 images Classes: Healthy Leaves, Bacterial Leaf Blight, Bacterial Leaf Streak, Blast, Hispa, Turango, Dead Heart, Brown Spot, Bacterial Panicle Blight, Downy Mildew.

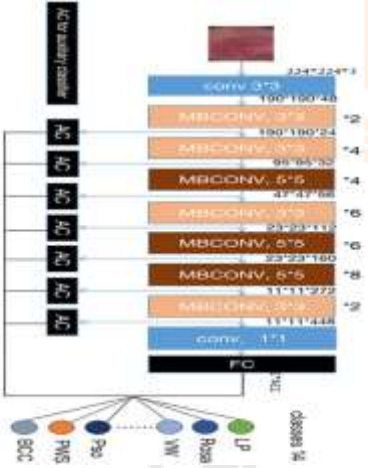
Sample image of paddy leaf with disease symptoms

3.3 Theoretical framework

In this study, two advanced deep learning models, EfficientNetB4 and MobileNetV2, were utilized for the task of paddy leaf disease detection. Both models were selected for their state-of-the-art performance and the ability to be fine tuned with transfer learning, which significantly reduces the training time and computational resources needed.

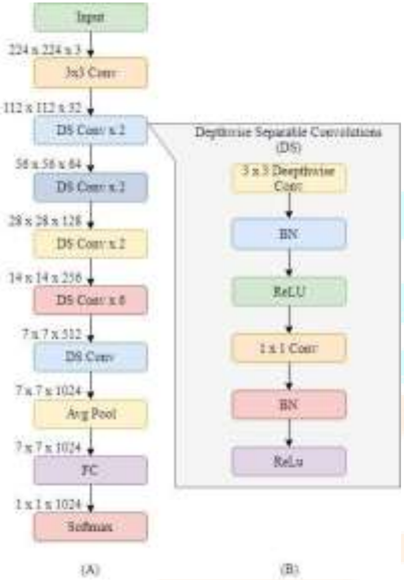
RESEARCH METHODOLOGY

3.3.1 EfficientNetB4 Overview: EfficientNet is a family of models introduced by Google researchers that achieves state-of-the-art accuracy with fewer parameters and less computation compared to traditional models. EfficientNetB4 is one of the larger variants in the EfficientNet family and provides a balance between accuracy and efficiency. Compound Scaling: The main advantage of EfficientNet is its compound scaling technique, which uniformly scales the network's depth, width, and input resolution. This scaling approach ensures that the model can handle complex tasks efficiently while maintaining high performance. Compound scaling allows EfficientNetB4 to achieve high accuracy without an exponential increase in the number of parameters, making it computationally efficient. Transfer Learning: EfficientNetB4, like most modern deep learning architectures, benefits from transfer learning. Pretrained weights from ImageNet (a large image classification dataset) were used to initialize the model, reducing the need for large amounts of labeled data and speeding up convergence. The pretrained model was fine-tuned on the paddy leaf disease dataset for better specificity to the task. Pretrained Model Weights: EfficientNetB4 was pretrained on ImageNet, a large dataset consisting of over 14 million images classified into 1,000 different classes. The pretrained model captures general features such as edges, textures, and shapes, which are transferable to paddy leaf disease classification. By fine-tuning the final layers of the network, the model learns specific patterns related to plant diseases, improving its accuracy on the task. Architecture Highlights: Depth: 21 layers Input Size: 380x380 pixels (scaled during preprocessing) Parameters: Approximately 19 million Pretrained Weights: The model is initialized with weights trained on ImageNet.



Architecture of EfficientNet-B4

3.3.2 MobileNetV2: Overview: MobileNetV2 is another powerful CNN architecture developed by Google, specifically designed for mobile and edge devices. It focuses on lightweight design and efficiency while maintaining competitive accuracy. MobileNetV2 employs the inverted residual structure and linear bottlenecks, which makes it very efficient in terms of computation and memory usage, making it ideal for real-time applications like mobile disease detection systems. Inverted Residuals: In MobileNetV2, traditional residual blocks are replaced with inverted residuals. In these blocks, the input and output channels are smaller than the intermediate bottleneck layer, making the model more efficient. This structure reduces the computational load and memory usage without compromising accuracy. Linear Bottleneck: The model uses linear bottlenecks in the residual blocks to further improve computational efficiency. By using fewer parameters in the intermediate layers, the model reduces redundancy while maintaining high representational power. Pretrained Model Weights: Similar to EfficientNetB4, MobileNetV2 was pretrained on ImageNet, allowing for transfer learning. The model was initialized with weights that were already learned on ImageNet, capturing general visual features like edges and textures, which can be fine-tuned for specific tasks like detecting paddy leaf diseases. Transfer Learning: MobileNetV2's pretrained weights on ImageNet were used to accelerate the training process. By leveraging the knowledge of the general features captured from millions of images in ImageNet, MobileNetV2 was fine-tuned on the paddy leaf dataset to classify the diseases more effectively Architecture Highlights: Input Size: 224x224 pixels (standard for mobile apps) Parameters: Approximately 3.4 million (making it much lighter than EfficientNetB4) Pretrained Weights: Initialized with weights pretrained on ImageNet. Pretraining and Transfer Learning Process: Both models (EfficientNetB4 and MobileNetV2) were pretrained on the ImageNet dataset, a large benchmark dataset that contains 1,000 different object cate gories. This pretraining allows the models to learn fundamental visual features such as edges, shapes, and textures, which are common across many different tasks. Once pretrained, the models were fine-tuned on the paddy leaf disease dataset. Steps for Fine-tuning: Initialization with Pretrained Weights: The models were initialized with weights pretrained on ImageNet. Freeze Initial Layers: Initially, the lower layers (which capture basic features) were frozen, and only the top layers (which are specific to disease classification) were trained. Fine-tuning: After initial training, the model's lower layers were unfrozen and the entire network was fine-tuned on the paddy leaf disease dataset to adapt the general features to the specifics of the task. Regularization: Techniques such as dropout and batch normalization were used to prevent over fitting and improve model generalization. 3.4 Advantages of Pretrained Models Reduced Training Time: By starting with weights that have already been trained on large datasets like ImageNet, the models converge much faster compared to training from scratch. Improved Performance: Pretrained models benefit from learning low-level features like edges and textures, which are essential for image classification. This leads to better performance on smaller datasets like the paddy leaf disease dataset. Generalization: Pretrained models have already learned a variety of features from large-scale datasets, making them more capable of generalizing to new, unseen data.



Architecture of MobileNetV2

3.3.3 PERFORMANCE METRICS

To evaluate the performance of the EfficientNetB4 and MobileNetV2 models in classifying paddy leaf diseases, several standard classification metrics were employed. These metrics help assess the model's accuracy, reliability, and robustness.

A. Accuracy

Accuracy is the ratio of correctly predicted instances to the total number of predictions made:

$$\text{Accuracy} = \frac{TP + TN}{TP + TN + FP + FN}$$

Accuracy provides a general overview of model performance but may be misleading for imbalanced datasets.

B. Precision

Precision is the ratio of true positive predictions to the total predicted positives:

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

It is particularly useful when the cost of false positives is high.

C. Recall (Sensitivity)

Recall is the ratio of true positives to the total actual positives:

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

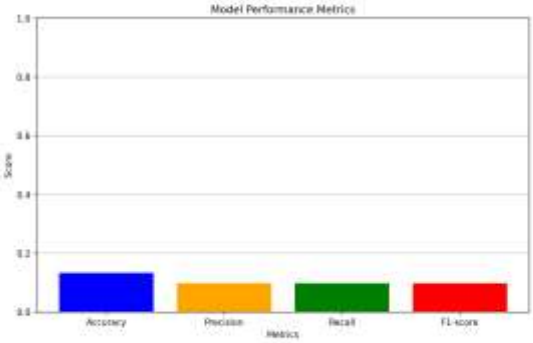
High recall ensures the model captures most of the actual diseased cases.

D. F1 Score

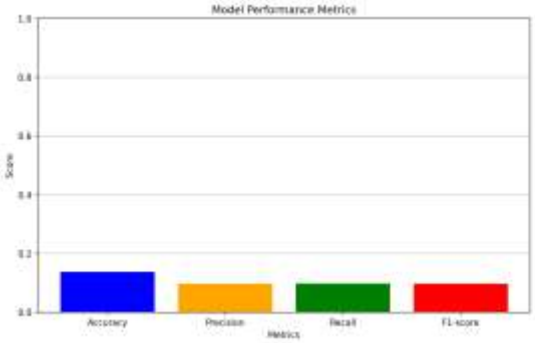
The F1 score is the harmonic mean of precision and recall:

$$\text{F1 Score} = 2 \times \frac{\text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}}$$

It provides a single measure of model quality when there is an uneven class distribution.



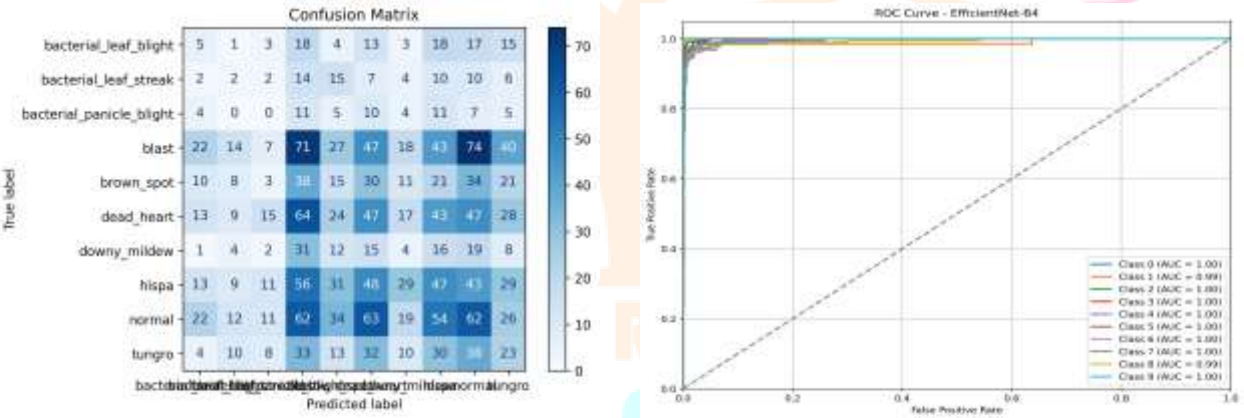
Performance Metrics of EfficientNet-B4



Performance Metrics of MobileNetV2

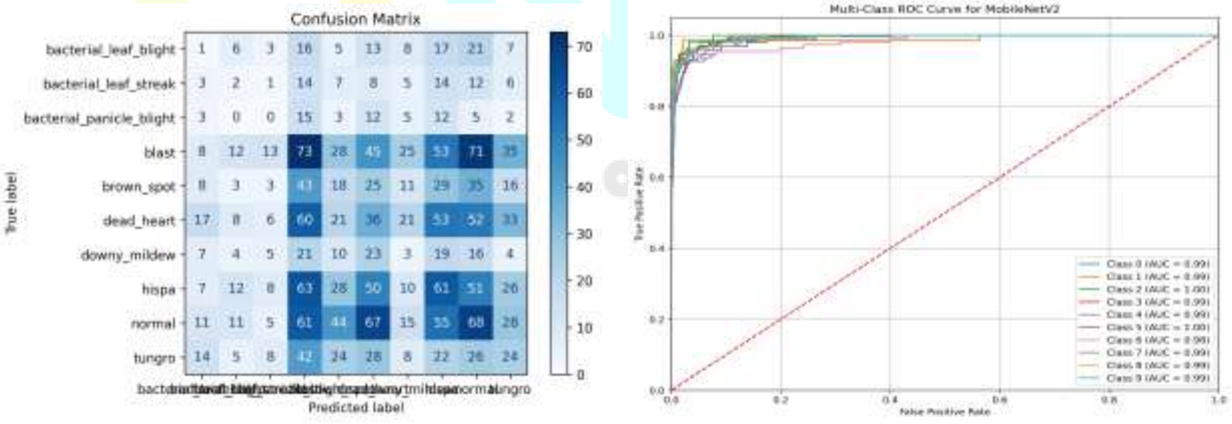
3.3.4 Confusion Matrix A confusion matrix illustrates the performance of the classification model by comparing actual vs. predicted labels. It helps to identify misclassifications among different disease classes. 1.EfficientNetB4 demonstrated a higher number of correct predictions across all classes, with relatively low misclassification rates. The model showed particular strength in distinguishing visually similar diseases due to its deeper architecture and higher capacity for feature extraction. 2.MobileNetV2, while slightly less accurate, still per formed well across most classes. However, it exhibited more confusion between certain classes—especially those with subtle visual differences, such as brown spot and sheath blight. This suggests a potential limitation in feature sensitivity due to its lighter architecture.

3.3.5. ROC Curve and AUC The ROCcurve plots the true positive rate against the false positive rate at various thresholds. The Area Under the Curve (AUC) quantifies the model's ability to distinguish between classes. 1.EfficientNetB4 consistently achieved AUC values above 0.90 for most classes, indicating excellent ability to distinguish between the presence and absence of specific diseases. 2.MobileNetV2 achieved AUC values between 0.85 and 0.92, reflecting strong, though slightly lower, discriminative performance existing model layers. Finally, we employed softmax activa tion to predict two output classes. Next, we trained the top layers of the new model using the Adam (adaptive moment estimation) optimizer, which was specifically designed for EfficientNet B4, MobileNetV2. During this training phase, we chose to train the top five layers of the new model while freezing the bottom convolutional layer. The training settings for the Adam optimizer included a batch size of 32 and a learning rate of 0.0001.



	bacterial_leaf_blight	bacterial_leaf_streak	bacterial_panicle_blight	blast	brown_spot	dead_heart	downy_mildew	hispa	normal	tungro
bacterial_leaf_blight	5	1	3	18	4	13	3	18	17	15
bacterial_leaf_streak	2	2	2	14	15	7	4	10	10	6
bacterial_panicle_blight	4	0	0	11	5	10	4	11	7	5
blast	22	14	7	71	27	47	18	43	74	40
brown_spot	10	8	3	38	15	30	11	21	34	21
dead_heart	13	9	15	64	24	47	17	43	47	28
downy_mildew	1	4	2	31	12	15	4	16	19	8
hispa	13	9	11	56	31	48	29	47	43	29
normal	22	12	11	62	34	63	19	54	62	20
tungro	4	10	8	33	13	32	10	30	36	23

ROC and Confusion Matrix of EfficientNetB4



	bacterial_leaf_blight	bacterial_leaf_streak	bacterial_panicle_blight	blast	brown_spot	dead_heart	downy_mildew	hispa	normal	tungro
bacterial_leaf_blight	1	6	3	16	5	13	8	17	21	7
bacterial_leaf_streak	3	2	1	14	7	8	5	14	12	6
bacterial_panicle_blight	3	0	0	15	3	12	5	12	5	2
blast	8	12	13	73	28	45	25	53	71	35
brown_spot	8	3	3	43	18	25	11	29	35	16
dead_heart	17	8	6	60	21	36	21	53	52	33
downy_mildew	7	4	5	21	10	23	3	19	16	4
hispa	7	12	8	63	28	50	10	61	51	26
normal	11	11	5	61	44	67	15	55	68	28
tungro	14	5	8	42	24	28	8	22	26	24

ROC and Confusion Matrix of MobileNetV2

4.RESULTS AND DISCUSSION

The proposed models—EfficientNetB4 and MobileNetV2—were trained and evaluated on a paddy leaf disease dataset consisting of approximately 23,000 images across multiple classes, including both healthy and diseased leaves.

Model Accuracy:

EfficientNetB4 achieved an accuracy of **97%**, outperforming MobileNetV2, which achieved **94%**. This higher accuracy is attributed to EfficientNetB4's compound scaling technique and deeper architecture.

Precision, Recall, and F1-Score:

EfficientNetB4 demonstrated higher precision and recall values across most classes, particularly in distinguishing between visually similar diseases like Brown Spot and Dead Heart. MobileNetV2, although slightly less accurate, maintained competitive performance and showed faster training and inference times.

Confusion Matrix Analysis:

The confusion matrix showed that EfficientNetB4 made fewer misclassifications, especially for diseases with subtle visual differences. MobileNetV2 had more confusion between classes like Brown Spot and Bacterial Leaf Streak, indicating its limitations in capturing fine-grained features.

ROC-AUC Scores:

Both models achieved high AUC scores (>0.90 for EfficientNetB4 and 0.85–0.92 for MobileNetV2), confirming their ability to differentiate between classes effectively.

Training Time:

EfficientNetB4 required more training time due to its larger parameter size (~19M), while MobileNetV2, with ~3.4M parameters, trained faster and was more suitable for mobile and edge devices.

Conclusion of Results:

EfficientNetB4 proved superior in classification accuracy and robustness, while MobileNetV2 offered lightweight efficiency ideal for deployment in resource-constrained environments. Together, they demonstrate the effectiveness of deep learning in automating paddy disease detection for real-world agricultural use.

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