

## Paddy Leaf Disease Detection using EfficientNet-B0 Using Deep Learning Model

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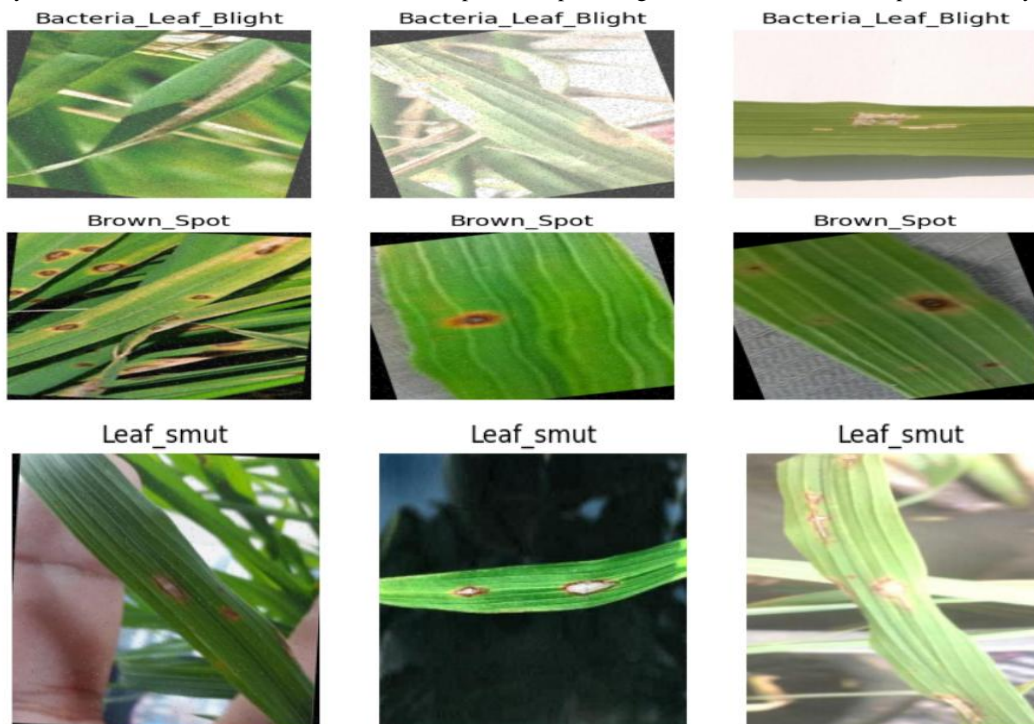
### Abstract:

As Agriculture plays an Important role in ensuring food security, rice (paddy) and it is the one of the most important and staple Crop worldwide. The paddy crop can be infected by many numerous types of diseases which affect both yield and quality. We need early and accurate detection of these Diseases is essential for effective crop management. This Research will provide a Deep-Learning Based System automatic detection of paddy leaf diseases using the EfficientNet-B0 Architecture. A dataset contains paddy leaf images that belongs to three classes (i.e: Bacteria Leaf Blight, Brown spot, and Leaf Smut) These are used to train and evaluate the model. The dataset was preprocessed through resizing, normalization, and augmentation techniques to improve the model performance. These model was trained and compared with other multiple models. The system is developed by this research can automatically identify the disease of paddy leaves through image analysis. The system can provide accurate results. This is because the model uses less processing power obtained important features of the images. This system will help farmers to identify the diseases easily during their initial stages.

**Keywords:** Paddy Disease Detection, Deep Learning, EfficientNet-B0, Image Classification, Precision Agriculture

### INTRODUCTION:

Rice is one of the most widely eaten foods and it plays a vital role in global food security. The cultivation of paddy rice provides essential contributions to the economies of the countries that produce them, with many of these being in developing nations. Unfortunately, the paddy crop is also susceptible to multiple diseases, including Bacterial Leaf Blight, Brown Spot Diseases, and Leaf Smut Disease. These diseases can severely affect crop yield and quality if not detected and treated at an early stage. The Agricultural experts have identified paddy crop disease by using visual examination methods, which is a lengthy process, labour-intensive, and often Prone human error. The Farmers in remote area may not have access to expert guidance, which further delays proper diagnosis and treatment. Recently the advances made in Artificial Intelligence (AI) and deep Learning techniques have opened up new possibilities for the automatic detection of crop disease. These AI models are now able to learn the complex visual patterns associated with an image of a plant leaf and identify the disease with a high level of accuracy. This research develops an automated system for the detection of paddy diseases using deep learning based on the EfficientNet-B0 architecture. EfficientNet-B0 models are a unique family of models that provide proportionate scaling of the model depth, width, and resolution, which allows enabling high performance with fewer parameters. The proposed approach aims to accurately detect paddy leaf diseases and compare its performance with multiple deep learning architectures to identify the most effective model. The dataset provides overall and before we start the training the deep learning model we need to do some things to the pictures in the dataset. This helps the models to work better and makes sure all the images look the same. We make all the images to same size as 224\*224 pixels. The EfficientNet-B0 model helps us to make changes of the numbers that make up the pictures so they are all, on the scale. The EfficientNet-B0 helps the deeplearning models to learn from the pictures easily when we are training them.



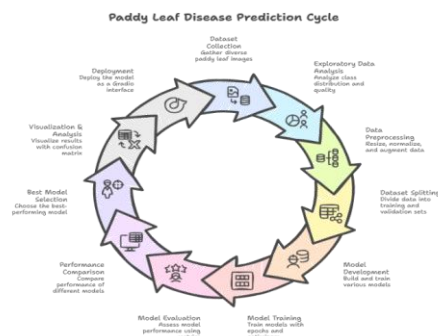
**Study Goals:** The main objective is to study an efficient and automated system that is capable of efficiently detecting paddy crop disease by

utilizing the concept of deep learning, especially the EfficientNet-B0 model. The system is expected to classify the paddy leaf images under the major diseases types of Bacteria Leaf Blight, Brown Spot, and Leaf Smut, reducing the need for manual inspection of the images by experts. Other objective is to identify the best model that is efficient, highly accurate, simple, and has good generalization with well data augmentation techniques. Third objective is to evaluate the performance of the model by utilizing the metrics including accuracy, precision, recall, and F1-Score, with ultimate of creating a solution that is efficient, effective, and user-friendly, which helps the farmers in early detection of crop disease.

**Scope and significance:** The scope of this study is centered on the development of deep learning-based system that can be used to detect paddy leaf diseases using image classification techniques with EfficientNet-B0 model as the basis of the system. The importance in this study can be seen in accuracy and speed at which the system can be used to detect crop diseases with less reliance on manual checks and knowledge. By using this system for crop diseases at the onset, the farmer can then take the necessary measures to prevent spread of disease, thus improving the yield of the crops.

**LITERATURE REVIEW:** The CNN architectures such as AlexNet, VGGNet, and ResNet have been utilized in many works in the classification of agricultural diseases. Due to the simplicity and efficiency of the architecture, which is based on deep convolutional layers that identify patterns in images, VGG16 is popular. ResNet architecture has been proven to be accurate and stable. MobileNet and DenseNet architecture has been used in agricultural applications. MobileNet is an architecture that is designed to be lightweight and thus suitable for mobile agricultural applications. DenseNet architecture that allows each layer in a network to be connected with each other layer in forward manner. This allows the network to be efficient and accurate. The EfficientNet architecture is popularly use because of their efficiency in scaling. The DieT series have been developed with the intention of enhancing data efficiency using knowledge distillation.

**RESEARCH METHODOLOGY:** The suggested method uses an organized deep learning pipeline to identify paddy diseases. In order to class distribution and image characteristics, the dataset comprising images of paddy leaves is first gathered and examined using exploratory data analysis. The image is preprocessed through resizing, normalization, and augmentation to improve model generalization. The dataset is divided into training and validation sets to evaluate model performance. Multiple deep learning architectures including CNN-based models and transformer-based models are trained on the dataset. Each model is evaluated using performance metrics such as accuracy, precision, recall, and F1-Score. The best architecture is determined by comparing ten different models. The EfficientNet-B0 is taken for the top performance model based on experimental findings. Created Gradio interface to deploy and develop the system for real-time consuming disease detection,

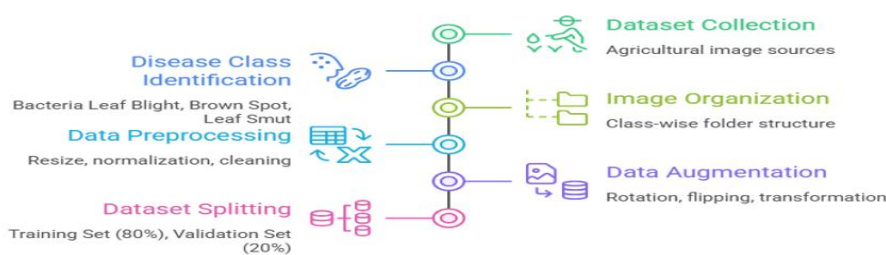


**DATASET DESCRIPTION:**

The dataset contains 5432 images, where these are organized into three different classes based on disease type. The classes are Bacteria Leaf Blight, Brown spot, Leaf Smut. These are the common damaging diseases in paddy cultivation. The bacterial Leaf Blight is a disease that affects plants. It caused by **Xanthomonas Oryzae**. This bacteria Leaf Blight disease makes the leaves turn yellow and dry out. Brown spot is another disease that affects plants. It caused by fungus. The brown spot disease has spots on leaves. Leaf smut is also a disease that produces dark powdery stuff on the leaves. Before we train the model the pictures into same size, which 224\*224 pixels. This is the size computer models need. We divide the pictures into two groups: one for training and one for testing. **We use 80% of the pictures to train the Models and 20% to test them.** The trained models shows the disease in different ways in different environments. This helps models to learn how to recognize the diseases even when they look a little different. Using the pictures and doing the right things to make them work better. It is very important to make the system that can detect diseases in paddy plants. The diseases like **Bacteria Leaf Blight, Leaf Smut, Brown Spot** diseases can be detected using the system with trained models.

DISEASE CLASS	NUMBER OF IMAGES
Bacterial Leaf Blight	2863
Brown Spot	1576
Leaf Smut	2209
<b>TOTAL IMAGES</b>	<b>6648</b>

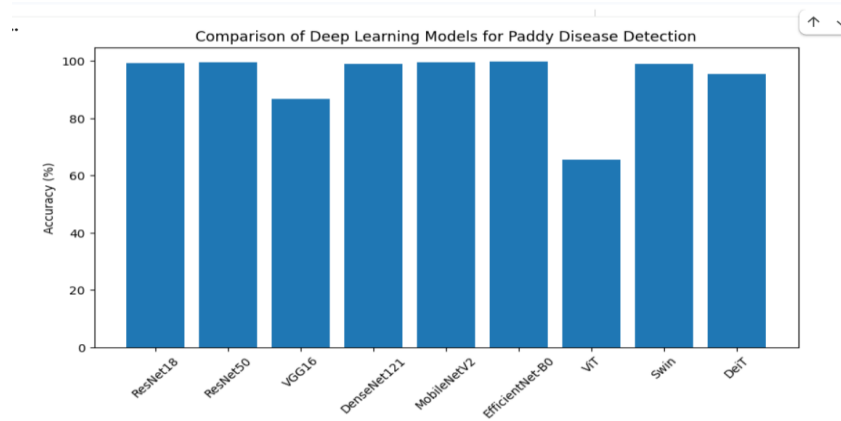
**Paddy Leaf Disease Dataset Preparation Timeline**



**COMPARISON WITH DIFFERENT MODELS:**

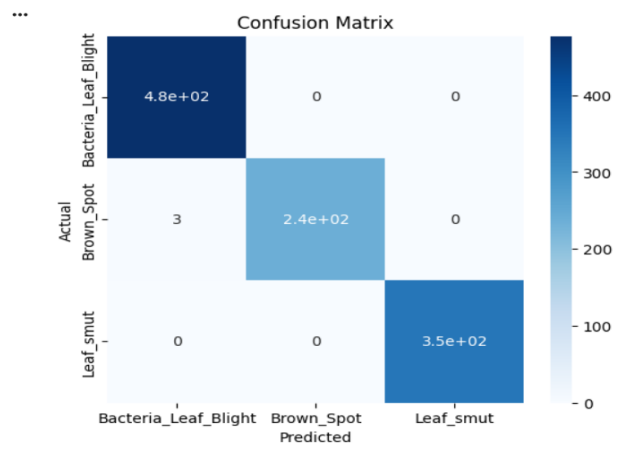
To Determine the effectiveness of the proposed system, different deep learning models are trained and tested on the same Paddy leaf image dataset.

- ResNet18
- ResNet50
- VGG16
- DenseNet121
- MobileNetV2
- EfficientNet-B0
- ConvNext
- Vision Transformer
- DeiT



**CONFUSION MATRICES:**

The confusion matrix is a performance evaluation tool used to visualize the classification performance of a machine learning or deep learning model. It shows how the model correctly predicts each class and identifies the type of errors made during classification. This is used to evaluate the classification performance of the EfficientNet-B0 model on the paddy leaf disease dataset.



**Performance Evaluation Metrics:-**

The performance of the model was evaluated using the following metrics:

- Accuracy
- Precision
- Recall
- F1-Score
- Confusion Matrix

These metrics are calculated based on the values obtained from the confusion matrix, which includes the following components:

- **True Positive (TP):** Correctly predicted disease images.
- **True Negative (TN):** Correctly predicted normal images.
- **False Positive (FP):** Incorrectly predicted disease images.
- **False Negative (FN):** Disease images incorrectly classified as another class.

**ACCURACY:-**

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

**PRECISION:-**

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

**RECALL (Sensitivity):-**

$$\text{Recall} = \text{TP}/(\text{TP}+\text{FN})$$

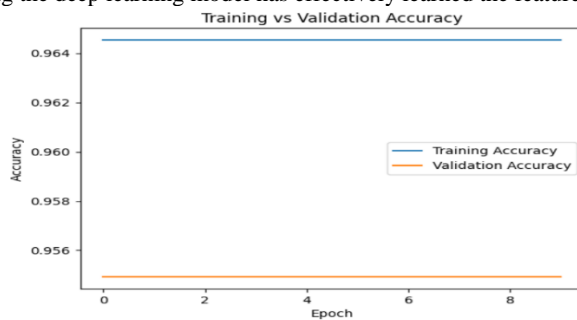
**T F1-SCORE:-**

$$\text{F1-SCORE} = 2*(\text{Precision} * \text{Recall}) / (\text{Precision} + \text{Recall})$$

	Metric	Value
0	Accuracy	0.997183
1	Precision	0.997201
2	Recall	0.997183
3	F1 Score	0.997179

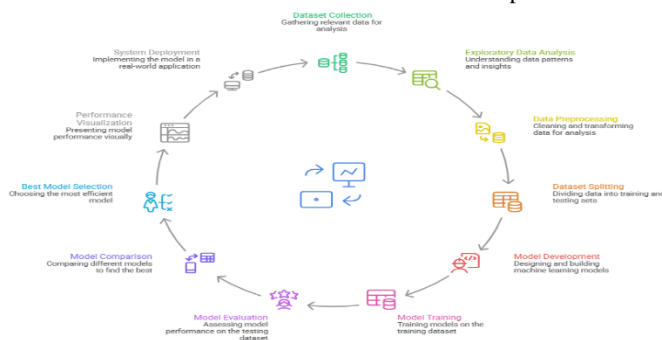
**Training VS Validation Accuracy Curve:-**

The training and Accuracy curves are employed to evaluate the learning the deep learning model. This helps us to visualize the effectiveness of the learning process of the model. While the deep learning model is trained, the accuracy of the model is calculated for both the training data and the validation data. The process is repeated for each epoch of the data. The efficientNet-B0 model has been trained for several epochs. It has been found that accuracy of the model gradually increases while the number of epochs increases, proving the deep learning model has effectively learned the features from the paddy leaf images.



**FUTURESCOPE:-**

Although a high accuracy level is recorded in detecting paddy leaf disease using a proposed deep learning based on EfficientNet-B0, there are various possibilities of improving and expanding this model in future research to increase its ability and accuracy in practical applications. One of the possibilities is to increase the dataset of paddy leaf disease and include various classes of disease that are common in rice crops, such as rice blast disease, sheath blight disease, and tungro disease. This would help in increasing the accuracy of detecting various classes of disease in crops and increases its ability to detect various crop diseases. Another possibility is to incorporate various agricultural data, such as weather conditions and soil parameters, into this proposed model. This would increase its accuracy in predicting diseases in crops and help in developing a comprehensive crop monitoring system. Moreover, other research directions may be considered to improve the system by employing advanced deep learning models or hybrid models with ensemble learning methods to improve the accuracy of predictions. In addition, provide visual explanations of the results of disease detection to enable users to understand the part of leaf contributed to the prediction results.



**CONCLUSION:**

The research proposed a deep learning- based technique for automatic detection and classification of paddy crop diseases using leaf image processing. Detection of diseases in plants at an early stage is critical for agriculture to avoid loss of yield and maintain crop production. Traditional approaches for identifying diseases in plants are manual, time-consuming and require expertise, for which automated systems are greatly beneficial for modern-day agriculture. A paddy leaf disease image dataset consisting of three major classes of diseases, namely Bacteria Leaf Blight, Brown Spot, and Leaf Smut, was created to train and evaluate several deep learning-based approaches for paddy leaf disease classification. Several state-of-art deeplearning architectures, including ResNet18, ResNet50, VGG16, DenseNet121, MobileNetV2, ConvNext, Vision

Transformer, Swin Transformer, DieT, and EfficientNet-B0, were implemented and compared to evaluate the effectiveness of the proposed approach. From the results, it is observed that the EfficientNet-B0 model had the best performance in terms of accuracy, precision, recall, and F1-Score. The model was able to learn the complex visual patterns contained in the images of paddy leaves was able to accurately classify the images into different disease classes. The experiment also proved the EfficientNet-B0 model is the deep learning model for disease detection by providing high accuracy and computational efficiency. From confusion matrix and accuracy curves, it is confirmed that the proposed model is reliable and stable for the training and validation process. The results prove the deep learning-based disease detection systems can greatly help farmers and experts in the agriculture sector to detect and diagnose different plant diseases quickly and accurately. The system plays an important role in improving crop monitoring and management

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