RICE LEAF DISEASE DETECTION USING EFFICEINTNET

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MAY 2024

RICE LEAF DISEASE DETECTION USING EFFICIENTNET

A major project submitted in partial fulfilment of the requirements for the Degree of

BACHELOR OF TECHNOLOGY

IN

COMPUTER SCIENCE AND ENGINEERING

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Declaration

We declare that this written submission represents our ideas in our own words and where other ideas or words have been included, we have adequately cited and referenced the original sources. We also declare that we adhered to all principles of academic and integrity and have not misrepresented or fabricated or falsified any idea/data/fact/source in our submission. We understand that any violation of the above will cause disciplinary action by the university and can also evoke penal action from the sources which have thus not been properly cited or from whom proper permission has not been taken when needed.

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Certificate

This is to certify that the major project report on "Rice Leaf disease detection using EfficientNet" submitted by DIBYANSHU PANDA, Registration No.: 2002050009 and SIBASUNDAR BEHERA, Registration No:2002041055 of Department of Computer Science and Engineering, VSSUT, Burla, Odisha for the award of the degree of B.Tech in Computer Science and Engineering, is a record of an original research work carried out by him under my supervision and guidance.

Dr. Suvasini Panigrahi
Head of Department

Dr. Santi Kumari Behera
Supervisor

ACKNOWLEDGEMENT

I extend my deepest appreciation to my esteemed supervisor, Dr. Santi Kumari Behera, whose unwavering support and guidance have been instrumental throughout the journey of this major project. Her insightful ideas, constant encouragement, and the welcoming work environment she provided have significantly contributed to the success of this endeavour. I am truly grateful for her invaluable assistance and mentorship.

I would also like to express my gratitude to Dr. Suvasini Panigrahi, the Head of the Department of Computer Science and Engineering, for facilitating and supporting the execution of this major project. My sincere thanks extend to all the dedicated faculties of the department for their continuous advice and encouragement.

Heartfelt thanks go out to my friends whose unwavering support and understanding have been a constant source of motivation. Their encouragement has played a vital role in overcoming challenges and achieving milestones.

In reflection, I acknowledge with gratitude the collective contributions of Dr. Santi Kumari Behera, Dr. Suvasini Panigrahi, the departmental faculties, and my friends, without whom this project would not have been possible.

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APPROVAL SHEET

The dissertation entitled "**Rice Leaf disease detection using EfficientNet**" by **Dibyanshu Panda** and **Sibasundar Behera** is approved for the degree of **Bachelor of Computer Science and Engineering**, department of Computer Science and Engineering.

Examiner

Date:

Supervisor

Place:

ABSTRACT

Our project introduces an innovative approach to assess the quality of rice leaves, employing sophisticated computer vision techniques to overcome the limitations of traditional manual inspection methods. Utilizing EfficientNet classification models, we classify rice leaves into diseased and healthy categories, subsequently categorizing the diseased leaves into three distinct disease types: bacterial leaf blight, leafblast and brownspot.

This study investigates the efficacy of EfficientNet models from B0 to B7 in detecting rice leaf diseases, achieving respective accuracies of 86.95,85.96,81.84,86.67,88.22,75.67, 82.36 and 86.29. Through comparative analysis of confusion matrices, it reveals nuanced performance variations among the models, with B4, B0 and B7 demonstrating the highest accuracies and fewer misclassifications, albeit requiring greater computational resources. We also measured the degree of infection by comparing and analysing the pixel intensity distribution graph of a healthy and diseased leaf. However, certain diseases present challenges across models, indicating trade-offs between complexity and performance. These findings underscore the importance of selecting models judiciously based on specific application requirements and computational constraints in agricultural disease detection tasks.

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CHAPTER 1

INTRODUCTION

1.1. Overview

One of the biggest producers and exporters of rice worldwide is India. According to USDA forecasts, by 2021–2022, India would produce 120.4 million metric tonnes (MMT) of rice, ranking it as the second-largest producer in the world behind China. India stands among the top exporters of rice worldwide in terms of exports. According to the Agricultural and Processed Food Products Export Development Authority (APEDA), India exported about 13.9 million metric tonnes (MMT) of rice in fiscal year 2020-21, bringing in around 7.06 billion USD in foreign exchange earnings. The primary markets for Indian rice exports are the Middle East, Africa, and Asia, with Senegal, Saudi Arabia, and the United Arab Emirates (UAE) being the top consumers. Growing demand for Indian rice in countries such as China, Indonesia, and the European Union in recent years has created new chances for the Indian rice industry to expand its exports [1].

In the eastern regions of Pakistan and India, rice stands as a primary agricultural product. However, recent years have witnessed a significant decline in rice production, owing to various factors, with plant diseases emerging as a prominent cause. Among these diseases, bacterial leaf blights, narrow brown spots, leaf blasts, and brown spots stand out due to their detrimental impact on rice production and grain quality. Despite their differences, these diseases share a common trait of causing lesions on the leaves of rice plants. Timely detection plays a crucial role in mitigating the associated damage, as is often the case with diseases. The fundamental issue lies in the lack of consistent monitoring of plants, leaving them vulnerable to these ailments. Contributing factors may include the inexperience of farmers, who may overlook the subtle signs of disease or fail to recognize the diseases pertinent to their crops and respective growing seasons. While these diseases can strike at any stage of plant growth, vigilant monitoring of plant health and developmental stages can curtail their spread effectively.

Given the expansive nature of rice fields, it proves arduous for farmers to manually patrol them on a daily basis. Moreover, even if such an endeavor were feasible, the sheer volume of plants would render individual evaluation impractical. Even supposing the feasibility, the cost and potential for human error in daily check-ups would be considerable, posing risks of inadvertently damaging nearby rice plants and yielding more negative consequences than benefits. The process of identifying issues demands considerable physical effort, necessitating observation of various factors such as conditions and surroundings [2]. The emerging trend in agricultural research is the exploration of machine learning (ML), artificial intelligence (AI), and deep learning to aid farmers and researchers in the early detection of rice plant diseases. This approach stems from advancements in scientific understanding, offering promising avenues for enhancing agricultural practices.

Deep learning algorithms have found practical application in agriculture, tackling diverse challenges such as identifying weeds and seeds, classifying plant diseases, counting fruits, and segmenting roots. This subset of artificial intelligence has proven effective in processing vast amounts of data, autonomously extracting relevant features from inputs, and generating outcomes based on predefined parameters. [3].

1.2. Types of Rice Leaf Diseases

Rice leaves can suffer serious damage from diseased leaves, which can reduce productivity. These diseases are primarily brought on by bacteria, fungus, and viruses, and once infected, they spread quickly, possibly affecting the entire crop if not detected in time. The following list of major diseases impacting the O. sativa crop(rice) discussed in this work is giver in further detail:

- **Brown Spot**: A fungal disease that affects the entire crop and is easily recognised in its early stages due to the brown oval or circular marks that it causes on the first seedling leaves. The cause of this is a particular kind of fungus called Bipolaris Oryzae, which not only reduces yield but also has an impact on grain quality shown in Fig. 1. It travels via the air from one plant to another across the field.

- **Bacterial Leaf Blight**: The bacterial leaf blight is a bacterium which penetrates through hydathodes cutting wounds in the tip of leaf leading to the death of seedling (Fig. 1). The wounds enlarge with a margin in wave shape which turns the straw into yellow within a few days. With the advanced stages of the disease, the lesions cause the entire leaf to change into straw-coloured or white. The cuts can be observed on the leaf sheath, and early in the morning, fresh lesions may have dew droplets containing bacterial masses on them.

- **Leaf Blast**: It is caused by Magnaporthe oryzae, which infects the crop by developing lesions on the plants leaves as well as the other parts of the plant such as stems, roots, and seeds. Unlike the brown spot, the patches found on the leaves in this case are boat shaped, with the centre in grey along with a thick outline of brown as shown in Fig. 1.

- **Sheath Blight**: Sheath blight is caused by the fungus Rhizoctonia solani. Although it can infect other sections like leaves and stems, it mostly affects the sheaths of rice plants. Initially, little water-soaked sores emerge on plants near the shoreline. These lesions progressively enlarge and lengthen, often becoming several centimetres in length. A white fungal growth may develop on the afflicted areas as the illness worsens, particularly in humid environments. Severs infections can cause a rice plant to wilt, lodge, and eventually die, which would drastically reduce production.

- **Leaf scald**-The fungus Microdochium oryzae is the source of leaf scald, a condition that gives leaves a scorched look. Wet weather, heavy nitrogen fertilizer, and close spacing all promote the development of diseases, which often attack mature leaves late in the growing season. It grows more quickly in injured leaves than in uninjured ones. Crop stubbles and seeds are the origins of infection. The illness is favoured by high nitrogenous fertilizer dosages and wet weather.

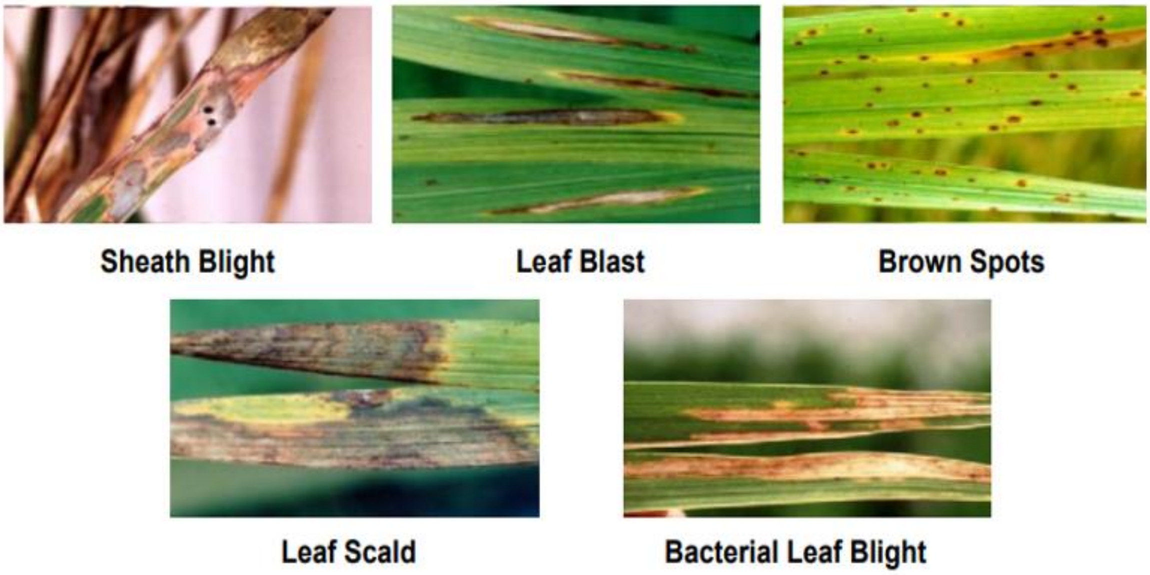


Figure 1: Rice leaf Diseases

1.3. Motivation

Agriculture is seen as a country's backbone. Since agriculture is the primary occupation that the village population depends on and it is generally believed that "India lives in its villages," this is even more important for a developing nation like India. As a result, the Indian economy is significantly impacted by agriculture. Farmers in India, on the other hand, are unable to keep up with new technology, rising demand, and producing high-quality crops due to their archaic traditions. A significant explanation for the high percentage of people living "Below Poverty Line" in India is that they are farmers. Our Honourable Prime Minister Shri Narendra Modi has highlighted the progress of Indian agriculture in a number of speeches, highlighting the applicability of this research area to contemporary trends.

Image processing and machine learning can be used to successfully automate farming techniques, leading to innovations that will reduce the amount of human labour needed in the agricultural sector while also improving the efficiency of farming methods and raising production levels. These advancements will enhance both the standard and productivity of Indian farming. Using image processing as a key application in an automated agricultural approach might give Indian agriculture a new direction. Therefore, the growth of agricultural methods is necessary due to advancements in many sectors. Estimating crop quantity and quality is the focus of agriculture. Because of this, machine learning and image processing methods are commonly used in yield mapping systems. In order to create an algorithm that may be used in automated systems for crop disease detection and grading, the proper approach has been applied.

1.4. Objective

The objective of our work is to develop an algorithm, that would be used in building an automated approach that can be effectively used in the field of agriculture, in the farming of crops, to classify different types of rice leaf disease, including bacterial blight, leaf blast, brown spot and healthy leaves. This project also aims to provide a reliable and efficient tool for farmers and researchers to detect and monitor rice leaf diseases, which can help in early disease diagnosis and prevention, ultimately leading to higher crop yields and better food security.

1.5 Organisation of the Work

The whole paper has been organized in the following manner.

Chapter 2 gives the ideas about the terminology and background knowledge.

Chapter 3 presents an existing methodology that has been implemented and analysed.

Chapter 4 presents the materials and methodology and its algorithms and flowcharts.

Chapter 5 is about results and discussion upon various sample dataset.

Chapter 6 concludes the paper with some prospects of future work.

CHAPTER 2

BACKGROUND STUDY

2.1 Basic Concepts

EfficientNet, a family of convolutional neural network architectures designed to be highly efficient in terms of computational resources while achieving state-of-the-art performance in image classification tasks. EfficeintNet was introduced by "Tan, Mingxing", and "Quoc V.Le" in their paper "EfficientNet: Rethinking Model Scaling for Convolutional Neural Networks" in 2019. EfficientNet attains its efficiency by employing a compound scaling technique that adjusts network width, depth, and resolution simultaneously using predefined scaling factors. This approach allows EfficientNet models to achieve better accuracy while being more computationally efficient compared to other architectures. To enhance both accuracy and efficiency, it's crucial to carefully consider the dimensions of network width, depth, and resolution when scaling ConvNets. Therefore, a novel compound scaling method has been introduced, utilizing a compound coefficient φ to uniformly adjust network width, depth, and resolution in a systematic manner.

F = $\alpha \cdot \beta^{\varphi} \cdot \gamma^{\varphi}$

F = d· $\omega^{\varphi} \cdot r^{\varphi}$

Where:

α is d : Depth scaling factor.

β is w : width scaling factor.

γ is r : resolution scaling factor.

F is network scaling factor.

φ is compound coefficient.

The value of α , β,γ are taken as constant -

α=Depth = 1.20

B=Width = 1.10

γ=Resolution = 1.15

Compound scaling suggest that the scaling of the network should be performed using a constant ratio in all the dimension. Now by applying grid search the value of φis taken and on changing the value of φ we get different ways to scale up.

2.1.2 EfficientNet architecture

To scale depth, width and resolution, a baseline model is needed which is called Efficient Net B0. EfficientNet-B0 is the baseline network developed by AutoML MNAS (MobileNet Neural Architecture Search). All other EfficientNet models from B0 to B7 are scaled version of base model. EfficientNet has two parts:

1. Create an efficient baseline architecture using NAS (Neural Architecture Search).

2. Use the Compound Scaling Method to enhance performance.

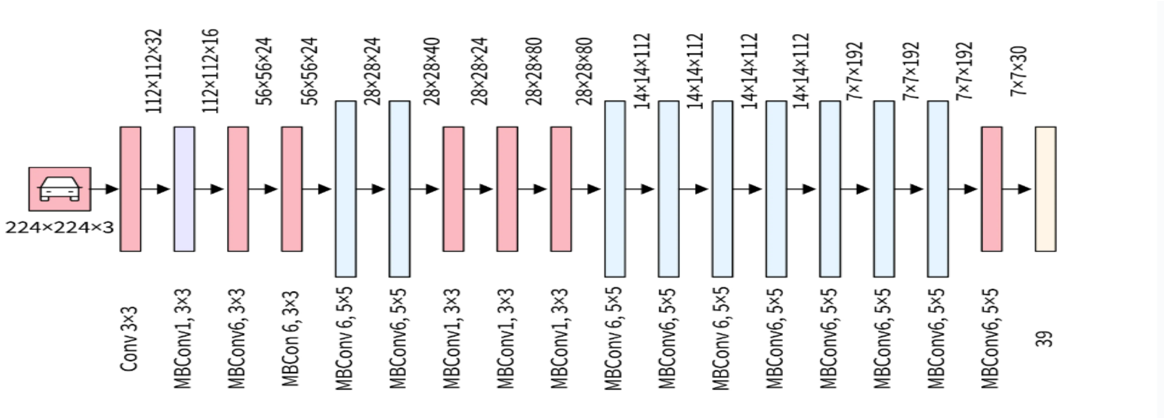


Figure 2: EfficientNet B0 architecture **[3]**

The base architecture consists of a stack of convolutional layers with batch normalization and activation functions. It typically includes inverted residual blocks, similar to those used in MobileNetV2. Depthwise separable convolutions are employed to reduce the number of parameters. EfficientNet models come in various sizes, denoted as B0, B1, B2, ..., B7. B0 is the smallest, and each subsequent model is larger in terms of parameter

s and computational requirements. The larger models are suitable for more complex tasks or datasets with higher resolution.

2.1.3 Resolution Scaling

Resolution scaling involves adjusting the input image resolution. If the input image is bigger(resolution), then there is more complex features and fine grained patterns will produce. Higher resolution images provide more detailed information but require more computational resources. By scaling the resolution, the model can adapt to different input sizes while controlling computational demands.

72 DPI **300 DPI**

Figure 3: Resolution Scaling [3]

The image on the right hand side is of high resolution so the feature extracted from it will be more than the feature extracted the figure in the left hand side.

2.1.4 Width Scaling

Width scaling involves increasing or decreasing the number of channels (or neurons) in each layer of the network. A wider network captures more diverse features in each layer but comes with increased computational cost. Width scaling allows adjusting the model's capacity based on the available resources. In order to get the whole information about the high resolution images we have to increase the number of feature maps. Increase the number of channels or feature maps.

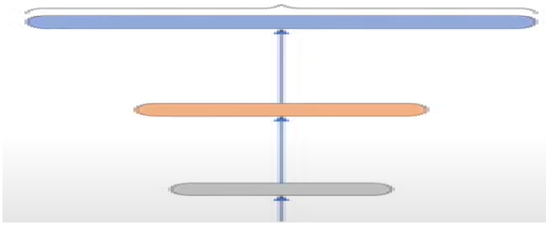


Figure 4: Width scaling **[3]**

2.1.5 Depth Scaling

Depth scaling is nothing but increasing the number of layers in the Neural Network. To handle the higher resolution images, We require deep neural network. Hence for high resolution image we have to increase the number of layers in the neural network. Deeper networks can capture more complex features but come with increased computational cost. Depth scaling helps strike a balance between model complexity and computational efficiency.

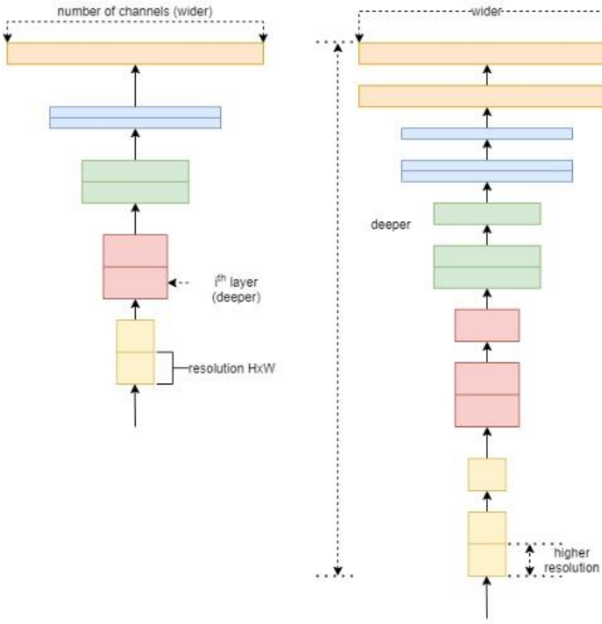


Figure 5: Depth scaling **[4]**

CHAPTER 3

RELATED WORKS

3.1 Literature Review

In the paper "EfficientNet: Rethinking Model Scaling for Convolutional Neural Networks" by Tan, Mingxing, and Quoc V. Le (2019) [4]. After systematically studying model scaling and identifying that balancing the network's width, depth, and resolution is crucial for improving both accuracy and efficiency. Building on this idea, they introduce a novel scaling technique that uniformly adjusts all these dimensions using a straightforward yet highly efficient compound coefficient. Additionally, they employ Neural Architecture Search (NAS) to create a new base network, which they then scale up to create a series of models known as EfficientNets. The largest variant, EfficientNet-B7, achieves a state-of-the-art top-1 accuracy of 84.3% on ImageNet, while being significantly smaller and faster—8.4 times smaller and 6.1 times faster in inference compared to the best existing ConvNet.

In the paper "Rice Leaf Diseases Classification Using Transfer Learning and Deep Convolutional Neural Network" by Vimal K. Shrivastava, Monoj K. Pradhan, Mahesh P Thakur(2019) [5] , the authors investigated the performance of various pre-trained deep CNN models for image-based rice plant disease classification using AlexNet for feature extraction and SVM for Classification. The dataset used in this study consists of 1216 damaged rice plant images. For an 80%–20% training–testing split, the suggested model can accurately diagnose rice illnesses with a classification accuracy of 91.37%.

In the paper "Rice Plant Infection Recognition using Deep Neural Network Systems" by Shivam, Surya Pratap Singh and Indrajeet Kumar (2021) [6]. In this work, identification of diseases present in the plant of rice is carried out using methods of Deep Neural Network. So as to achieve image accession, a dataset having 2212 leaf images with different diseases is used. In this work, the entire dataset is divided into two classes in which class 1 contains the healthy leaves and the other class contains infected leaves. The identification is done using VGG-19, LeNet5, and MobileNet-V2 predefined Convolutional Neural Network (CNN). Once the experiment was completed successfully, it was observed that the accuracy achieved of VGG-19, LeNet5, and MobileNet-V2 was 77.09 %, 76.63 %, and 76.92 %respectively.

In the paper "Deep Learning for Rice Leaf Disease Detection in Smart Agriculture" by Nguyen Thai-Nghe, Ngo Thanh Tri, and Nguyen Huu Hoa(2022) [7]. The deep learning algorithm presented in this paper offers a method for detecting rice leaf disease on smartphones. With 1790 photos used for training, the model yielded 95% validation accuracy. The proposed model was used to create an Android application for the detection of rice leaf disease.

In their paper “Rice plant disease classification using color features” by Shrivastava Vimal and Pradhan Monoj (2021) [8] they stated that colour is a significant factor for classifying rice plant diseases. They introduced an image-based rice plant disease classification technique based solely on color cues in their work. The performance of seven different classifiers was evaluated, and it was proven that the support vector machine (SVM) classifier had the greatest classification accuracy of 94.65%. The optimistic findings of this article suggest that color traits can play an essential part in the development of a rice plant disease classification system, allowing farmers to take preventive measures that result in higher product quality and quantity.

In the paper “Transfer Learning based Approach to Crops Leaf Disease Detection: A Diversion Changer in Agriculture” [9] published in the year 2022, the authors Md. Tarikul Islam and Md. Shamsuzzaman suggests utilizing a deep transfer learning technique to train and identify a multi-plant leaf disease dataset that contains three pre-trained models—MobileNet-V2, Inception-V3, and ResNet-50—for the detection and identification of different leaf diseases in pepper, tomato, and potato.By fine-tuning the pre-trained models, powerful deep features were utilized. Then they compared and evaluated the performance of the transfer learning. The accuracy in diagnosing leaf illnesses in MobileNet-V2 was 97.54%, Inception-V3 was 94.01%, and ResNet50 was 99.01%.

In the paper, “Detection of plant leaf disease using digital image processing.” by N. Nandhini et al.(2020) [10]. They suggested machine learning techniques for disease classification in plant leaves, including K-NN, SVM, and decision trees. To isolate the diseased portion from the leaf image, they employed a feature extraction method that includes multiple steps: converting the RGB image to a Lab color space model; grouping the color pixel values of the leaf using K-means clustering; extracting color features using a histogram and fast Fourier transform; extracting shape features using a scale-invariant feature transform; and reducing vector size using principal component analysis. The above-mentioned algorithms are used for classification and SVM gave a better output than the other two methods.

In the paper “Plant disease detection and classification using machine learning models” by Panchal poojan, Vignesh Charan Raman, Samla Mantri (2019) [11] employed a random forest classifier to recognize the illnesses bacterial spot, late blight, and early blight in plant leaves. To extract features from the picture, the gray level co-occurrence matrix was utilized in conjunction with the Herpes Simplex Virus (HSV) approach to divide the leaf into its healthy and diseased halves. The accuracy of the model was 98%.

3.2 Summary of Literature Review

This table shows all the previous related works that had been done in the recent past:

Table 1: Summary of Literature Review

Sl. No	Year	Author	Publication	Technique	Result
1	2019	Tan, Mingxing, and Quoc Le	"EfficientNet: Rethinking model scaling for convolutional neural networks."	EfficientNet	84.3% (ImageNet), 91.7% (CIFAR 100), 98.1% (Flower) Accuracy
2	2019	Shrivastava, Vimal K., Monoj K. Pradhan, Sonajharia Minz, and Mahesh P. Thakur	"Rice plant disease classification using transfer learning of deep convolution neural network."	AlexNet	91.37 % Accuracy
3	2021	Shivam, Surya Pratap Singh, and Indrajeet Kumar	"Rice plant infection recognition using deep neural network systems."	LeNet MobileNet-V2 VGG 19	76.63% 76.92% 77.09% Accuracy
4	2022	Thai-Nghe, Nguyen, Ngo Thanh Tri, and Nguyen Huu Hoa	"Deep learning for rice leaf disease detection in smart agriculture."	Deep Learning	95% accuracy
5	2021	Shrivastava, Vimal K., and Monoj K. Pradhan.	"Rice plant disease classification using color features"	Image base drice plant disease classification technique based on colorcues	SVM classifier had highest accuracy of 94.65%
6	2022	Md. Tarikul Islam and Md. Shamsuzzaman	"Transfer Learning based Approach to Crops Leaf Disease Detection: A Diversion Changer in Agriculture"	Deep Transfer leaening	MobileNet-V2 was 97.54%, Inception-V3 was 94.01%, and ResNet50 was 99.01%.
7	2020	N. Nandhini et al.	"Detection of plant leaf disease using digital image processing."	ML algorithm	SVM performed better than KNN for predicting plant leaf disease.
8	2019	Panchal poojan, Vignesh Charan Raman, Shamla mantri	"Plant disease detection and classification using machine learning models"	ML algorithm	98% accuracy

CHAPTER 4

MATERIAL AND METHODOLOGY

4.1 Dataset Collection

We have collected the dataset containing images of healthy rice leaves and leaves infected with brown spots, leaf blast and bacterial blight from two sources

(i) Rice Disease Image Dataset from Kaggle [11]

(ii) Paddy Disease Classification Dataset from IEEEDataPort [13]

We have collected around 1900 leaf images of brown spot, 1100 images of bacterial blight, 1100 images of leaf blast and 1285 images of healthy leaves.

4.2 Data Augmentation

Several transformations for data augmentation were carried out such as randomly rotating the image by up to 20 degrees, and randomly flipping the image horizontally. These transformations are intended to help prevent overfitting by artificially increasing the size and diversity of the training data. The images are resized according to efficient net model starting from to 224 pixels to 600 pixels and then crop the centre to 224 pixels, before converting the image to a tensor and normalizing it using the specified means and standard deviations. These sets of transformations are intended for use with validation and testing data, respectively. 80% data is used for training and 20% for testing.

4.3 Model Building, Training and Evaluation

A preprocessing pipeline is defined using Keras's preprocessing layers. A pre-trained EfficientNetB1 model is loaded without the top classification layer. Custom classification layers are added on top of the pre-trained model. The model is compiled with an optimizer, loss function, and evaluation metric. The model is trained using the training and validation data Callbacks like early stopping and model checkpointing are used to monitor and improve training. The trained model is evaluated on the test data. Training and validation metrics (accuracy and loss) are plotted over epochs to visualize model performance.

4.4 Prediction and Visualisation

The model predicts labels for the test images. Random images from the test set along with their true and predicted labels are displayed Classification report and confusion matrix are generated to evaluate model performance.

4.5 Proposed Methodology

Following is the diagrammatical representation of our work flow

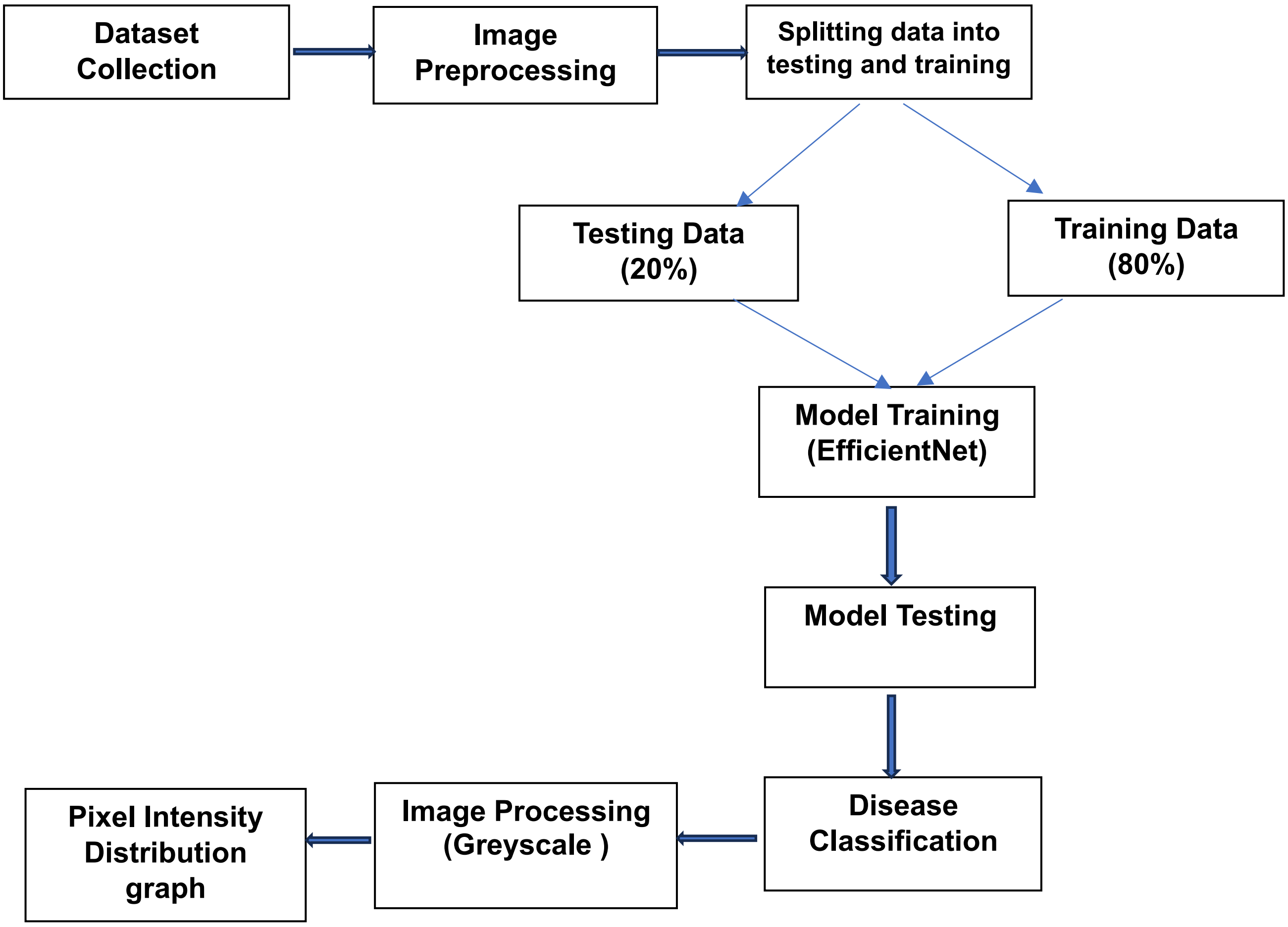


Figure 6: Work Flow of Proposed Methodology.

CHAPTER 5

RESULT AND DISCUSSION

The dataset after being passed through different EfficientNet model from base model B0 to EfficientNet B7, the results of their accuracy on determining whether it is healthy leaf, leafblast, bacterial blight or brownspot was noted and analyzed. Following is the report obtained:

5.1 EfficientNet B0:

Test Loss: 0.41496
Test Accuracy: 86.95%
Training Accuracy: 72.64%

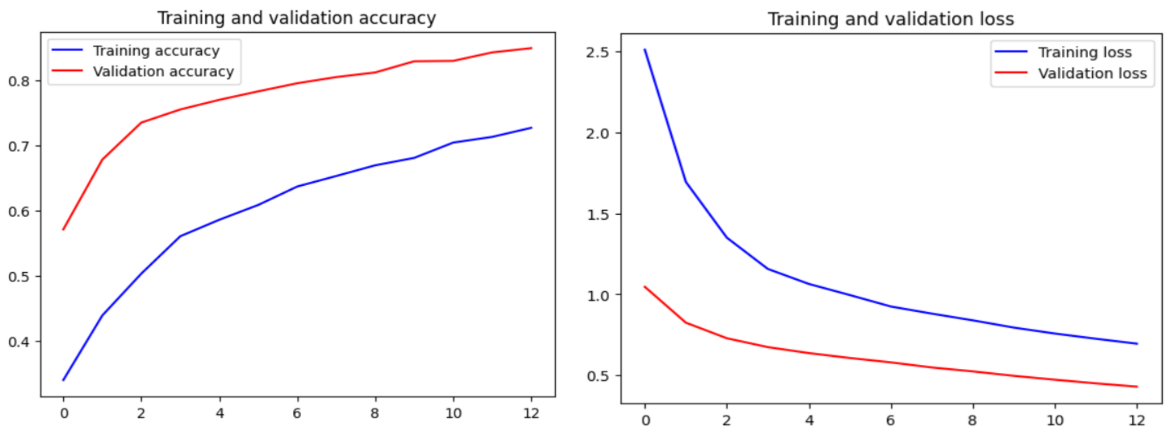


Figure 7: Training and validation Curve

5.1.1 Classification Report

	precision	recall	f1-score	support
bacterialblight	0.833333	0.932018	0.879917	456.000000
blast	0.909091	0.746667	0.819912	375.000000
brownspot	0.903546	0.817715	0.858491	779.000000
healthy	0.839527	0.984158	0.906108	505.000000
accuracy	0.869504	0.869504	0.869504	0.869504
macro avg	0.871374	0.870139	0.866107	2115.000000
weighted avg	0.874105	0.869504	0.867640	2115.000000

Figure 8: Classification Report B0

5.1.2 Confusion Matrix

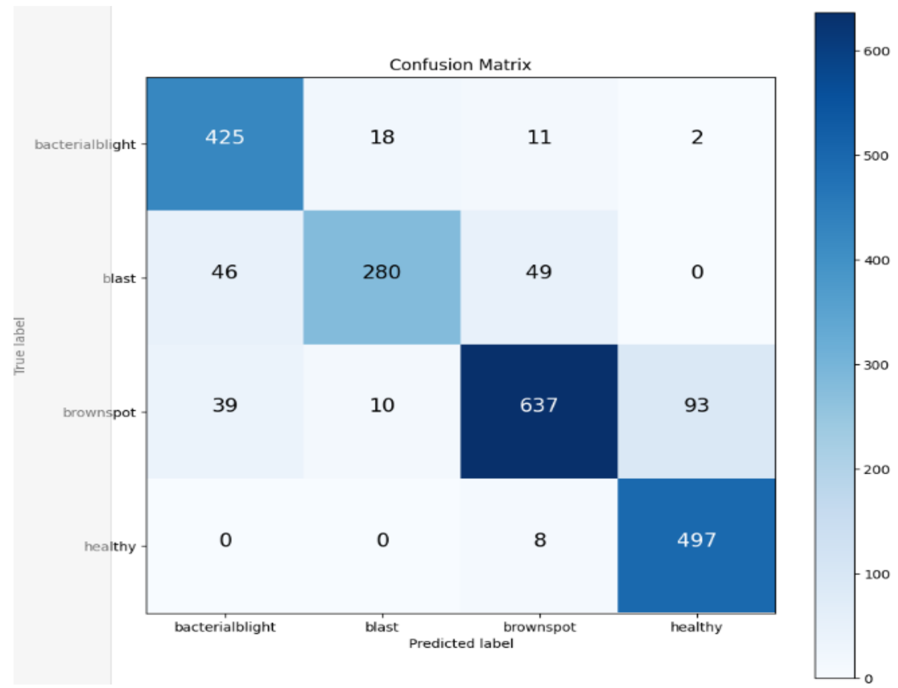


Figure 9: Confusion Matrix B0

5.1.3 ROC Curve

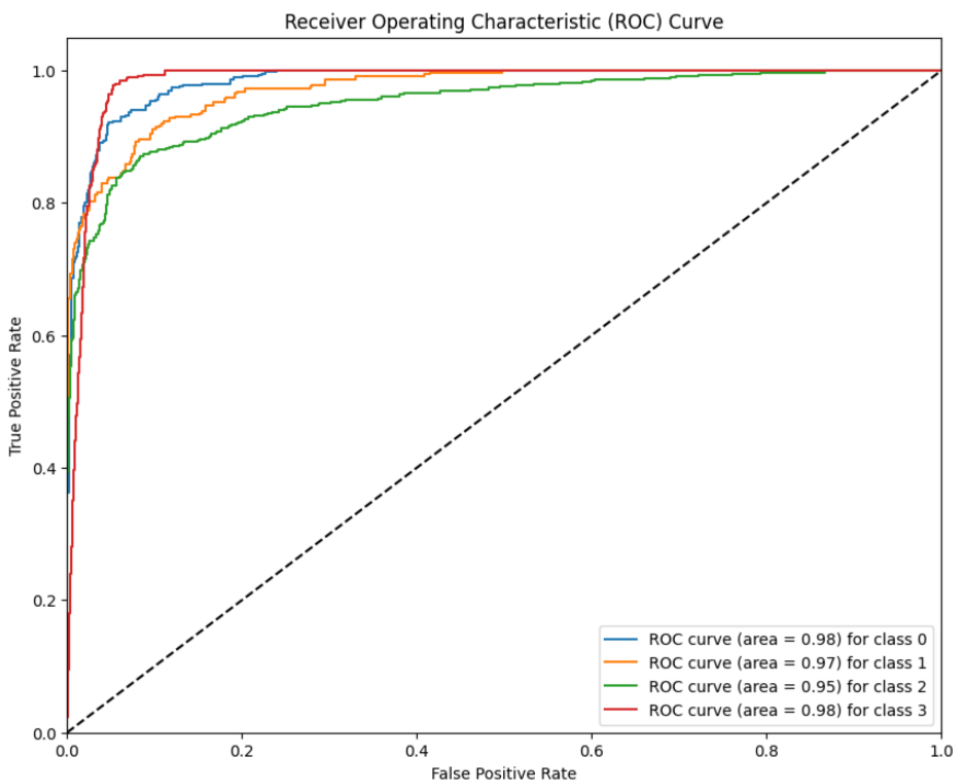


Figure 10: ROC Curve

5.1.4 Model Prediction

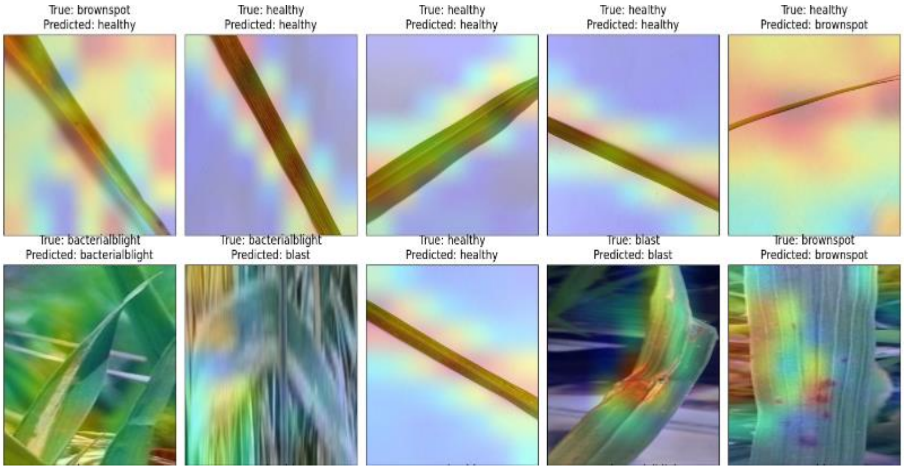


Figure 11: Disease Prediction

5.2 EfficientNet B1:

Test Loss: 0.41982
Test Accuracy: 85.96%
Training Accuracy: 72.88%

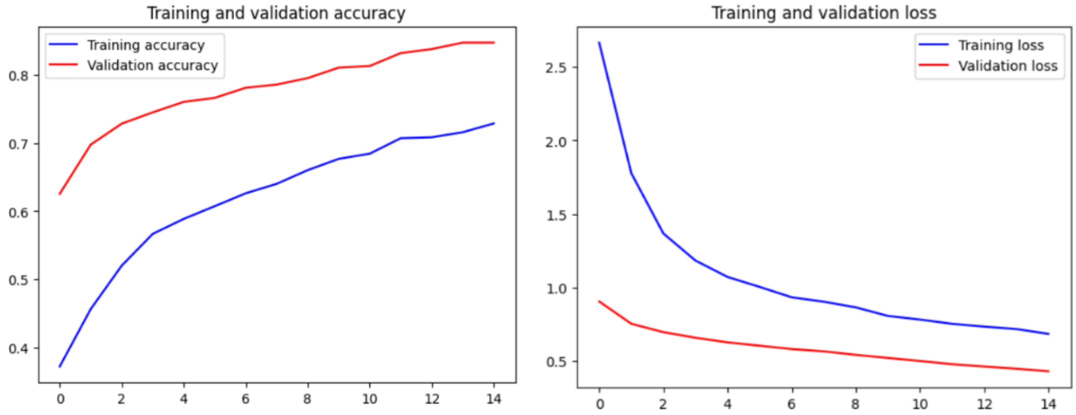


Figure 12: Training and validation Curve

5.2.1 Classification Report

	precision	recall	f1-score	support
bacterialblight	0.801603	0.877193	0.837696	456.000000
blast	0.837061	0.698667	0.761628	375.000000
brownspot	0.909847	0.842105	0.874667	779.000000
healthy	0.859107	0.990099	0.919963	505.000000
accuracy	0.859574	0.859574	0.859574	0.859574
macro avg	0.851904	0.852016	0.848489	2115.000000
weighted avg	0.861489	0.859574	0.857469	2115.000000

Figure 13: Classification Report B1

5.2.2 Confusion Matrix

Figure 14: Confusion Matrix B1

5.2.3 ROC Curve

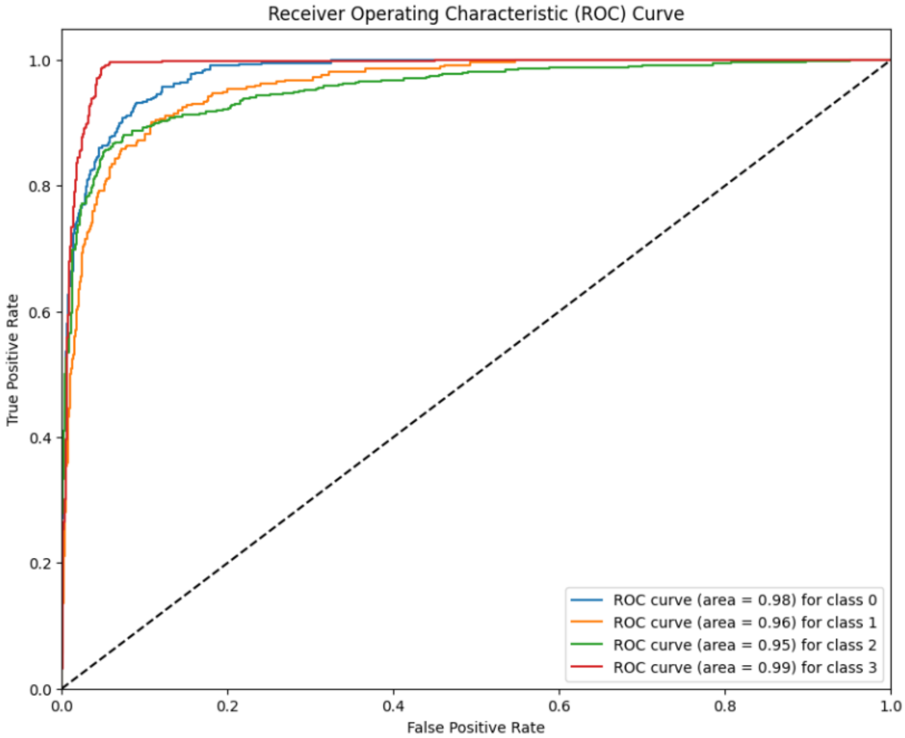


Figure 15: ROC Curve B1

5.2.4 Model Prediction

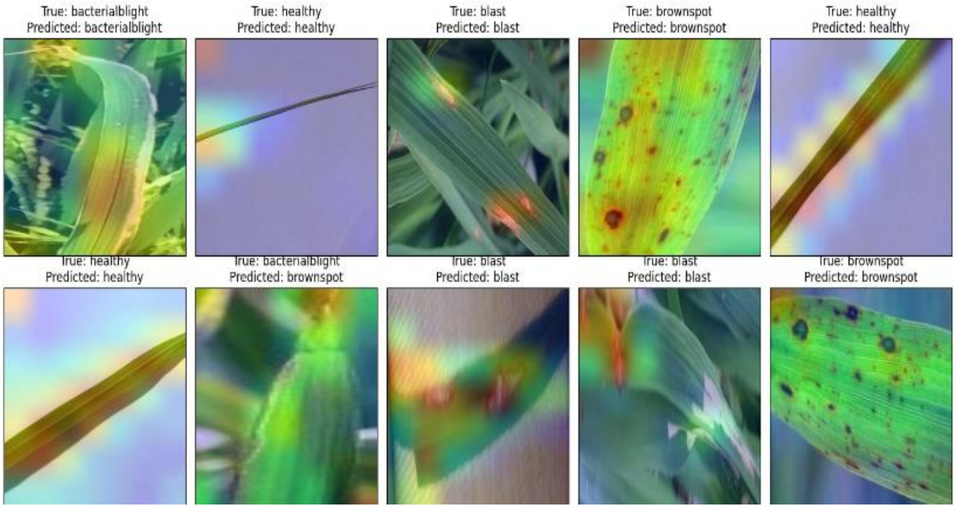


Figure 16: Disease Prediction B1

5.3 EfficientNet B2:

Test Loss: 0.51236

Test Accuracy: 81.84%

Training Accuracy: 66.14%

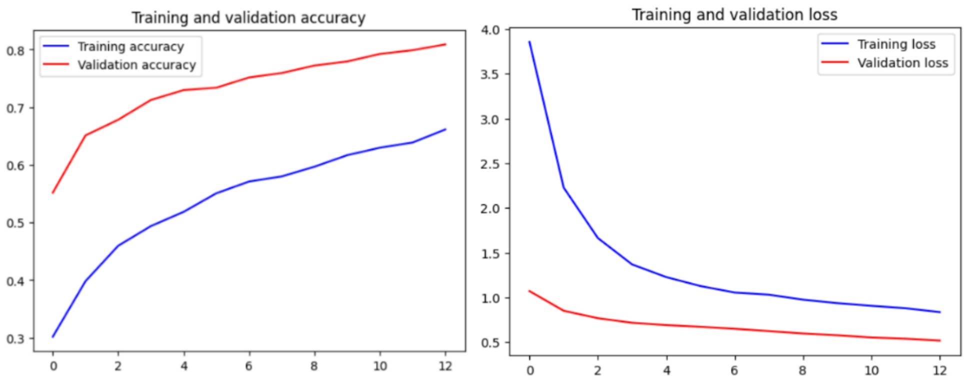


Figure 17: Training and validation Curve

5.3.1 Classification Report

	precision	recall	f1-score	support
bacterialblight	0.756436	0.837719	0.795005	456.00000
blast	0.750000	0.608000	0.671576	375.00000
brownspot	0.869146	0.810013	0.838538	779.00000
healthy	0.844828	0.970297	0.903226	505.00000
accuracy	0.818440	0.818440	0.818440	0.81844
macro avg	0.805102	0.806507	0.802086	2115.00000
weighted avg	0.817914	0.818440	0.814995	2115.00000

Figure 18: B2 Classification

5.3.2 Confusion Matrix

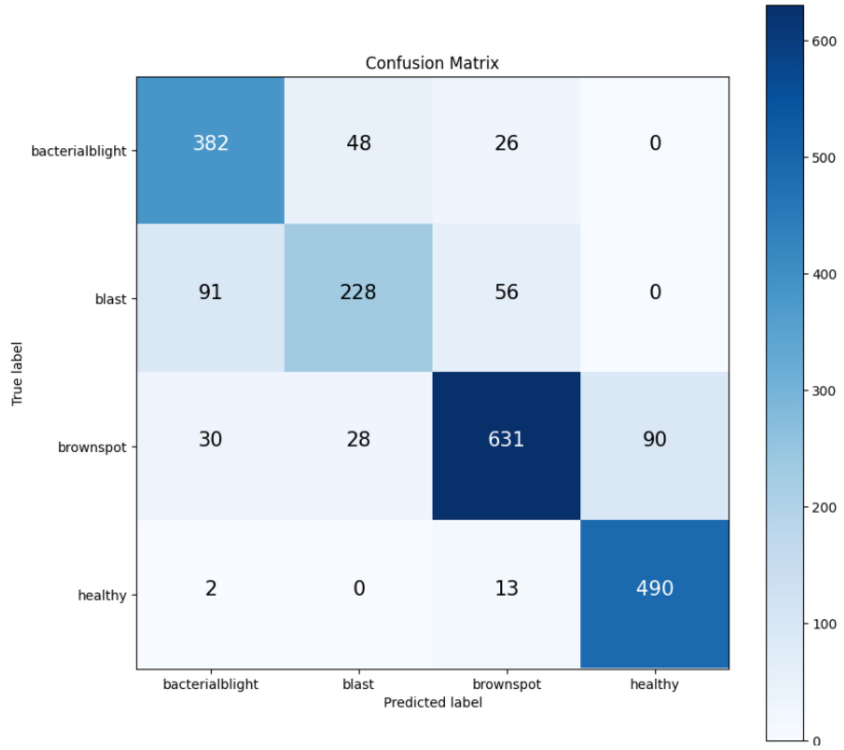


Figure 19: Confusion Matrix B2

5.3.3 ROC Curve

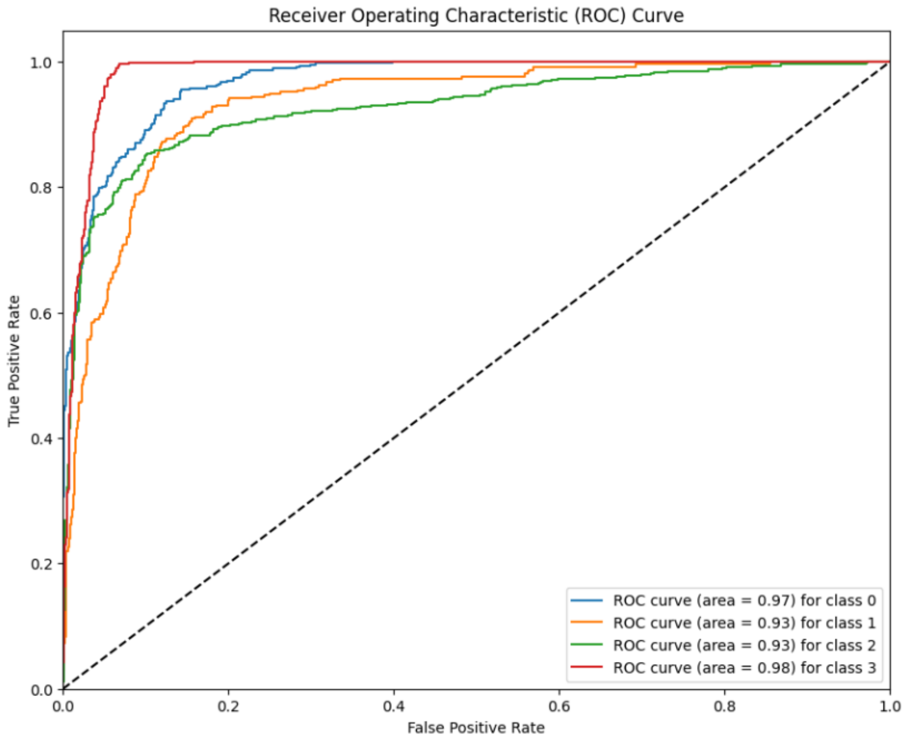


Figure 20: ROC Curve B2

5.3.4 Model Prediction

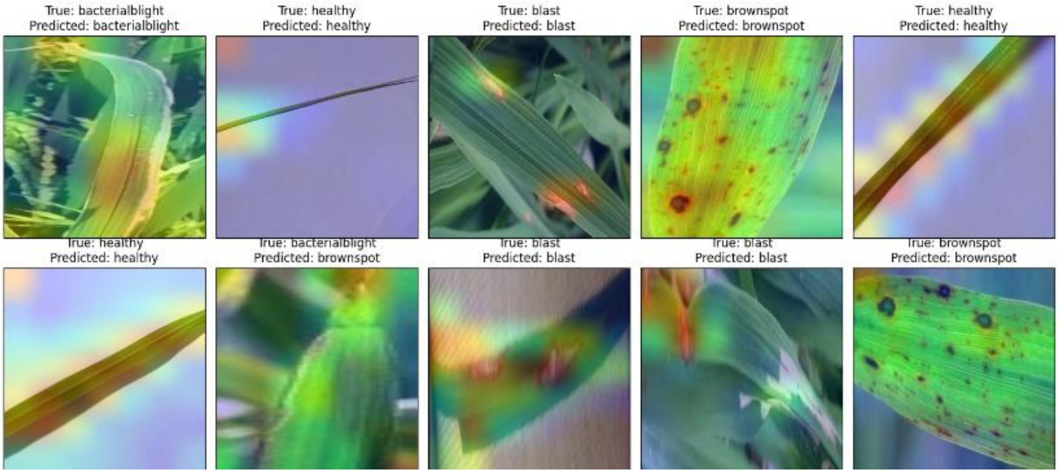


Figure 21: Disease Prediction B2

5.4 EfficientNet B3:

Test Loss: 0.40206
Test Accuracy: 86.67%
Training Accuracy: 75.13%

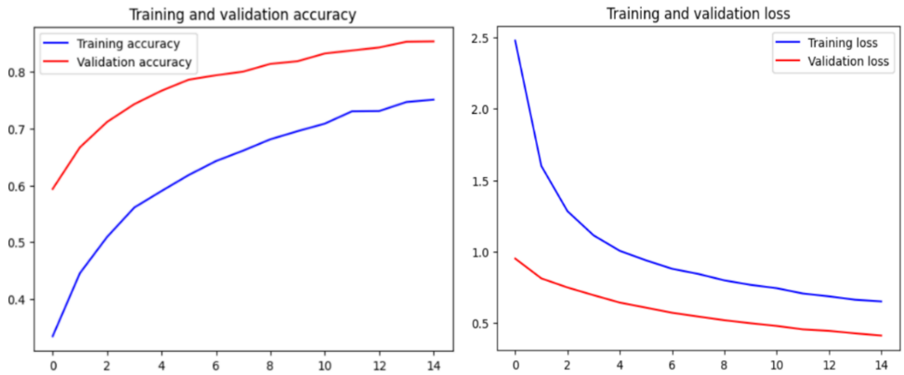


Figure 22: Training and validation Curve

5.4.1 Classification Report

	precision	recall	f1-score	support
bacterialblight	0.833663	0.923246	0.876171	456.000000
blast	0.812500	0.728000	0.767932	375.000000
brownspot	0.907932	0.822850	0.863300	779.000000
healthy	0.876761	0.986139	0.928239	505.000000
accuracy	0.866667	0.866667	0.866667	0.866667
macro avg	0.857714	0.865059	0.858910	2115.000000
weighted avg	0.867556	0.866667	0.864671	2115.000000

Figure 23: Classification Report B3

5.4.2 Confusion Matrix

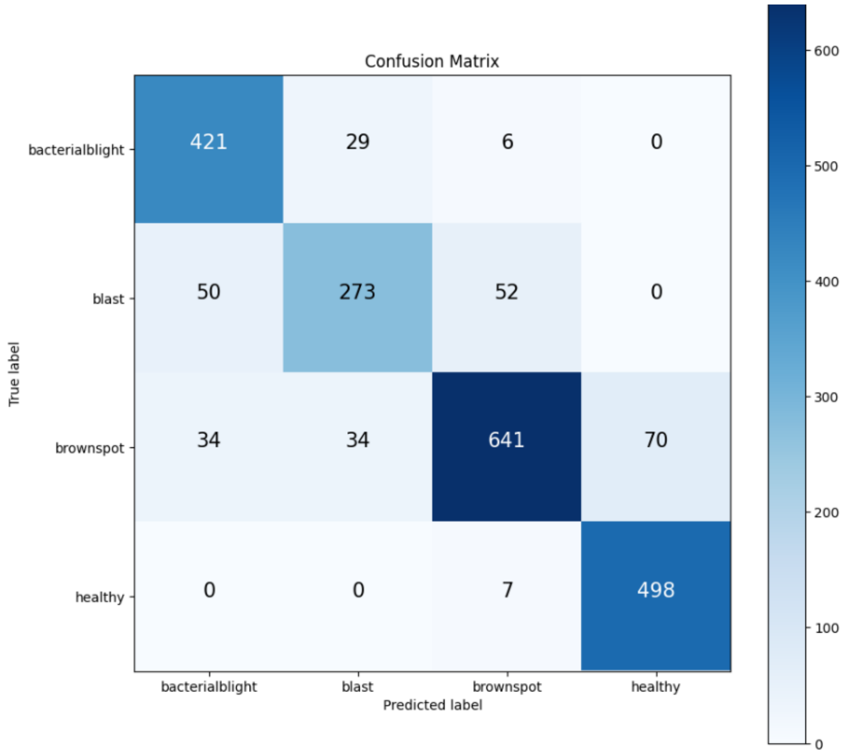


Figure 24: Confusion Matrix B3

5.4.3 ROC Curve

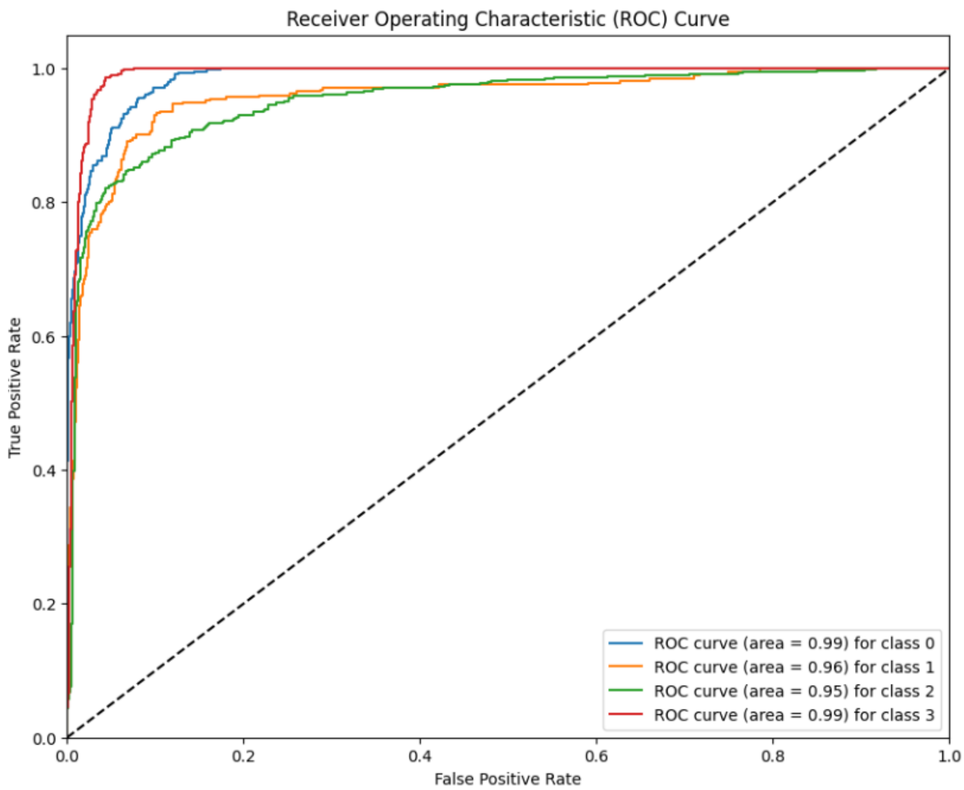


Figure 25: ROC Curve B3

5.5 EfficientNet B4:

Test Loss: 0.37797
Test Accuracy: 88.23%
Training Accuracy: 77.15%

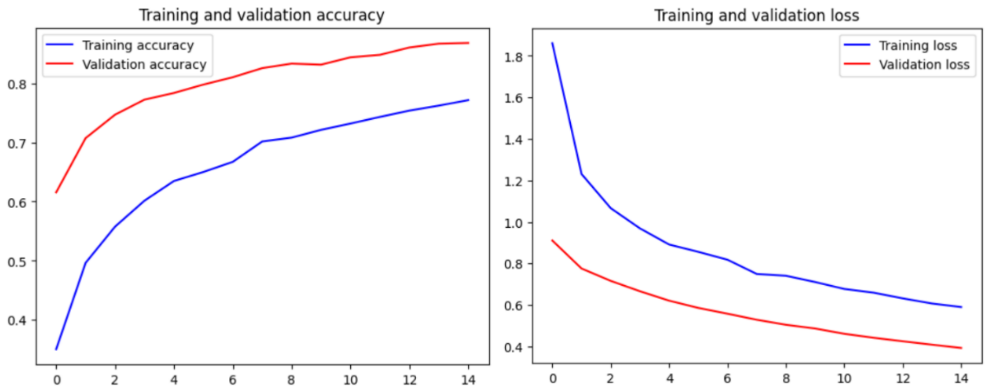


Figure 26: Training and validation Curve

5.5.1 Classification Report

	precision	recall	f1-score	support
bacterialblight	0.817490	0.942982	0.875764	456.00000
blast	0.899642	0.669333	0.767584	375.00000
brownspot	0.912117	0.879332	0.895425	779.00000
healthy	0.894454	0.990099	0.939850	505.00000
accuracy	0.882270	0.882270	0.882270	0.88227
macro avg	0.880926	0.870437	0.869656	2115.00000
weighted avg	0.885286	0.882270	0.879126	2115.00000

Figure 27: Classification Report B4

5.5.2 Confusion Matrix

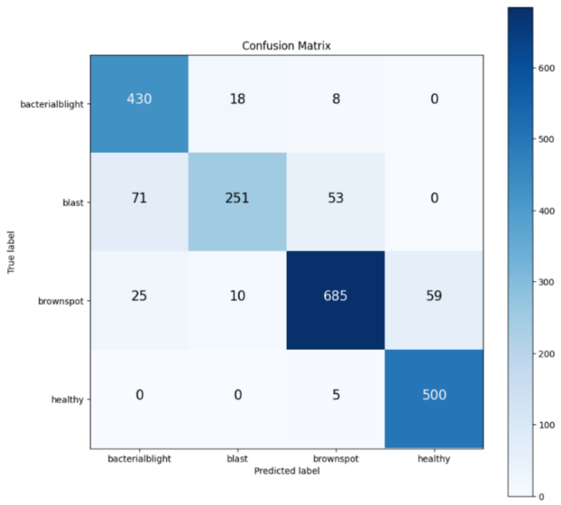


Figure 28: Confusion Matrix B4

5.5.3 ROC Curve

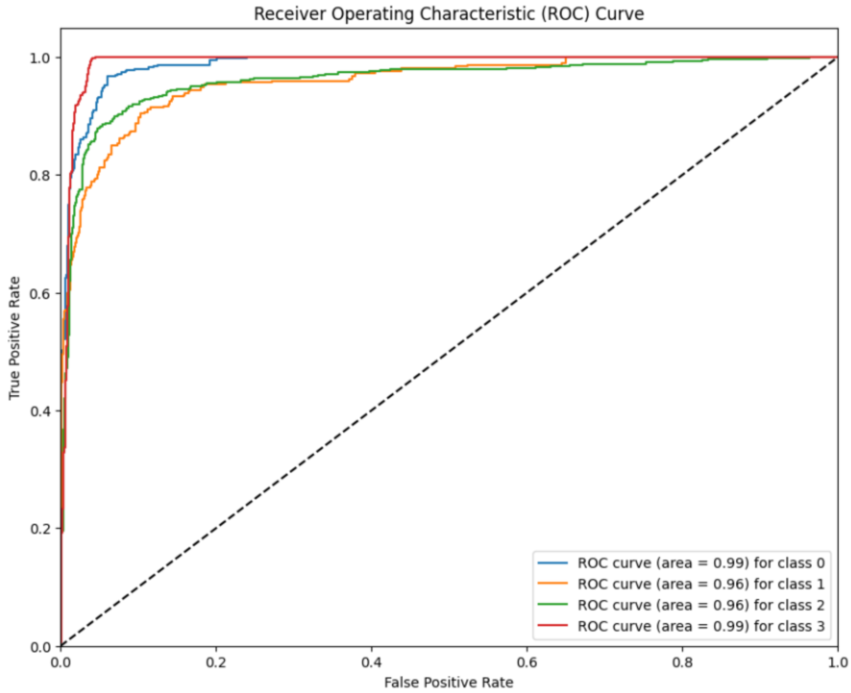


Figure 29: ROC Curve B4

5.5.4 Model Prediction

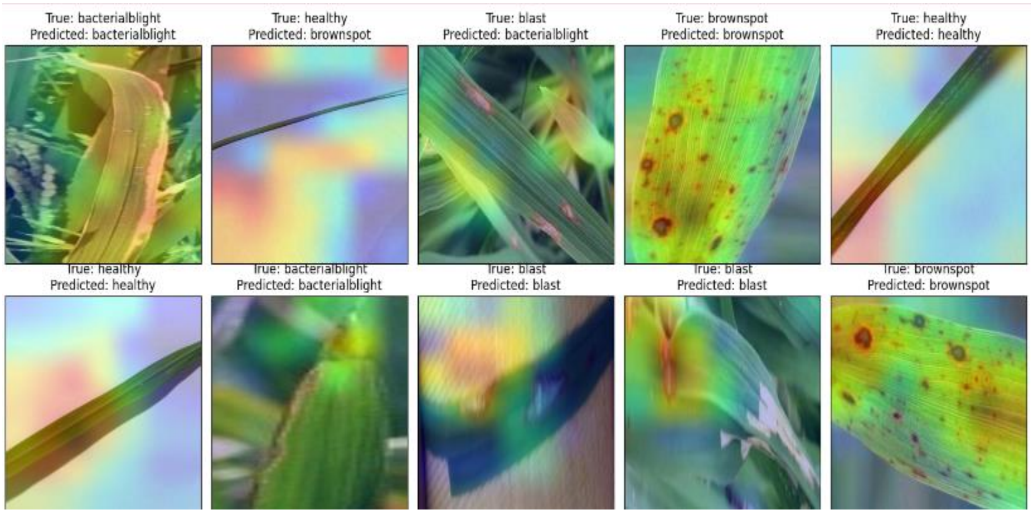


Figure 30: Disease prediction B4

5.6 EfficientNet B5:

Test Loss: 0.49690
Test Accuracy: 83.45
Training Accuracy: 70.68

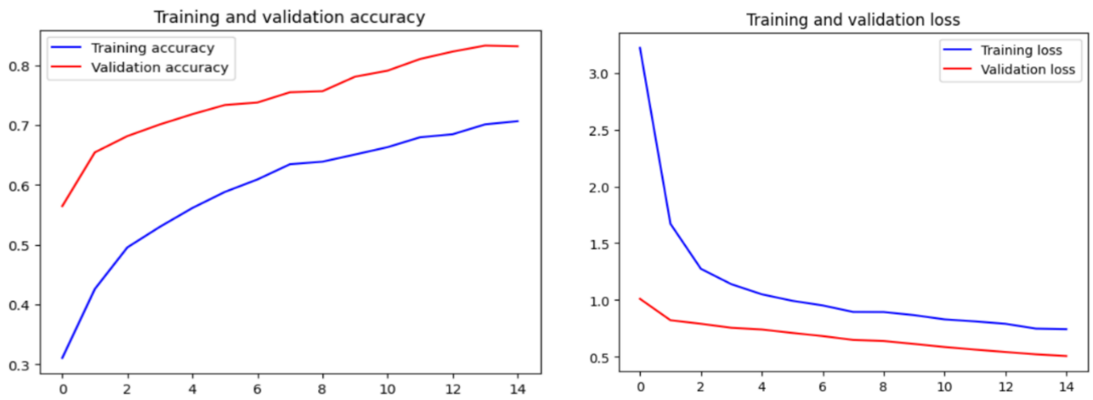


Figure 31: Training and Validation Curve

5.6.1 Classification Report

	precision	recall	f1-score	support
bacterialblight	0.756705	0.866228	0.807771	456.000000
blast	0.839041	0.653333	0.734633	375.000000
brownspot	0.876231	0.799743	0.836242	779.000000
healthy	0.850847	0.994059	0.916895	505.000000
accuracy	0.834515	0.834515	0.834515	0.834515
macro avg	0.830706	0.828341	0.823885	2115.000000
weighted avg	0.837806	0.834515	0.831345	2115.000000

Figure 32: Classification Report B5

5.6.2 Confusion Matrix

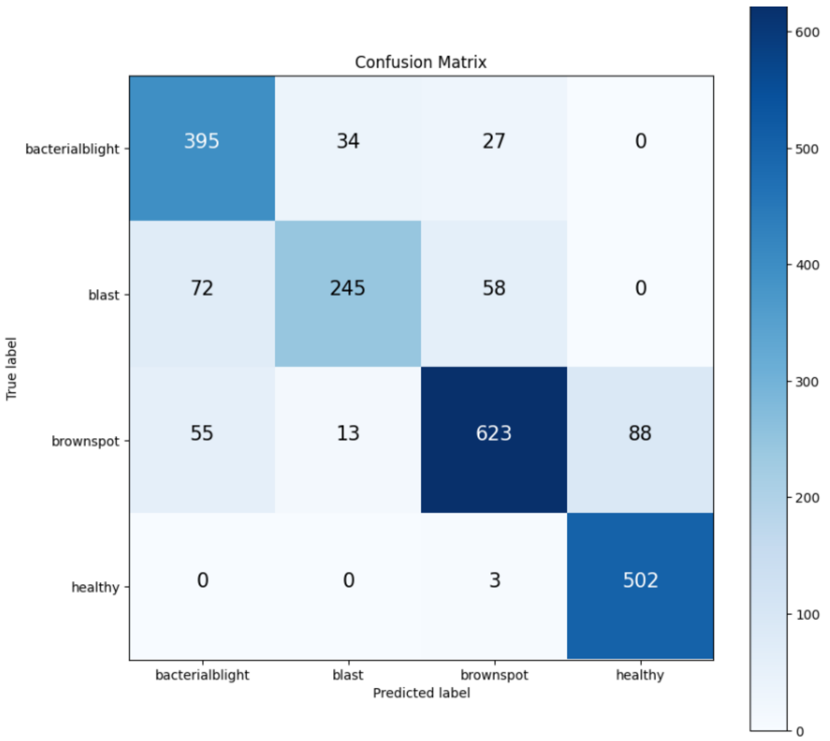


Figure 33: Confusion Matrix B5

5.6.3 ROC Curve

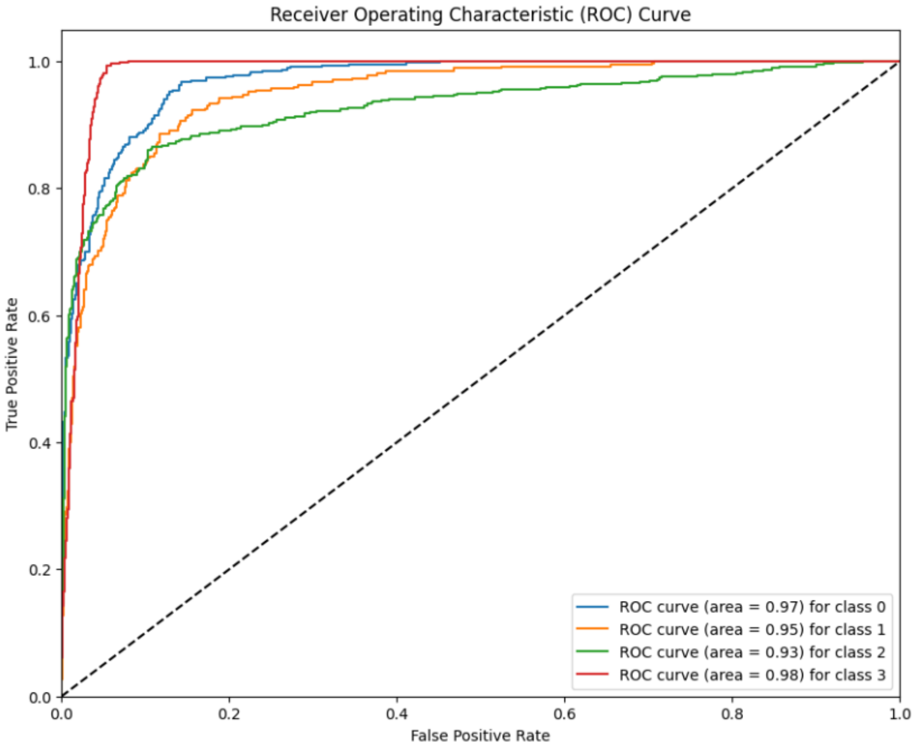


Figure 34: ROC Curve B5

5.6.4 Model Prediction

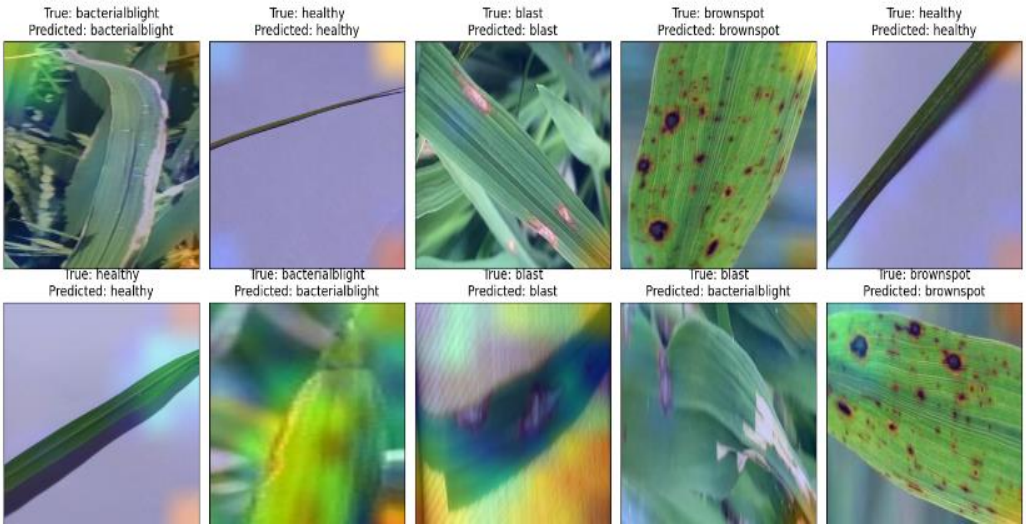


Figure 35: Disease Prediction B5

5.7 EfficientNet B6:

Test Loss: 0.47316
Test Accuracy: 82.36%
Training Accuracy: 73.93%

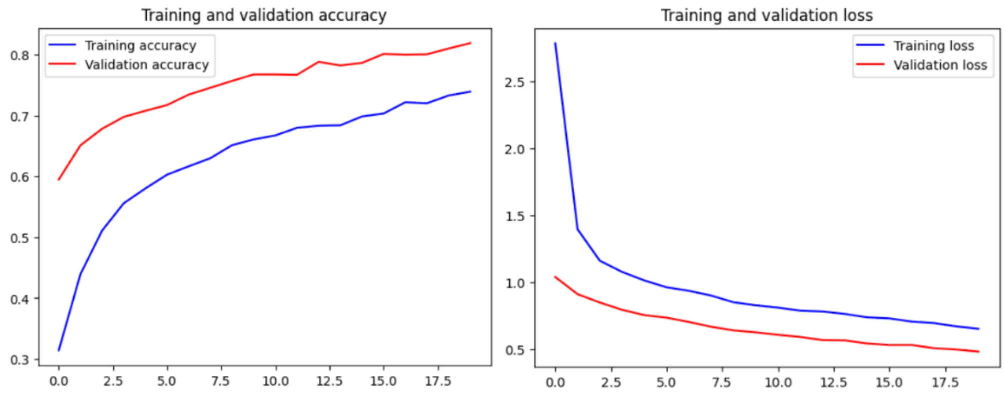


Figure 36: Training and Validation Curve

5.7.1 Classification Report

	precision	recall	f1-score	support
bacterialblight	0.721612	0.864035	0.786427	456.000000
blast	0.807971	0.594667	0.685100	375.000000
brownspot	0.873144	0.830552	0.851316	779.000000
healthy	0.865942	0.946535	0.904447	505.000000
accuracy	0.823641	0.823641	0.823641	0.823641
macro avg	0.817167	0.808947	0.806822	2115.000000
weighted avg	0.827198	0.823641	0.820541	2115.000000

Figure 37: Classification Report B6

5.7.2 Confusion Matrix

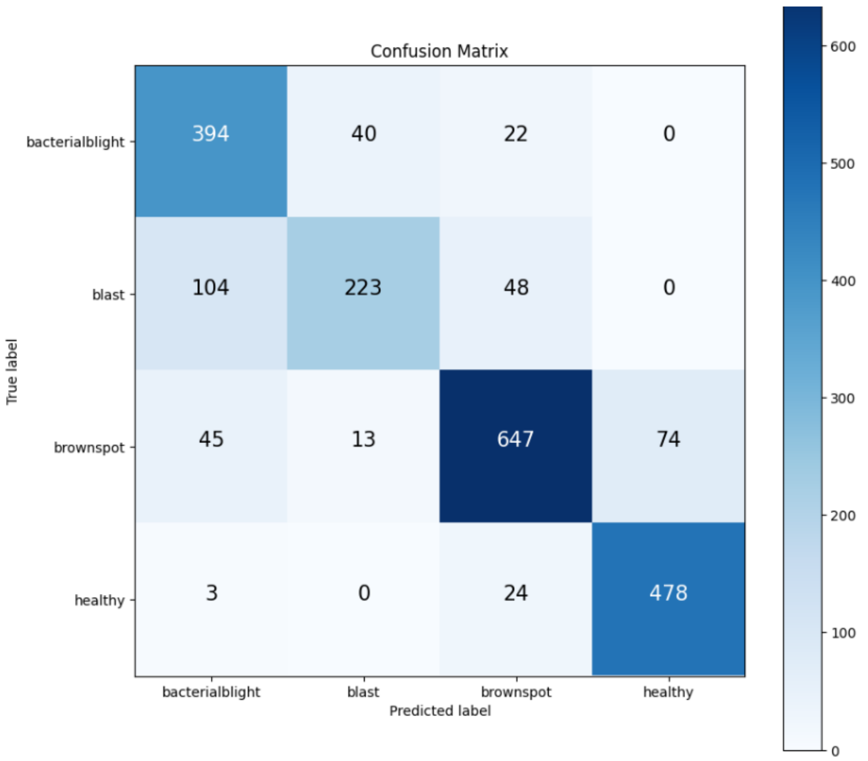


Figure 38: Confusion Matrix B6

5.7.3 ROC Curve

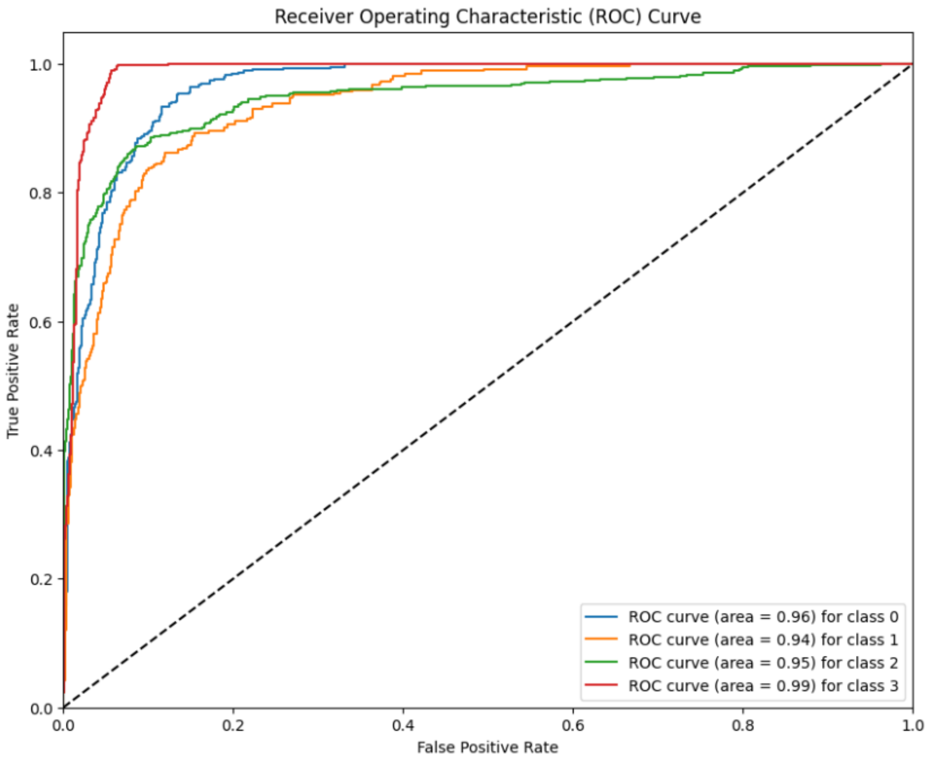


Figure 39: ROC Curve B6

5.7.4 Model Prediction

Figure 40: Disease Prediction B6

5.8 EfficientNet B7:

Test Loss: 0.42532
Test Accuracy: 86.29%
Training Accuracy: 76.04%

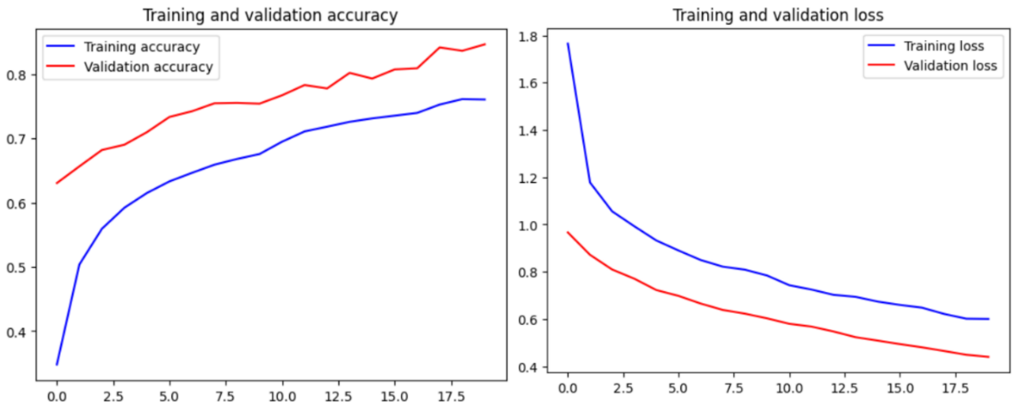


Figure 41: Training and Validation Curve

5.8.1 Classification Report

	precision	recall	f1-score	support
bacterialblight	0.810976	0.875000	0.841772	456.000000
blast	0.822430	0.704000	0.758621	375.000000
brownspot	0.897987	0.858793	0.877953	779.000000
healthy	0.885099	0.976238	0.928437	505.000000
accuracy	0.862884	0.862884	0.862884	0.862884
macro avg	0.854123	0.853508	0.851696	2115.000000
weighted avg	0.862753	0.862884	0.861048	2115.000000

Figure 42: Classification Report B7

5.8.2 Confusion Matrix

Figure 43: Confusion Matrix B7

5.8.3 ROC Curve

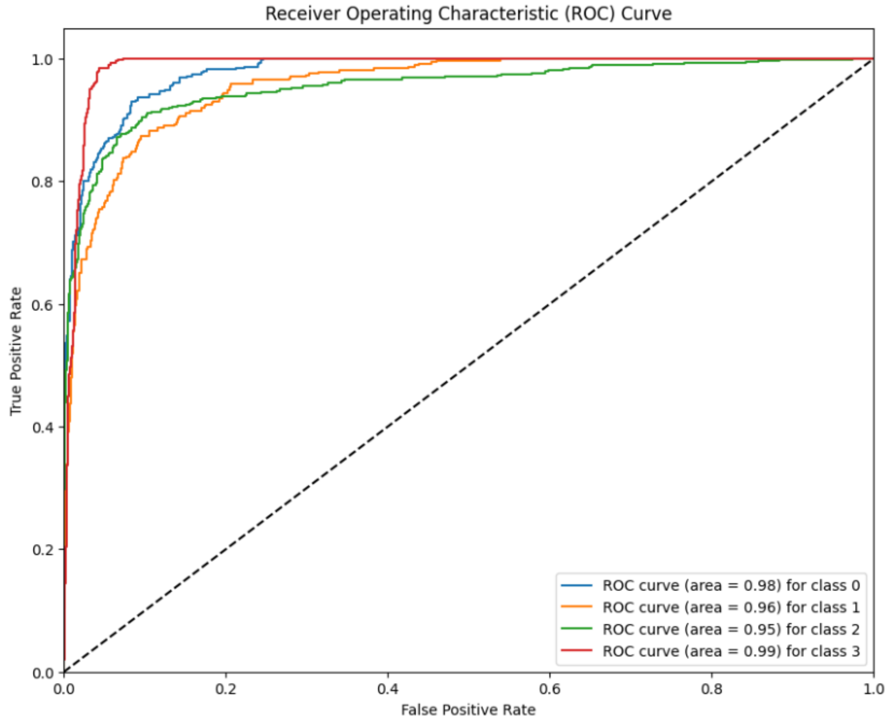


Figure 44: ROC Curve B7

5.8.4 Model Prediction

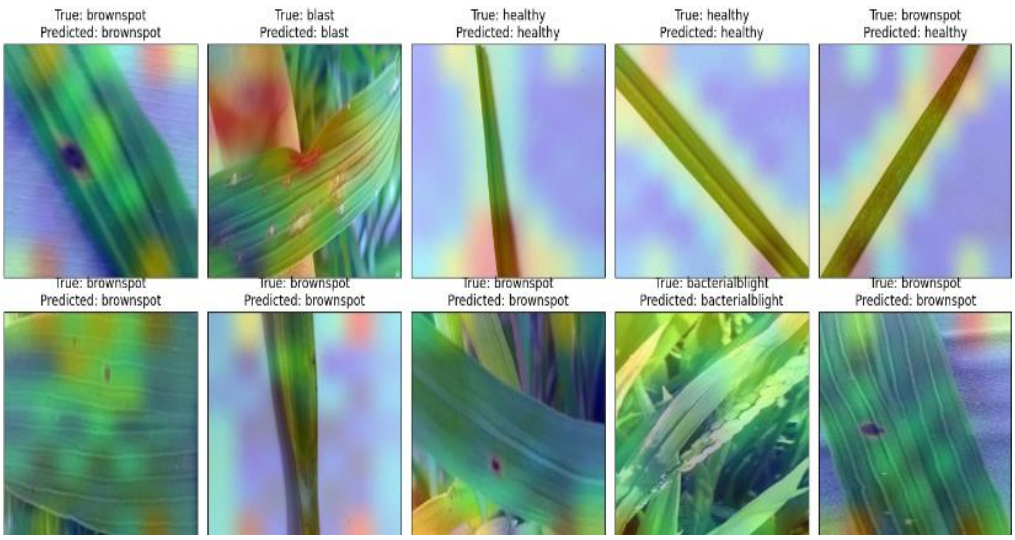


Figure 45: Disease Prediction B7

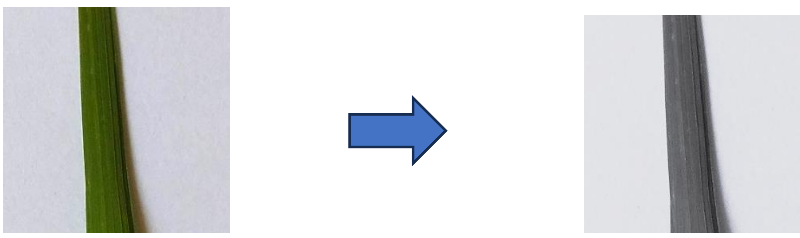
5.9 Comparison & Analysis:

Table 2: Comparison of EfficientNet Models

		B0	B1	B2	B3	B4	B5	B6	B7
Accuracy		86.95	85.96	81.84	86.67	88.22	75.67	82.36	86.29
Precision	Bacterial Blight	83.33	80.16	75.64	83.36	81.74	83.90	72.16	81.09
	Leafblast	90.90	83.70	75.00	81.25	89.96	87.62	80.79	82.24
	Brownspot	90.35	90.98	86.91	90.79	91.21	85.08	87.31	89.79
	Healthy	83.95	85.91	84.48	87.67	89.44	83.45	86.59	88.50
Recall	Bacterial Blight	93.20	87.71	83.77	92.32	94.29	86.62	86.40	87.50
	Leafblast	74.66	69.86	60.80	72.80	66.93	65.33	59.46	70.40
	Brownspot	81.77	84.21	81.00	82.28	87.93	79.97	83.05	85.87
	Healthy	98.41	99.00	97.02	98.61	99.00	99.40	94.65	97.62
F1-Score	Bacterial Blight	87.99	83.76	79.50	87.61	87.57	80.77	78.64	84.17
	Leafblast	81.99	76.16	67.15	76.79	76.75	73.46	68.51	75.86
	Brownspot	85.84	87.46	83.85	86.33	89.54	83.62	85.13	87.79
	Healthy	90.61	91.99	90.32	92.82	93.98	91.68	90.44	92.84
Support	Bacterial Blight	456	456	456	456	456	456	456	456
	Leafblast	375	375	375	375	375	375	375	375
	Brownspot	779	779	779	779	779	779	779	779
	Healthy	505	505	505	505	505	505	505	505

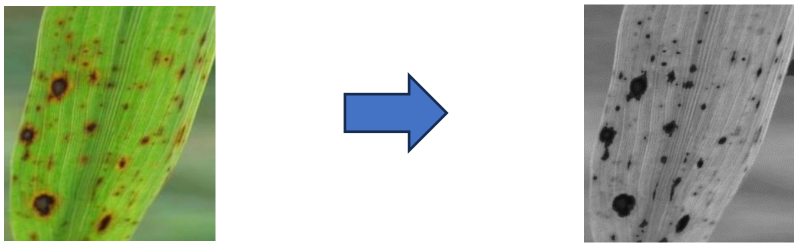
5.10 Pixel Intensity Distribution

This is to measure the degree of infection in a diseased rice leaf.



(a) Healthy (b) Greyscale

Figure 46: Conversion of healthy leaf to greyscale



(a) Brownspot (b) Greyscale

Figure 47: Conversion of brownspot leaf to greyscale

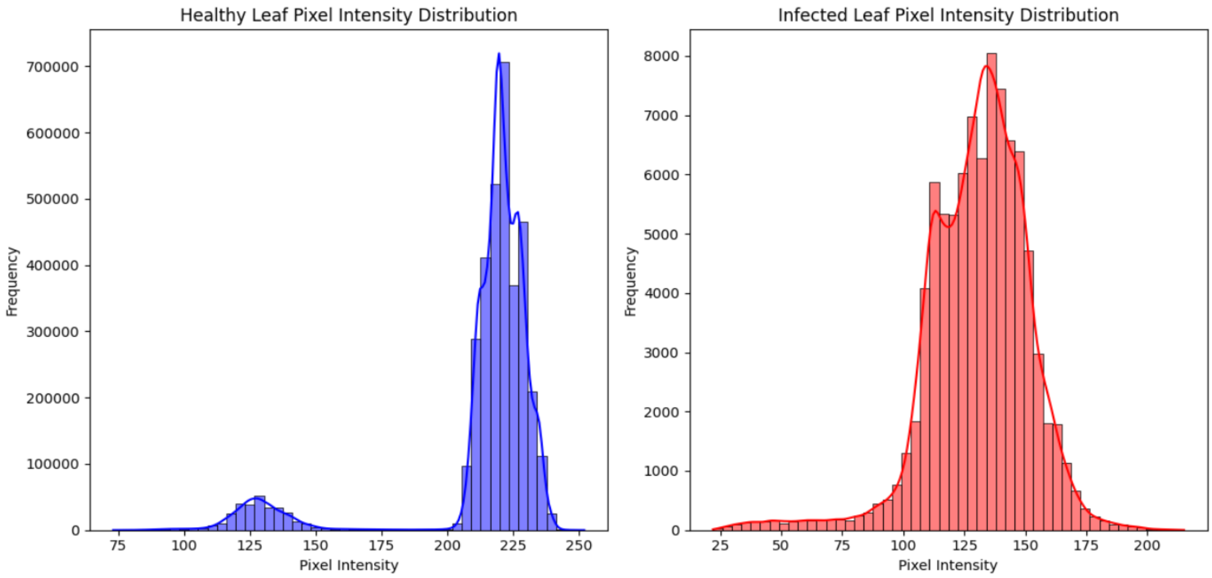


Figure 48: Pixel Intensity Distribution

Analysing the graph of pixel intensity distribution from white to black pixels involves understanding the distribution of pixel intensity values across the grayscale range. Here's how to interpret and analyse the degree of infection:

1. X-Axis (Pixel Intensity): The x-axis represents the range of pixel intensity values. In grayscale images, pixel intensity values typically range from 0 (black) to 255 (white). Intermediate values represent shades of Gray.

2. Y-Axis (Frequency): The y-axis represents the frequency or count of pixels with a specific intensity value. Higher peaks on the y-axis indicate a higher frequency of pixels with that intensity.

3. Peak Distribution: Peaks in the histogram represent clusters of pixel intensity values that occur frequently in the image. These peaks can indicate important features or regions within the image. For example, if you have a leaf image, peaks in the histogram might correspond to areas with high contrast or distinct textures.

4. Skewness: The shape of the histogram can indicate the overall distribution of pixel intensities. A symmetrical distribution with a peak in the middle suggests balanced intensity values across the image, while a skewed distribution towards one end (e.g., towards black or white) indicates an imbalance in intensity values.

Chapter 6

CONCLUSION

In conclusion, our study successfully classified rice leaf into healthy and infected categories, further categorizing them into specific diseases such as bacterial blight, leaf blast, brownspot. We employed EfficientNet B0 to EfficientNet B7 for this task and conducted a comprehensive comparison and analysis of their performance.

Our results indicate that EfficienNet outperformed other CNN models for rice leaf disease classification, achieving an highest accuracy of 88.22% with EfficientNet B4 followed by EfficientNet B0 with 86.95%. This higher accuracy can be attributed to low computational cost and compound scaling feature, which allows for efficient feature reuse and propagation, leading to better learning capabilities. Additionally, EfficientNet's compound scaling contributes to its computational efficiency, making it a practical choice for tasks with limited computational resources.

Furthermore, our analysis revealed that EfficientNet models exhibited superior performance in terms of F1 score, precision, and confusion matrix metrics. This indicates that EfficientNet not only achieved higher accuracy but also demonstrated better overall classification performance and robustness

Overall, our study demonstrates the effectiveness of transfer learning model, particularly EfficientNet, in classifying rice leaf diseases. The application of these models can significantly improve the efficiency and accuracy of disease classification processes in the agricultural industries. Additionally, our research contributes to the broader understanding of EfficientNet models in agricultural research and underscores the importance of choosing the right model from B0 to B7 architecture for specific classification tasks.

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https://www.kaggle.com/datasets/minhhuy2810/rice-diseases-image-dataset