Rice Disease Detection for Sustainable Farming using Machine Learning

by

Tasnim Tabassum
22101005
Lamia Afrida
21201450
Humaira Kabir
24341178
Sadia Karim Roza
21201278
Sirajum Munira Tasnim
21201692

A thesis submitted to the Department of Computer Science and Engineering
in partial fulfillment of the requirements for the degree of
B.Sc. in Computer Science and Engineering

Department of Computer Science and Engineering
Brac University
February 2026.

Declaration

It is hereby declared that

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2. The thesis does not contain material previously published or written by a third party, except where this is appropriately cited through full and accurate referencing.

3. The thesis does not contain material which has been accepted, or submitted, for any other degree or diploma at a university or other institution.

4. We have acknowledged all main sources of help.

Student's Full Name & Signature:

Tasnim Tabassum

22101005

Lamia Afrida

21201450

Humaira Kabir

24341178

Sadia Karim Roza

21201278

Sirajum Munira Tasnim

21201692

Approval

The thesis/project titled "Rice Disease Detection for Sustainable Farming using Machine Learning" submitted by

1. Tasnim Tabassum 22101005
2. Lamia Afrida 21201450
3. Humaira Kabir 24341178
4. Sadia Karim Roza 21201278
5. Sirajum Munira Tasnim 21201692

of Fall, 2026 has been accepted as satisfactory in partial fulfillment of the requirement for the degree of B.Sc. in Computer Science in 28 January,2026.

Examining Committee:

Supervisor:
(Member)

Mr. Dewan Ziaul Karim

Senior Lecturer
Computer Science and Engineering
Brac University

Thesis Coordinator:
(Member)

Dr. Md. Golam Rabiul Alam

Professor
Computer Science and Engineering
Brac University

Head of Department:
(Chair)

Sadia Hamid Kazi

Associate Professor & Chairperson
Department of Computer Science and Engineering
Brac University

Abstract

The rice leaf diseases cause not only loss in their yield, but they are also a significant source of food insecurity especially in countries that are dependent on agriculture like Bangladesh where rice is the staple crop. The reason is that such diseases should be identified early enough and properly in order to take care of the crops and make relevant decisions. This paper provides one of the deep learning models utilizing image, a model that includes the use of digital images to automatically identify and categorize rice leaf diseases. The dataset of 1560 rice leaf images divided into six classes, five disease classes and one healthy class of images were gathered through the assistance of expert validated samples that were collected at Bangladesh Rice Research Institute (BRRI) and through the addition of publicly available internet access to online farming image collections in order to enhance the dataset variety. Preprocessing of the photos included resizing, normalization, and data augmentation and was followed by the division of the photos into training, validation, and testing sets in 70:20:10. A convolutional neural network was designed and trained in an original way and other known convolutional neural networks were used as benchmark models under the same experimental conditions. The test analysis indicates that the proposed model has had a total test performance of approximately 91.67% and the training and validation performance was approximately 94.87% that was the indication of persistent learning behaviour and consistent generalisation performance.The results demonstrate that the proposed method works well in the classification of rice leaf diseases and can be useful in practice with regard to the application in the agricultural monitoring and decision-support systems.

Keywords: Machine Learning,Deep Learning, Transfer Learning, Rice Leaf Disease Detection,Convolutional Neural Network, Image Processing, DenseNet121

Acknowledgement

We are, first of all, grateful to the Almighty, the supreme source of knowledge and strength, who brought us to this way. This thesis would have been impossible without the support and the continuous persuasion provided by a number of individuals. We would particularly like to thank Mr. Dewan Ziaul Karim, our supervisor, without whom we would not have been in a position to complete this thesis. His wisdom and his pieces of advice provided us with the direction we needed and helped us to get through numerous troubles on our way. We do not overestimate his dedication or his patience and the invaluable time he devoted to us, during this venture.

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Chapter 1

Introduction

1.1 Background

Rice production faces major challenges due to a number of disease,which inhibit the health of the leaves hence affecting the yield and quality of the grains. Many of these diseases that decrease yield are treatable and eliminable through the early observation of the leaf diseases and thereby reducing the effects of such diseases thus alleviating yield loss and therefore increasing agricultural production through the implementation of timely interventions. Recent developments in artificial intelligence systems, and specifically, deep learning and Convolutional Neural Networks to analyze images are making it easier to automate the process of detecting plant diseases and providing more objective means of diagnosing a particular plant disease.

1.2 Rational of the Study or Motivation

This project will utilize the benefits of CNN in the automatic and accurate detection of rice leaf diseases. The technology offers a cost-effective, scalable and fast diagnostic tool to give farmers and agronomists real time disease management capabilities. Its effects can be used to increase yields and agricultural management and reduce costly effects and economic losses. This work is valuable because of modern ways of measuring the health of crops in agriculture.

1.3 Problem Statement

Production is highly diminished by the occurrence of cuticle diseases even though rice is a major staple crop to almost half of the human population. The conventional disease surveillance systems tend to fail, and are untrustworthy and unreachable by all farmers. Currently, automated systems, which are able to detect various diseases on rice leaves sufficiently, are lacking. The absence of this causes information imbalance and misinformed management decisions which results in crop destruction and money loss. Consequently, there is a need to have a specific automated detection system with the application of the most up-to-date machine learning techniques.

1.4 Objective

The general aim of the research is to have a sound model of a convolutional neural network able to discriminate and categorise the images of the common diseases of the rice leaves accurately by means of leaf images.

- This is because it was intended to capture a varied sample of photos of rice leaves under varying disease conditions.
- Finally, training and developing a structure of convolutional neural networks to designate the difference between a healthy leaf and various forms of disease.
- The model is to be tested regarding dependence on accuracy, precision and recall.

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1.5 Methodology in Brief

The study uses supervised deep learning algorithms based on the Convolutional Neural Networks to classify pictures.The workflow is started with Data acquisition and Dataset Collection of domain specific images. This is followed by subsequent preprocessing using resizing, augmentation, and normalization. The segmentation is subsequently performed by the use of adaptive thresholding to identify regions of interest. In classification, we will be constructing, training, and validating several CNN designs on the processed dataset. The last objective produces prediction results. The accuracy is to be used in model evaluation, which is accompanied by the use of confusion matrices, F1-scores in model evaluation, whereas a comparative analysis of CNN architectures will allow defining optimal performance.

1.6 Scopes and Challenges

The study acknowledges challenges that will need to be overcome to successfully produce a user-friendly product, including an acquisition of a large, balanced dataset, image variations with respect to lighting and background images, and ensuring the model has robustness across multiple rice varieties and disease stages. In addition, there are future challenges with deploying and gaining usability from farmers who may not have any prior experience with computer and digital technologies.

1.7 Team Overview

The team consists of five members with expertise in a range of areas. The team leader manages the project and coordinates activities. Also, the theoretical and technical knowledge of the outcome is fused by the team to optimize the effectiveness and accuracy of rice disease detection.

1.8 Key Learnings and Insights

This study demonstrates the feasibility and effectiveness of CNN to detect diseases in plants. It explores the challenges of image based diagnostics in agriculture and the current potential benefits of applying Artificial Intelligence in crop monitoring and management. The study will help to gather evidence that supports technology led sustainable agriculture practices in Bangladesh and other regions.

Chapter 2

Literature Review

2.1 Preliminaries

Rice is a universal crop of food and plays a significant and worthwhile role in food in the world particularly in Asia and Africa but it is continuously threatened by the various forms of diseases such as brown spot, blast, sheath blight, bacterial blight among others. These diseases may decrease the quality and impact on the livelihood and food supply of the farmers. Technically, rice farmers practice manual inspection to detect these ailments that also pose a health risk to rice plants. This is so time consuming and inaccurate at times and not available in the remote regions. With the assistance of Artificial intelligence, and more specifically, deep learning, it has become a smarter and faster approach to the detection of rice diseases. The works on image processing obviously involve the use of Convolutional Neural Networks (CNNs). CNNs are more effective in analyzing and interpreting the images of leaves and identifying the patterns of the disease. In order to make these examinations strong researchers combine CNNs with different methods into hybrid techniques. The images are prepared using the preprocessing methods such as image augmentation, color extraction, and noise filtering, and the separation of the affected parts of the disease is done by the segmentation methods. Different CNN networks are tried. CNNs represent a type of deep learning model and also contain convolutional layers and pooling layers as well as fully connected layers. The final aim is to develop models that can be used on mobile phones or low power devices that are not that expensive in order that farmers can be able to purchase and use them in remote or rural areas.

2.2 Review of Existing Research

In [10], the article is a comprehensive study of the creation of a mobile application to detect rice diseases using the method of deep learning. The dataset I used to do this study consisted of 33,026 images. These images harbor six kinds of rice diseases, viz. leaf blast, false smut, neck blast, sheath blight, bacterial stripe disease and brown spot. The purpose of the study was to create a deep learning network model to diagnose the aforementioned diseases after evaluating the performance of the model, the diagnosis method is eventually applied in a cloud-based mobile application and experimented. This approach was based on the Ensemble Model that integrated numerous sub models. The major algorithm is deep learning which

4 is based on Convolutional Neural Networks (CNNs). A number of models were evaluated and the end result model comprises the best three models in terms of performance: SE-ResNet-50, DenseNet-121 and ResNeSt-50. Training, validation, and test sets were used in the ratio of 7:2:1 respectively to train the models. Within the training, the batch size was 64 and the Stochastic Gradient Descent (SGD) optimiser was used with the learning rate of 0.001 and 200 epochs. Each network model was used to make the disease prediction results which were classified into four categories, True Positive, False Positive, True Negative, False Negative. These were the results used to calculate the performance measures; accuracy, precision, recall, F1 score and Matthews Correlation Coefficient (MCC). The Ensemble Model had an accuracy of 91 percent when it was tested on external sources of images. The F1 scores of the various diseases were 0.83 to 0.97 and the overall performance was also stable in terms of the precision, recall and F1 scores. The limitations of this study include high costs in computations, possible misclassification and imbalance in data.
The authors in [20] The paper suggested a CNN based-model which has a potential of identifying three varieties of rice diseases. The training dataset was taken in agricultural fields of different sections of India. Images of healthy leaves and 3 other diseases, which are blast, brown spot, and bacterial leaf blight, are found in the dataset. Convolutional Neural Network is the principal algorithm applied in this case. The samples were divided into 7:1.5:1.5 ratio of training, validation and testing individually. Each convolutional layer was followed by a max pooling layer and a max ReLU activation function that extracts features in the images. There are two entirely interconnected neurons, 512 and 128 applied to categorisation. The soft max activation function was also applied in the output layer to classify the input images into 4 classes namely health, blast, brown spot and bacterial leaf blight. The input images were further expanded by 224 x 224 pixels. The training was done on the Adam optimiser with a learning rate of 0.001. F1-score, accuracy, precision and recall were used to measure the performance of the model during the 50 epochs of training. The general correctness of the model was 96.5%. Blast had precision of 95.2, a recall of 96 and an F1 score of 95.6. Brown Spot had a precision of 97, recall of 96.5 and F1 of 96.7. Bacterial Leaf Blight attained a precision of 96.8, recall of 97.2 and F1 score of 97. The accuracy, recall, and F1 score of healthy leaves are 97.5, 96.8 and 97.1 respectively. A part of the weaknesses of this research is that the data is restricted to 3 types of the diseases and the performance of the model could be influenced by environmental factors.
In [5],this paper aims at developing a special CNN model through calibration of the model parameters, which will detect various rice diseases. This CNN model is developed using several convolution and pooling layers, a dense layer, and a softmax layer. The advantage of this method in machines with limited memory is that it greatly reduces the parameters. The dataset in this case consists of 4199 images of 5 diseases of rice namely: Blast, Bacterial Leaf Blight, Sheath Blast, Brown Spot and Tungro. The best algorithm in this case is convolutional Neural Network(CNN). The fewer parameters used to construct a network are based on a custom CNN architecture. The network layers are convolutional, pooling and dense. The data was split into 50% training, 30 percent validation and 20 percent test set. The model uses the Categorical Cross Entropy as a loss. One optimizes the loss function using Adam optimizer. The size of the batch and epochs used in this experiment 5

are 50 and 32, respectively. Information was added, swiveled, translated, amplified and blow-up. The Conv1, the Conv2 and the Conv3 filter sizes were 3x3 with 16, 32 and 64 filter sizes. The 2x2 max pooling size was used in the pooling layers. The AUC of Bacterial leaf blight and Brown spot classes is 0.99 with the maximum AUC value 1.00 being of the Blast, Sheath Blight and Tungro classes. The general performance of the model was measured in terms of performance measurement of accuracy, precision, recall and F1 score. CNN model yielded average accuracy, precision, recall and F1 score of 97.82, 94.8, 95 and 94.6 respectively. The model can identify various diseases of rice on varying image backgrounds. And an independent test image accuracy of 97.82 was obtained. Minimal among the limitations of this study is that this data is only restricted to 5 diseases and the performance of the model may be influenced by environmental factors. This model could also face problems in generalization where there is the introduction of new data.
In [2],the study seeks to present a CNN model, which is efficient in memory as well as accuracy in classification to classify and detect rice disease and pest, to the farmers, who lack access to good internet connectivity. The data consists of 1426 pictures of rice diseases and pests in BRRI paddy fields. Among the nine diseases to compose the dataset, there are False Smut, Brown Plant Hopper, Bacterial Leaf Blight, Neck Blast, Stemborer, Hispa, Sheath Blight/Sheath Rot, Brown Spot, and Others. In this study, a new CNN architecture was proposed called Simple CNN Architecture that was used to classify rice disease; this architecture is memory efficient compared to other more sophisticated CNN architecture such as VGG16andInceptionV3. Similar to other models, the Simple CNN Architecture has 0.8 million parameters, which is relatively small. Training of the model was done in two phases. In the 1 st stage, the 9 classes were divided into 17 classes and in 2 nd stage, it was re-trained with the original 9 classes of the data. The output layer utilized softmax and the intermediate layers utilized ReLU. As a loss function, Categorical Crossentropy has been adopted. The hyperparameters that are adopted are Adam optimizer, dropout rate of 0.3, learning rate of 0.0001, mini batch size of 64 and 100 epochs. Random rotations, shear transformations and flipping, skewing and intensity transformations were added to the data. The performance of the models was tested by ten-fold cross-validation. Additionally, other models have been evaluated using training from scratch, transfer learning, and fine tuning to evaluate the performance of the models. However, the accuracy of various CNN architectures using various training methods ranged between 42.76% and 97.12% but Simple CNN had an accuracy of 94.33%. The weakness of this study is that although the Simple CNN model was successful even without pre-training on ImageNet, it still needs to be refined to be used in real-life situations especially with additional data such as weather and soil conditions.
In [6],the objective of the given paper is to come up with a method of early rice disease detection through the combination of localisation and classification. It is done using the approach which is based on Mask R-CNN and recognizes the affected portion of the plant and provides appropriate information regarding crop health. The data used in this case was collected in a fertile region near the Chenab River which originates in the Himachal Pradesh of India and flows into the Punjab River of Pakistan and becomes the Indus. The photos were captured by mobile phone cameras and the infected localities were labeled using LabelMe which is a Python based application. The number of images of rice crops that was infected and healthy

6 was 1700. Its underlying algorithm is the Mask R-CNN, which is a deep network with the ability to classify and locate. This model was adjusted to help in identifying the disease as well as the part of the plant that was affected. Moreover, a CNN model was trained in order to compare it with three convolutional layers, batch normalization and pooling layers, which used 20 percent of photos as a testing sample, and the rest (80 percent) as a training sample. The model was trained on the batch size of 2 and 60 epochs. To train the process the weights were randomly initialised and trained with a learning rate of 0.001 and learning momentum of 0.9. The CNN model is a basic convolutional network that consists of three convolutional layers and their activation and pooling layers are separated by a batch normalisation layer. Whereas the output layer used the sigmoid activation, the hidden layers used the ReLU activation. The accuracy, precision, recall and F1-score were used to assess the performance of both the CNN and Mask R-CNN model. Mask R-CNN model has accuracy of 87.6%, precision of 82.1, recall of 96.2, F1-score of 88.6 and mean average precision of 0.65. The CNN model on its own, however, has accuracy of 58.4 percent and precision of 59.8 percent with a recall of 66.2 percent and F1 of 62.8 percent. Mask R CNN improves accuracy by 49.4 points, precision by 36.29 points, recall by 45.3 points and changes in F1-scores by 41. Weaknesses in this research are that the dataset is small. The model can also not work well when taken in a dim light and this will impact its effectiveness in a real life situation.
In [9],this study paper provides a mass review of the techniques employed in processing of images in diagnosing rice diseases. It has given attention on feature extraction, feature selection, and picture segmentation through comparison of the studies made in the period of 2007-2018. Nonetheless, some of the common diseases like Sheath Blight, False Smut, Rice Blast, Bacterial Leaf Blight etc. were discussed in this paper. Both diseases are explained with their effects and symptoms on rice crops. The paper identified different image processing methods used in detecting disease i.e. Preprocessing (Gaussian Filtering, Wiener filtering, HSV color extraction), Segmentation (Fuzzy C-Means, K-Means Clustering, Otsus thresholding), Feature Extraction (Texture, Color, Shape, Edge Detection), Classification, Probabilistic Neural Network [PNN], CNN. In this study the dataset was formed using 134 diseased rice leaf images on which 94 images were taken as a training, and the rest was taken as a validation as well as a test image. Some of the algorithms and models that were used in this research include Preprocessing Algorithms(Gaussian Filtering, Weiner Filtering), Segmentation also Feature Extraction (PCA, Texture, Shape, and Edge Detection) and as far as classification is concerned Support Vector Machine (SVM), Back Propagation Neural Network (BPNN) and also(CNN) have been used. The research paper also derives the findings and accuracy of such algorithms and models where SVMandBPNN demonstrate high accuracy and the numbers are 97.2% and 95.83% (7.5% higher than traditional BPNN, 2.5% higher than SVM). The majority of the studies identify five diseases and few CNN models may identify up to ten diseases. CNN techniques demand a lot of computation.
In [14],the research paper gives a broad deep learning-based research to detect rice plant diseases. This dataset was sourced from kaggle which has 10080 images also it had nine rice diseases categories and one healthy category. Each class contains at least 1000 images with the same lighting and having the white background. The resolutions of the images were 128×128 pixels. However, the model started with an image processing method which used the Improved Threshold Neural network(ITNN).

ITNN helped to improve the image's quality, then segmentation was executed by implementing the segment Multiscale neural slicing process to get affected leaf regions. There are 2 stages of feature selection, one is Spectral Scaled Absolute Feature Selection and another one is known as Feature Closest Weight(S20-FCW). Moreover, there is also a deep learning model called Deep Spectral Generative Adversarial Neural Network(DSGAN2) which recognizes the plant diseases on some selected features. This model gained absolute outstanding performance results with having the 99% accuracy and 92% precision, recall and specificity of 98.8% overcome with existing models like CNN(91)%, AlexNet(82%), and APS- DCCNN(78%). However, it demonstrated a low false rate of 40.8% and a faster processing time of 98 ms. The research paper has outstanding performance though it has some limitations as it has lack of field-based testing and has relayed on dataset. In the end, the paper can give a good amount of solution for automated rice disease detection.
In [17],the research paper gives us a detailed overview about using deep learning techniques for detecting diseases in rice. As rice is an important global food crop, we need early and accurate detection so that we can prevent major crop losses. It has reviewed more than 80 high quality articles and the articles published between 2017-2023 which have categorized in 4 major groups: custom-built CNN models, transfer learning using pre-trained networks, ensemble learning and the hybrid mod els. However, these four major groups combine deep learning techniques with SVM or RNN. These models have used various public and private datasets, including Kaggle, Mendeley having image counts over 16000. The models detect diseases like blast, leaf smut, sheath blight and bacterial blight etc. Moreover, Combinations of AlexNet, GoogleNet, and Mobilenet achieved accuracy of 99% high precision, recall also scores of F1. Though the paper has so many impressive results, the paper has limitations. Limitations are lack of diversity, lack of real world deployment, poor model generalizability to field conditions, the challenge of detecting multiple diseases in a single image, there is also the risk of confusions about nutrient deficiencies . The authors had suggested focusing on building larger and more datasets to overcome the limitations. In short, the paper gives a practical and crystal clear overview about deep learning's reshaping process of rice diseases detection and what we have to do to make the tools field-ready.
In [22],the research paper is telling us that the farmers of Indonesia who produce rice are struggling to detect diseases like bacterial blight and blast which are affecting their crops. As they are struggling to detect the diseases, they are leading to significant losses in yield by 20%-40% according to data. This paper is giving the solution by using Artificial intelligence to detect the diseases of rice crops early. The team trained a deep learning model by giving it the dataset of around 6000 images having the size of 256×256 pixels across four classes of diseased rice leaves from kaggle and they taught the model to recognize four common types of infections with accuracy of 99%. By analyzing leaf patterns through a neural network, the system can detect the trouble before it spreads through entire fields. However, the researchers intentionally blurred the images , horizontal flips, rotated it to make sure that the Ai is working under real- world different field conditions, and enhanced the diversity of the dataset. The CNN architecture features 2 convolutional layers, max pooling layers and a 128- neuron dense layer. The performance of detecting the diseases were very impressive as the precision was 100% for bacterial blight and the recall was 92% for the diseases blast. Farmers could use a mobile phone app

to detect diseases of rice leaf instead of relying on guesswork. The recent results of this model is really impressive but the researchers suggested that this system could be improved by testing it with more images and different weather conditions. This paper can help the indonesian farmers to improve the rice quality without using harmful pesticides also it can help to improve food security.

In [12],the paper discusses the application of ML and image processing to identify rice diseases at their early stages which would improve the production of rice crops. Traditional methods of disease detection are tedious, more expensive, and time-consuming, and thus, there is high demand to look into automation. In this study, various image processing and machine learning models were considered to aid in the diagnosis of rice diseases. To carry out the research, it studied the data of UC Irvine Machine Learning Repository, ImageNet, NIKON D90 Dataset and actual field locations. The pictures were either reduced or enlarged according to the needed resolution (5760x3840, 222x222) and had between 40 and more than 3000 pixels per width. Clustering and segmentation are done using K-Means Clustering and Otsu Method and Region Segmentation, and Classification and real time object detection are done by Support Vector Machine (SVM), K-Nearest Neighbor (KNN),Decision Tree,Naive Bayes,Artificial Neural Networks(ANN) and YOLO v3. Even though SVM and KNN are used to classify data depending on the color, texture and form, the majority of the modern classification tasks performed with the help of deeplearning involve CNNs that include several convolutional and pooling layers. ANNs and PCA techniques are also applied in feature extraction and picture recognition as well, but they do not work as well as CNNs. YOLO v3 has been utilized to identify and cut down items straight away on the live streams. Parameters employed during CNN are convolution, pooling and fully connected layers whereas the learning rate, the size of an image and the number of classes are used in YOLO v3. Such feature extraction techniques, which are available in RGB values, PCA, Gabor Filters, Histogram Features, Texture, Shape and Color, are significant. Among all the methods, CNNs gave the highest accuracy over ANN, SVM with CNN/SoftMax and YOLO v3, 90.9 percent to 98.63 percent against one another in the identification of diseases in rice. Nonetheless, correct research is needed to address the challenges associated with the power of computers, rapid identification and lower volumes of information. Although the outcomes are promising, there are certain issues like small data, fluctuating nature, more samples of one type than another, costly processing and time-intensive detection. In case of insufficient data, the quality of the model becomes lower and issues such as lights and weather also damage the identification performance. It becomes more difficult to detect less common diseases when there is an unproportionality in classes and training proper deep learning models consumes much computing power. In agriculture, it is still difficult to differentiate a disease in real time.

In [15]In this work, two tiny Convolutional Neural Network (CNN) designs, including MobileNetV2 and FD-MobileNet, running on ARM Cortex-M4 microprocessors in real-time rice disease classification are compared. The research used two data sets: the first one with 5932 images of four disease types, which included bacterial blight, blast, brown spot, and tungro; and the second one with 10407 images of ten different disease types.Both models are quantized and compressed to be embedded, which optimizes resource consumption, getting a 0.5 percent decrease in RAM and 1.14 percent in flash memory, but validated accuracy has been noticed to rise by 9 9 percent. MobileNetV2 achieved a classification accuracy of 97.5%, 93% detection accuracy of tungro, which surpassed FD-MobileNet, which achieved 90% accuracy under all conditions.The parameters of the model (depthwise separable convolutions, quantization level and compression ratio) were optimized to compromise between the low-power performance and computational efficiency. Limits are a little lower accuracy in FD-MobileNet, the sensitivity to the environmental changes (such as lighting), and possible problems with scalability when more classes of diseases are added. Nevertheless, the paper provides a resilient edge-AI application of crop monitoring in a resource-constrained, connectivity-challenged environment.

In [11],the paper considers how AI and ML can be applied to diagnosing rice plant diseases. It works with a file of more than 100 rice leaf images that belong to various disease types. Image preprocessing comes first and then machine learning algorithms such as Support Vector Machines (SVM),Decision Trees and Convolutional Neural Networks (CNN) are used for classification. Providing detailed values for learning rate,batch size and optimizer is not part of the paper, but it measured a 92% classification accuracy, proving how well these models worked. CNN is mainly used to extract useful features and identify diseases in images because it performs very well using visual information. The study points out that finding and treating diseases early and correctly helps achieve higher crop yields and prevents losses. At the same time, it points out that there are limits, including not enough data, a small number of disease groups focused on and problems with some models learning too much from the same image samples. Therefore, using wider and more general data and models, seems important for their use in the real world. The paper mentions that AI can benefit agriculture more, but it stresses the importance of having future systems that are more scalable and reliable.

In [8],The machine learning approach was built to detect rice diseases by studying 115 images showing bacterial blight, rice blast,Tungro and false smut diseases. The data used in the study was assembled by collecting information from myself and common online sources. Feature extraction with regards to the shape and color of the diseased areas in the leaf was done. SVM and k-NN are the two machine learning algorithms used for classifying records. The k-NN classifier in the suggested system gave a high accuracy on both the train set (93.33%) and the test set (73.33%). Performance testing on the training set gave the SVM a 97% accuracy rate and on the test set it had an 80% accuracy rate. Based on these results, the model might work well in identifying rice leaf diseases with the help of extracted features. Even so, there are some limitations in the findings acknowledged by the study. The model could be challenged by its ineffectiveness in other settings given that the data provided is not enough and limited. The accuracy of classifiers may vary with lighting and quality of the image.The disease detection system's robustness and preciseness could be improved by expanding the database, adding extra features and trying out new classification strategies in the next steps.

In [18],the research "Rice Plant Disease Detection using Convolutional Neural Networks" signifies a method for classifying rice diseases using image data based on deep learning.The authors resolve a clear class imbalance by applying class weighting.The study used a dataset of 10 407 images that represented ten disease categories such as leaf blast, tungro, brown spot and bacterial leaf blight. A variety CNN models, including Xception, EfficientNet, MobileNet, and DenseNet, that had been trained for successful categorizing are examined in this study.Weights & Biases (WandB) is used to track these models once they are trained using Lightning AI.A total of 1.3 million neurons and 7.9 million parameters are in DenseNet.Its architectural complexity results in a higher computing cost. EfficientNet-B4 has 24.5 million parameters, 5.3 million neurons, and 55 layers.The Xception architecture has 71 layers and is highly accurate and fewer parameters and complexities. In the same vein, MobileNet provides efficiency in terms of parameters that is mediated by a lightweight design.According to the results,DenseNet121 had the greatest accuracy of 97.50% and had 13.46% test loss.An accuracy of 96.25% was achieved by the EfficientNe B4 model and the MobileNetV3 Large model while it had a loss of 23.66% and 21.99% respectively. While DenseNet had fluctuations, EfficientNetB4 and Xception showed smoother convergence, and all models displayed robust learning curves in terms of validation performance. In all models, training and validation losses went down by a large margin and training accuracies reached 100% during the last epochs. Nonetheless, the large computational cost of DenseNet121 restricts its application to edge devices and real-time application.Despite its size, the dataset lacks environmental variation, such as backgrounds and lighting, raising questions about the feasibility of the model. Besides, the work lacked the feature of integration into the IoT systems, real-time deployment, and the feature of integration with the environmental parameters, e.g., soil and weather conditions. Also, such important performance measures as precision, recall, and F1-score were not presented, and the models were evaluated in controlled laboratory settings not in actual field conditions.Particularly, for mobile or rural agricultural environments, these limitations hinder fast practical utilization.

In [16],the paper , a VGG16 model of convolutional neural network is used to detect and predict diseases of rice plants. The dataset includes 120 JPG-extension rice leaf images with three varieties of disease.The images are segmented into three classes: leaf smut, brown spot and bacterial leaf blight and separated into 105 training and 15 testing photographs. VGG16 uses the Keras Api and Tensorflow library to train the model.It has several parameters with a batch size of 32 epochs and 100 epochs . Google Colab was used while performing the model which took approximately 5 to 10 minutes. 100% and 93.33% accuracy was obtained by the training dataset and test dataset of the model. Image augmentation was used to enhance the dataset artificially, improving the model's performance. In addition, it shows, the VGG16 model outperforms previous SVM-based approaches, offering a more accurate solution for rice disease detection and prediction, which can assist farmers in early disease management. Several limitations in the study could impact the study's overall efficiency and utility. Firstly, the model's capacity to generalize to a variety of environmental variables and unknown data may be limited by the small size of the dataset only 120 images that was used. Secondly, the test accuracy falls to 93.33% even though the training accuracy is almost perfect at 100%, indicating possible overfitting and inconsistent model performance when exposed to fresh inputs. Finally and certainly not least, the dataset only contains three different kinds of rice diseases, which limits the model's diagnostic range and could make it insignificant for identifying a larger variety of diseases that are frequently seen in rice farming.

In [21],the paper "Rice Plant Disease Detection Using EfficientNetV2" proposes a robust, scalable system using EfficientNetV2, aimed at real-time rice disease identification with features like geo-specific tagging, multilingual dashboard support, and fertilizer recommendations. The system compares its performance with Incep

11 tionV3, YOLOv8, ViT (Vision Transformer), and MobileNetV3 using a variety of deep learning models, most notably EfficientNetV2. Transfer learning and Data Augmentation are used in the dataset which has 10,080 pictures that represents numerous rice diseases, including brown spot, leaf smut and bacterial blight. This improves performance and generalization.EfficientNetV2 was chosen due to its ability to maximize the economy of computing and still provide accuracy, enabling it to be deployed to edge and mobile devices. Although the number of parameters that EfficientNetV2 has is not revealed, the study makes it clear that this model is lightweight and compares it positively to more complex CNNs and YOLO versions. Models of EfficientNetV2 were able to reach a certain accuracy of about 86.50, and the InceptionV3 model was able to reach an accuracy of 88.85. MobileNetV3 achieved the performance of about 72-74% after prolonged training compared to other architectures, including YOLOv8, which achieved a performance of 84.4%. In order to comprehensively evaluate the models, performance indicators were used, namely recall, accuracy, F1-Score, specificity, and mean Average Precision (mAP). There are limitations of the system. The lack of adequate generalization of different geographic or environmental factors is due to datasets that are often unbalanced and not diverse. Despite the fact that it is one of its key goals, real-time detection still faces reliability issues in real-life implementation, especially in relation to noise, light change, and connectivity. In addition, the models are unable to differentiate between the diseases and dietary deficiencies, and this is likely to result in either false positive or negative.In addition, even though such technologies as Vision Transformers are outlined, they have not yet been fully implemented. Lacks of field testing and integration with overall agricultural management systems are the barriers to adoption. To bridge the gap in terms of applied use and laboratory results, further research is required involving hybrid models, interpretability tools, and IoT connection.

In [13],The VGG16 model based on transfer learning and convolutional neural networks is used in the study as a method of presenting a practical solution to the problem of rice disease identification. The dataset that was utilized in the study is publicly accessible at Kaggle and includes over 1,000 rice leaf photos (healthy and infected with three primary diseases): leaf blast, brown spot, and bacterial blight. The preprocessing and augmentations involved on the images were large and then split into training, validation and test set. The model was also trained over 25 epochs using Adam as an optimizer and categorical cross-entropy as a loss and finally achieved the impressive 95 percent accuracy. Though the results are promising, the article concludes about a variety of issues, including the quality of photos, labelling, sensitivity to the background and lighting settings, and deep learning models processing capabilities.

In [4],The article by Sudarshan S. Chawathe rice disease detection through image analysis describes the process of automatic detection of rice diseases through smart image processing and machine learning. The given technique consists of three stages: image analysis in order to identify leaves and lesions, feature computation based on the characteristics of leaf and lesion, and classification based on the recognized algorithms. The system is evaluated against publicly available datasets proving its ability to identify such illnesses like bacterial leaf blight, brown spot, and leaf smut. It is computationally effective, gives excellent precision because of metricbased attribute selection and also suitable for real-time application. Some well known algorithms

like Logistic Model Trees, Random Forest Sequential Minimal Optimization for Support Vector Machines are used in the classification phase. This solution is developed in the Kawa Schema language and operates on the OpenJDK Java Virtual Machine (JVM), with OpenCV and WEKA tools used for low-level image processing. ZeroR and OneR serve as baselines, and accuracy is ensured by 10-fold cross validation and many trials. The system can identify diseases with 90accuracy and a F-measure near 0.9. It makes the method suitable for real-time by reducing training time 160 ms. The study depends on image quality factors such as shadows, glare and low resolution. They all can cause misidentification of lesions. Also, it is confined to a few diseases that limit other rice diseases. The method relies on manually created features and classical machine learning algorithms which may not perform on complicated image data.
In [7],The paper by Minu Eliz Pothen and Dr. Maya L Pai (Detection of Rice Leaf Diseases Using Image Processing) gives the critical contribution of the diseases of rice leaf to food production and livelihood of farmers.The paper employs image processing and machine learning to identify prevalent rice diseases such as the bacterial leaf blight, brown spot and leaf smut. The methodology will entail the splitting of the leaf pictures with using the thresholds of Otsu, extraction of features with the Local Binary Patterns (LBP) and the Histogram of Oriented Gradients (HOG) and classification of the diseases with the help of the Support Vector Machines (SVM) with the help of the linear, polynomial and RBF kernel functions. Using HOG with SVM with Polynomial kernel, the study achieved an accuracy rate of 94.6 percent using 70 percent of the data as a training set and 30 percent as a testing set; the other combinations used in the research are LBP+SVM (polynomial) at 90.23 percent, HOG+SVM (linear) at 92.01 percent and HOG+SVM (RBF) at 89.0 percent. These indicate that HOG features are superior to LBP with the best classification outcome being the one with the poly-kernel. The accuracy of the proposed method was also found to be superior to the past researches with the accuracy varying between 74 to 89 percent in identifying the rice leaf diseases. The research has certain significant limitations. It relies on the three of the diseases leaving out a wide range of other rice leaf diseases. It depends on a limited set of data comprising of 120 images. It also employs manual feature engineering (LBP and HOG) which may miss intricate patterns that may be revealed by deep learning.
In [1],The paper by Sachin D. Khirade and A.B. Patil, which is named Plant Disease Detection Using Image Processing, in [1], highlights the essence of prompt identification of plant disease as a key to increasing the productivity of agriculture and reducing the losses. The authors present an automated approach to diagnosing the disease through analyzing the images, preprocessing, segmentation, feature extraction, and classification by using the Artificial Neural Networks (ANN). The process starts with the step of RGB images acquisition and their preprocessing, such as the smoothing and the histogram equalization. The Otsu thresholding and K-means clustering techniques are used in defining sick areas. It also examines hardware implementation that uses FPGA and DSP technology in real-time monitoring.Color, texture, morphology, and GLCM-based statistics are retrieved and categorized using Neural Network (ANN) with backpropagation and Self-Organizing Feature Maps (SOFM). While no specific accuracy data are offered, recent research suggests that ANN performs well, particularly with morphological characteristics. The method is successful and adaptable to a variety of crops and disease categories. The paper has

13 some limitations. It does not use a standard dataset or specific accuracy metrics. It makes the result difficult to replicate and it relies on manual feature extraction and traditional classifiers such as ANN which may lack modern deep learning. Also, inability to differentiate similar diseases and environmental sensitivity are the other limitations.
In [3],The paper Rice Leaf Disease Detection Using Machine Learning Techniques suggests that machine learning is to be used in detecting Leaf Smut, Bacterial Leaf Blight, and Brown Spot using 480 images (432 training images, 48 test images). ColorLayoutFilter was used as preprocessing and CorrelationAttributeEval was used to reduce 5 most relevant features. These are KNN (K=1,3), J48 Decision Tree, Naive Bayes and Logistic Regression. Decision tree model was the best with 97.92 test accuracy and high values of TPR, preciseness, recall, F1-score, and AUC with Naive bayes coming in the weakest. The paper determines that the best method of automated detection is the Decision Trees. The small dataset, omission of recent methods of deep learning, and absence of field validation are limitations and limit its applicability in the real-life agricultural context.

2.3 Summary of Key Findings

Summing up all the results and studies, one thing is crystal clear that deep learning like CNN is the most effective method to detect rice diseases. Transfer learning, and lightweight CNNs are often provided and give us better results than the traditional methods which make the systems more practical for mobile apps use and fieldwork. CNN-based models consistently showed outstanding performance than older machine learning methods. One of the studies focused on creating a mobile app which would detect different rice diseases using a deep learning model. It combined various types of powerful CNNs which reached an accuracy of 91%. However it required high computing power and was confused at times about similar-looking diseases. In- one paper, researchers built a simple CNN model that used fewer resources but achieved accuracy of almost 94% which makes a good choice for mobile apps and for the farmers in the rural areas where internet is not that much available and hardware is limited. Using mask R-CNN, the model identified the diseases and highlighted the infected area. This method worked better than traditional CNNs but it had short datasets and better lighting was needed. Some studies used advanced models like EfficientNetV2 and MobileNetV3 which showed promising results and reached above 96% accuracy. Some of them were tested in real-world farming. Some earlier studies used classical models like KNN, SVM and decision trees and these models worked well for easy and simpler tasks but normally could not match the performance of deep learning CNN-based models. While many studies focused on AI, some studies used the biological views behind rice crop diseases or tried to look for farming practices which are sustainable. These studies used background knowledge but could not use any Artificial intelligence. However, combined models and using transfer learning showed such performance but with more accuracy and reliability also improved the model. Memory- efficient models which are smaller but useful for real world mobile applications. Moreover, many models struggle when it was tested in the actual fieldwork and farming areas especially with light changing, blurry images, or unfamiliar images with diseases which are absent in the dataset of the model. It became a challenge for some models because of the lack of large, balanced datasets. These findings show that systems are advanced in lab settings and we have to do more work in the real world and in the field environment and our research work should focus on building bigger, well balanced datasets which will be tested in real situations to help farmers to detect diseases of rice crops early and accurately.

Chapter 3

Requirements, Impacts and Constraints

3.1 Final Specifications and Requirements

The proposed system contains a multi-class image classification issue in projecting rice leaf condition across 6 classes. To increase reliability and reproducibility in the evaluation, the dataset is split into 70/20/10 percent of the training, validation and testing samples with random image shuffling with a known fixed seed to ensure the evaluation is repeatable. The input samples are all processed as RGB images and then rescaled to the standardized resolution of 224x224x3 to fit the needs of the custom CNN pipeline and trained with a batch of 32. The maximum number of epochs is set to 80, and EarlyStopping is used to avoid overfitting, and ReduceLROnPlateau is used to automatically change the learning rate to staged periods where performance does not improve to enhance convergence stability and true generalization.

The custom model is configured as a CNN structure with ResNet-style residual blocks to enable the deeper feature learning, which still has stable gradient flow and it is also enhanced by the Squeeze-and-Excitation (SE) attention so that the network could prioritize the most informative feature maps. L2 weight decay ($\approx 3 \times 10^{-4}$) is introduced as a regularization measure to prevent the occurrence of overfitting, and a dropout rate of 0.3 is applied in the dense classification head. AdamW is applied to optimize the model with the learning rate set to 2×10^{-4} and weight decay set to 3×10^{-4}, which facilitates faster convergence as well as enhanced weight regularization. The training objective uses Categorical Focal Crossentropy ($\gamma = 2.0$, $\alpha = 0.25$) to emphasize hard samples and reduce the impact of class imbalance.

It is created and implemented using Google Colab, but can be trained in any other similarized GPU-enabled platform. It is based on typical Python machine learning software, general scientific computing software, such as TensorFlow/Keras to develop and train the model, NumPy to perform numerical tasks, Matplotlib to plot, and scikit-learn to provide evaluation measures, with seaborn to produce more understandable representation of the confusion matrix.

3.2 Societal Impact

This project will enable the automatic and early detection of crops/leaf diseases, which will bring direct benefits to society in various interests. It has the possibility of assisting farmers and agricultural extension services by far minimizing diagnosis time and minimizing the need to rely on experts in the field of competition through manual inspection. Our system strengthens food security because it helps in the prevention of crops and food production due to the speed of identities and response to outbreaks of diseases. It also has the indirect health and safety benefits of encouraging more focused application of pesticides, which can lead to less unintended over-spraying of pesticides, and less exposure of chemicals that could cause health problems in farmers, consumers, and communities around the areas treated. Legally and culturally speaking, in case the system is implemented with the purposes of a farmer-facing solution, it should explicitly convey that it is a decision-support mechanism but not an alternative to certified agronomists, becoming accountable, using it responsibly, and maintaining long-term trust in rural populations.

3.3 Environmental Impact

Environmentally, the project has a number of apparently sustainable advantages as it will allow detection of diseases with greater accuracy and hence lead to the decrease of the overall load of chemicals through the more accurate and precise and need-based pesticides which does not begin applying pesticides in the wrong location and without having a particular purpose. Better early detection also leads to reduction in crop loss which reduces pressure to clear farmland to ecologically sensitive areas that sustain biodiversity and land preservation. In addition, more effective management of the disease leads to a more efficient use of resources, enhancing the ratio of money to yield of water, fertilizer, and labor. Nevertheless, environmental costs are also present in the approach, because training deep learning models also needs a computer, and thus needs energy. To deploy sustainably, the system must concentrate on efficient deployment (e.g., optimized edge or cloud deployment) and refraining and retraining to required frequency, between performance and low energy use.

3.4 Ethical Issues

Ethical and professional consequences were considered in this project, beginning with data rights and consent, where all dataset images were legally obtained, appropriately licensed for use, and correctly referenced. Bias and generalization were also treated as significant concerns, as model performance may decline under real-world conditions that differ from the training environment, including variations in lighting, camera quality, geographic location, and crop cultivar; such variations can reduce reliability for certain user groups unless the system is tested and validated using diverse field samples. Moreover, the probability of false positives and false negatives were minutely taken into account since false predictions may lead to either a loss of money, delay in treatment, or an unnecessary use of chemicals; therefore, the system should provide a confidence value and encourage human verification, particularly when the confidence is low. To ensure transparency, explainability methods (including Grad-CAM and LIME) were introduced, which make it possible to formalize the use of AI by ensuring the process of prediction making by the models is explained. Lastly, it involves responsible usage with clear warnings, non-dangerous and safe instructions with adequate referral channels that will allow users to consult the advice of an agricultural expert when they are in need which will curb the damage that could be caused during practical use.

3.5 Project Management Plan

The project workflow process will start with a requirement analysis and literature review, which will be followed by dataset preparation and the classification to subdivide into classes in order to have a reliable set of training, validation, and testing. Then, the model is modeled and put to test, which includes a custom CNN architecture with residual connectivity and contribution of Squeeze-and-Excitation (SE) attention, followed by training the model and modifying hyperparameter settings, including loss model, optimizer, and data augmentation policy. Subsequent to training, the project will feature thorough testing and reporting based on common performance metrics and confusion matrix as well as apply explainability methods like Grad-CAM and LIME and finalize documentation to enhance transparency and interpretability. The last phase is devoted to the work on the thesis and its presentation. Resource wise, the project is capable of being finished by one researcher with optional supervisor feedback utilizing the use of GPU-based computation via Google Colab, dataset and output storage via Google Drive as well as a standard Python machine learning stack. Primary anticipated expenses are optional compute (e.g., Colab Pro or cloud credits required on a GPU in case of resource inadequacy) and data storage/ backup needed in order to ensure secure and consistent dataset and outcome manipulation.

3.6 Risk Management

Risk	Description	Mitigation
Data imbalance	Some diseases may have fewer samples	Focal loss, augmentation, balanced sampling, collect more images
Overfitting	High training accuracy but low real performance	Dropout, L2, early stopping, stronger validation/testing
Domain Shift	Field images differ from dataset	Test on real-field photos, retrain with diverse data
Misclassification impact	Wrong diagnosis causes wrong treatment	Confidence thresholds + "consult expert" rule
Compute limits	GPU/RAM constraints	Mixed precision, efficient batch size, model checkpointing
Reproducibility gaps	Results vary across runs	Fixed seed, logging, versioning model configs

Table 3.1: Risks, Descriptions, and Mitigations in the Model

3.7 Economic Analysis

The total project cost structure comprises development expenses which consist of: the time spent in conducting research and implementation, computational resource needs for the use of GPU to train the model, space to store data and results, and the resources to repeat experimental models to fine-tune the model. In the event of expansion of the system to be more capable of operating in the real world, there might be extra costs relating to data, such as the purchase and labelling of various images in the field, with varying environmental conditions. The project, in its turn, has a major payoff, including decreased crop losses due to disease outbreak by means of their early detection, lowered input expenses (including the use of pesticides and labor) by making the interventions pertinent to the area requiring the intervention, and enhanced productivity due to faster response to decisions by the farmers and agricultural extension officers. It is also very scalable, as the solution requires few users to have a model trained to serve many users with minimal marginal cost per prediction. In terms of cost-benefit the smallest decrease in seasonal yield loss due to disease can yield economic returns which will outweigh the compute and development investments, especially when implemented on a community or an extension-service scale.

Chapter 4

Proposed Methodology

4.1 Design Process or Methodology Overview

In this paper, a deep learning topology is given to the automatic image classification of the rice leaf diseases. The proposed model contains methodical stages such as data gathering, picture processing, dataset separation, model training and execution assessment. These are the images of the rice leaves taken at the Bangladesh Rice Research Institute (BRRI) where all the samples were examined and verified by the agriculturalists to ensure that the disease is diagnosed properly. There was a high maximization of sources of data to maximize the diversity of the data and the power since the more the images of rice leaves the more the power one has online. All the images were first processed to scale and normalize the images to the same input dimension and like pixel distribution in image. This was divided into training, validation and testing sets (70: 20: 10). The strategy will render viable learning, observation through the assistance of validation, and objective evaluation of subtle data. The main advantage of the research is that a custom convolutional neural network (CNN) will be designed which will be utilized to categorize rice leaf diseases. The innovative CNN proposed is trained to considerable extent in order to lead in identifying the peculiarities of the disease in rice leaves.The Squeezer-and-Excitation (SE) attention blocks were added into the custom residual CNN model. The first convoluted layer and max pooling are used to extract low level features in the model. This is then followed by a set of residual blocks whose filter sizes (64, 128, 256 and 512) are of progressively successively increasing sizes. The grid size was 32 and the maximum epochs were 80. The mixed precision training was also allowed to hasten the determination by the hardware of the GPUs. AdamW optimizer was chosen where the regularization of weight decay and learning rate 2×10^{-4} were applied to enhance convergence stability. The training was followed by the validation loss and accuracy with the following callbacks; ReduceLROnPlateau, to plan the adaptive learning rate, early stopping, to avoid overfitting, model checkpointing, to save the most performing model. In addition to the suggested custom CNN, one may utilize more popular CNN models, such as VGG16, VGG19, InceptionV3, and ResNet50, as well as, DenseNet121, and EfficientNetB4 as benchmark models only. Besides the recommended custom CNN, there are also such other popular CNN networks as VGG16, VGG19, InceptionV3, ResNet50, DenseNet121, and EfficientNetB4. The suggested methodology will not refer to the utilization of the pretrained architectures, but will refer to the probability of the pretrained architectures to simply analyze the performance of the custom CNN, in addition to performing the procedure of the comparative analysis of the identical experiments. The whole procedure of categorizing rice diseases of the leaf is proposed in Figure 4.1.

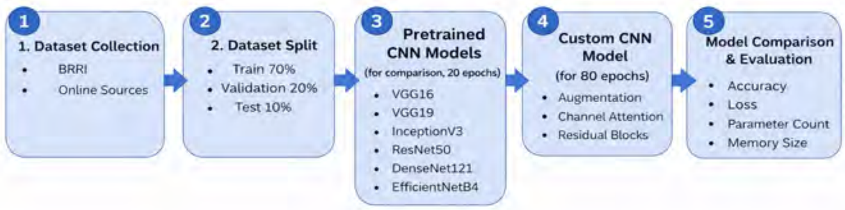


Figure 4.1: Overall workflow of the rice leaf disease classification system comparing a proposed custom CNN model with pretrained CNN models

4.2 Preliminary Design or Design Specification

4.2.1 Problem Defination

The research problem under the investigation of this paper is a multi-class image classification problem. A rice leaf input image is provided, the goal being to categorize the image into one of six pre-defined classes, i.e. a disease classification plus a healthy classification. x will be an input picture of a rice leaf and y will be the related class tag of a picture. The idea is to obtain a function f (x) that will convert the input picture into the corresponding sickness that it represents.

4.2.2 Configuration of the Benchmark Model

Several known CNN architectures were used as a benchmark model to determine the classification performance of the proposed custom CNN compared to the existing CNN architectures. The models were built to standard configuration and trained in comparable conditions in the experiment to give justifiable comparisons. The proposed technique did not include the benchmark models that were used to measure the comparative performance of the custom CNN model.

4.2.3 Deep Learning Architectures of Choice

The Rice Disease Detection uses a variety of deep learning models to detect and classify rice diseases based on photos of leaves. The pretrained models that will

be used in this study are ResNet50, DenseNet121, VGG19, InceptionV3, EfficientNetB4, and VGG16. These models were chosen because they have been successful in image classifying tasks, and that they can find more complex patterns on image data.Each model was adjusted to the rice disease detection problem by modifying the task of classifying the rice leaves into one of six classes one of which defined a disease and the other one defined a healthy plant. The models are grounded on the Convolutional Neural Networks (CNNs) that are highly effective at classifying images since they have the capacity to learn the spatial hierarchies of information.
VGG16: VGG16 model, similar to VGG19, is a model that uses a series of max-pooling and 3x3 convolutional layers. Even though VGG16 as a picture classifier is not particularly deep as VGG19, its simplicity and enormous size permit it to be effective on picture classification problems.
VGG19: VGG19 is a 19-layer deep CNN model that uses max-pooling layers and 3x3 convolutional filters. VGG19 is effective in picture classification and is very simple because of its simple architecture and the ability to gather hierarchical features.
InceptionV3: Due to its modular design, InceptionV3 can learn different feature optimal map types at different scales. This model employs 5x5 convolutions in expanded receptive fields, 3x3 convictions in feature extraction and 1x1 convictions in dimensionality reduction. It also uses auxiliary classifiers to boost the gradient flow in the course of training.
ResNet50: This network can prevent the problem of degradation when training very deep networks but with the help of residual connections that allow deeper networks to exist. ResNet50 was refined on ImageNet and then used to detect rice illnesses in the provided dataset.
DenseNet121: DenseNet121 is built with dense connections between all the layers, with each layer receiving input connections on all its predecessor layers. The architecture minimizes the use of parameters and optimizes the relay of features.DenseNet121 has proved to be effective in a fine-grained classification task, but it can be particularly useful with sparse data.
EfficientNetB4: EfficientNetB4 is the part of the EfficientNet family and is a depth, width, and resolution optimization network based on compound scaling. It is established that EfficientNetB4 is more accurate with less model size than various other CNN architectures such as computing economy.
Each model was then terminated with a fully connected layer and the probability of each class was then emitted with the help of a softmax activation function. The models were trained on rice illness dataset to classify pictures into one out of six classifications.

4.3 Data Collection

4.3.1 Primary Dataset Source

[19]Primary data in this research paper was collected in the presence of the expert in the Bangladesh Rice Research Institute (BRRI). Dr. Mohammad Ashik Iqbal Khan, Head and Principal Scientific Officer provided the rice leaf photographs. Bangladesh Rice Research Institute, Gazipur, Bangladesh. The pictures by BRRI were also annotated and confirmed by a qualified rice pathologist and ensured complete reliability and biological accuracy of the disease categories. The reliance on both

expert-validated data will add much to the credibility and scientific validity of the suggested system.

4.3.2 Expanding Dataset and Increasing Diversity

Although the BRRI dataset had high-quality images that were labeled by experts, the sample size was a limitation. Additional photos of rice leaves were come across by searching online fields of agricultural image banks which are publicly available to increase model generalization and enhance the variety of data in the dataset. The selected photographs are truly in line with the disease categories as determined by the BRRI experts. The possibility of incorporating variability in lighting conditions, complexity of the surrounding, orientation of the leaves and the severity of the diseases is made possible by the use of numerous sources of photos, therefore contributing to the strength of the trained models in the area.

4.4 Dataset Composition and Class Distribution

The last dataset has six classes with 5 categories of rice leaf disease and one healthy:
1.Bacterial Leaf Blight

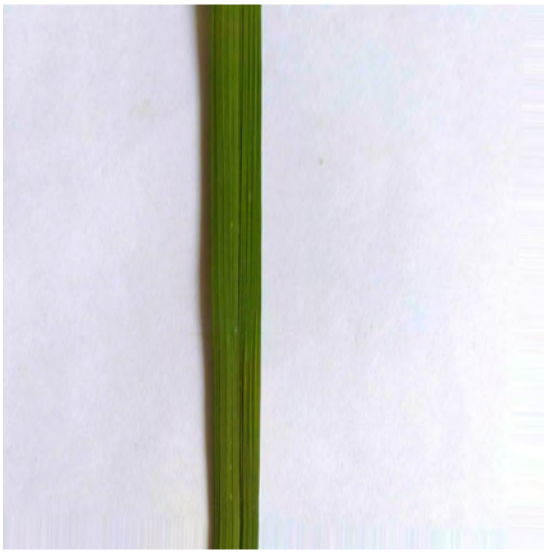
2.Leaf Blast


3.Neck Blast


4.Rice False Smut

5.Sheath Blight

6.Healthy Rice Leaf



There are 1,560 images in the dataset, and the number of photos assigned to all classes is equal (260). Balanced datasets are essential to minimize bias during the classification and ensure the model is effective during all categories. Figure 4.2 shows the occurrence of every type of class in the dataset. Figure 4.2 shows the occurrence of every type of class in the dataset.

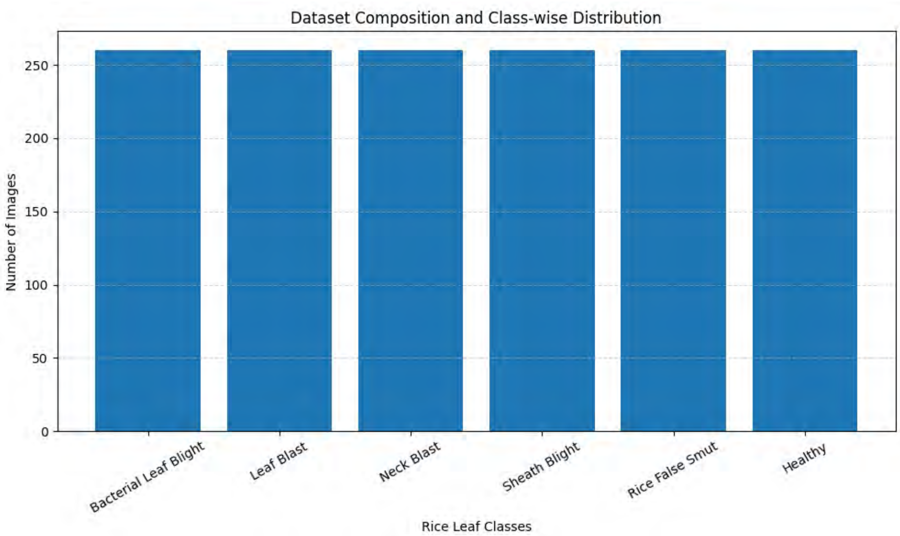


Figure 4.2: The count of each class within the dataset

4.5 Dataset Splitting Strategy

In order to objectively test the performance of the models, a stratified splitting technique was used to divide the data into training, validation and testing subsets. The data was split into 70: 20: 10 ratio as follows:
•Training dataset: 1,092 images (70%)
•Validation dataset: 312 images (20%)
•Test dataset: 156 images (10%)

This splitting strategy makes sure that one has enough data to use in training the model and has an independent validation and objective performance evaluation. Figure 4.3 demonstrates the plan of data division.

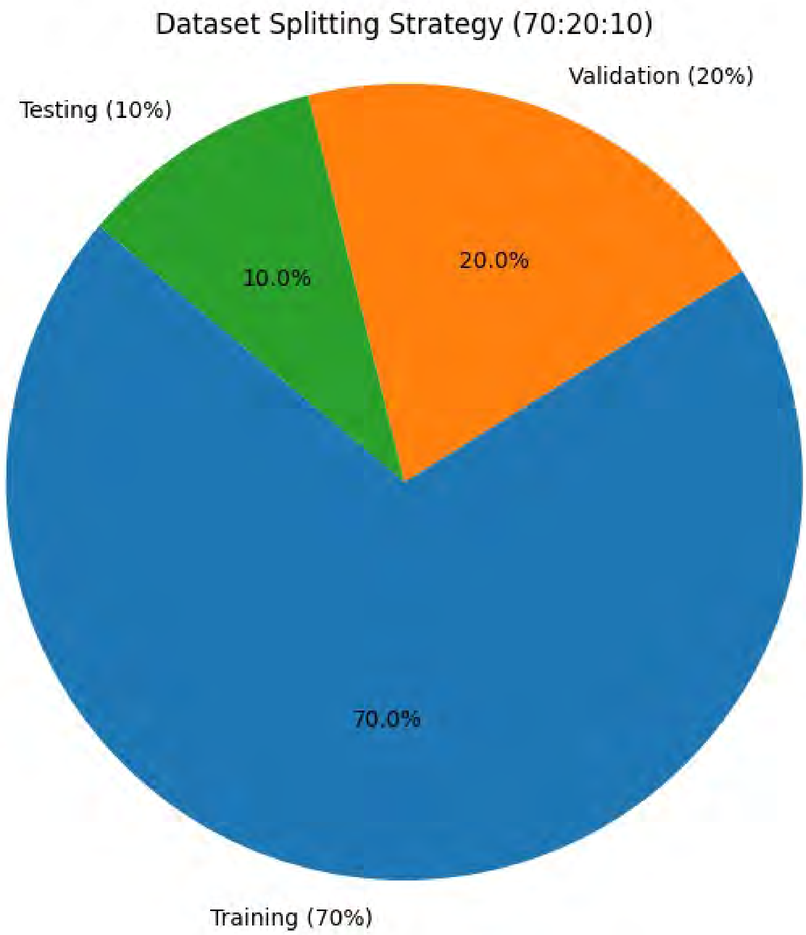


Figure 4.3: Data Split Strategy

4.6 Data Preprocessing and Augmentation

4.6.1 Image Preprocessing

Initially, the initial image dataset, which was sorted into folders consisting of classes, was shuffled off a fixed seed (seed = 42) to produce reproducibility. The split was then done class wise (training 70%, validation 20%, and testing 10%) maintaining class balance in all the splits. All images were automatically resized to the size of 224 × 224 pixels and converted to RGB format using TensorFlow during the dataset loading, labels were also one-hot encoded to fit the multi-class classification goal. On-the-fly data augmentation was only used on the training data to enhance the generalization and minimize the overfitting process, which included random horizontal flipping, rotation, zooming, contrast adjustment, and slight translations. This enhancement was done in the model pipeline and did not permanently change the data. Lastly, data were batched (batch size = 32) and continuously streamed to the model, and the input dimensions were consistent and the training behavior was consistent.

4.7 Model Training and Implementation

4.7.1 Training Configuration

All tests were run with a standardized training set up to ensure that there was a fair and equal comparison of the models. Adam optimizer was chosen due to its adapting learning ability and steady convergence. The batch size and learning rate were maintained. The CNN model in its unique design was trained up to a maximum of 80 epochs. The absence of pretrained weights during the training of the model increased the time of successful feature learning with the use of rice leaf images. Validation performance in the course of training was used to assess convergence and stability of learning. Pre-trained models had less epochs required to reach a point of convergence in terms of classifying rice leaf diseases due to their architectural complexity and long history of generic visual representations. In order to reduce losses, Categorical Focal Crossentropy is used in the proposed custom CNN model to classify difficult data and reduce the contribution of the ones that can be easily classified. Categorical crossentropy standard loss was used to evaluate the benchmark CNN models. Classification accuracy was used as the main parameter to be considered and the training and validation loss curves were analyzed to determine the convergence and overfitting tendencies.

4.7.2 Configuration of Model Parameters

The number of parameters, the sum of trainable parameters and the amount of non-trainable parameters are essentially the factors that determine the complexity, functionality, and efficiency of deep learning models in terms of computing. Total parameters are used to denote the overall capacity of a model and trainable parameters are the weights that are altered during the training process. The untrainable parameters do not change during training, and they refer to the untrained architectural elements. This research compared the parameters distribution across the proposed CNN model and a number of benchmark CNN magnifications. The benchmark CNN models were selectively fine-tuned by training only the classification layers and keeping the other layers intact. This approach led to reduced trainable parameters, improved training stability and reduced overfitting. The proposed proprietary CNN model was trained extensively, which allowed optimization of all the parameters in the training phase. The differences in the total trainable and non-trainable parameters of the models are indicative of the differences in learning behavior, architectural depth and complexity of design. The table 4.1 gives a comparative summary of the parameters combinations of every model.

4.7.3 Analysis of Training and Validation Performance

To evaluate the dynamics of learning and convergent behavior of the chosen convolutional neural network models, training and validation accuracy and loss were calculated at every epoch. These learning curves are very important in availing insightful information about the stability of the model, its rate of convergence as well as possible overfitting and underfitting problems. Figure 4.4 represents the training and validation accuracy and loss curves of VGG16 model. This value indicates the change in model performance during training and its similarity between training and validation performance, and thus it is an indication that it has the ability to generalize.

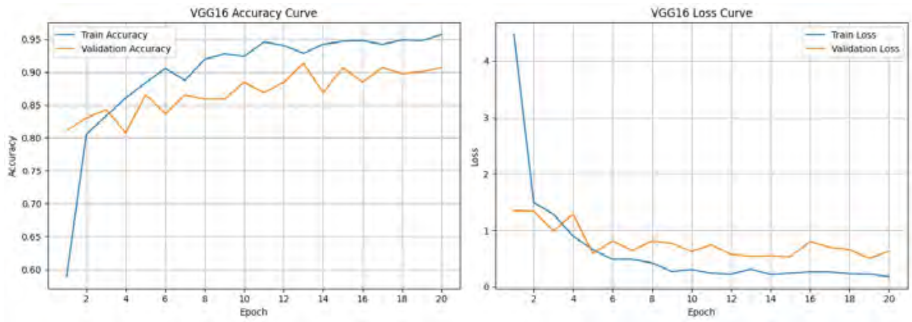


Figure 4.4: Accuracy and Loss Curve of VGG16

Figure 4.5 shows the learning curves obtained with the VGG19 architecture. The picture shows the training dynamics of a more powerful VGG-based model with a comparison of the depth effects on convergence behaviour.

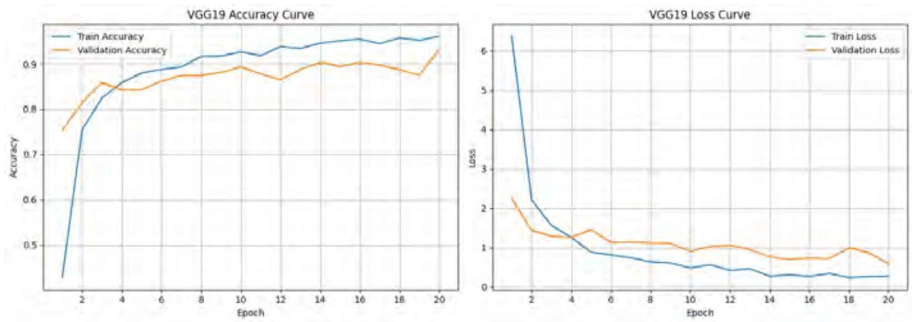


Figure 4.5: Accuracy and Loss Curve of VGG19

Figure 4.6 shows the performance of InceptionV3 model in terms of training and validation. The graphic illustrates convergence characteristics of an architecture employing a multi-scale feature extraction that demonstrates how the performance remains stable as compared to validation across epochs.

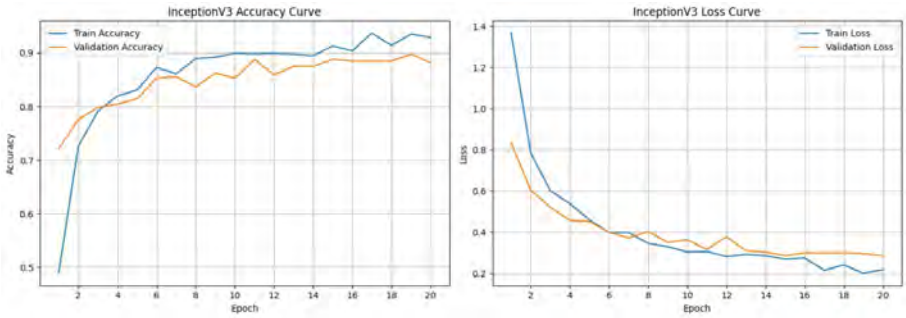


Figure 4.6: Accuracy and Loss Curve of InceptionV3

The learning dynamics of ResNet50 design is represented in figure 4.7. This picture demonstrates how the residual connections influence converting to stability and enhancing generalization over the training process as reflected in the curves of training and validation.

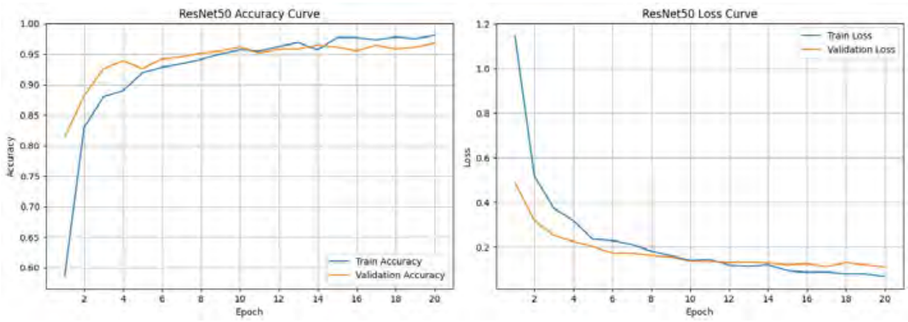


Figure 4.7: Accuracy and Loss Curve of ResNet50

The training and validation curves of the DenseNet121 are illustrated in Figure 4.8. This value provides a contribution to the learning behavior of dense-interconnected systems, namely on the feature reutilization and convergence reliability.

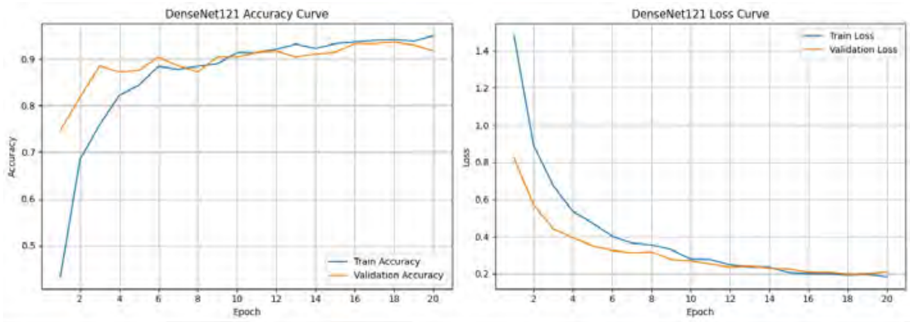


Figure 4.8: Accuracy and Loss Curve of DenseNet121

The performance of the EfficientNetB4 training and validation is presented in figure 4.9. The picture shows that compound scaling is effective in achieving stable learning behavior through effective use of parameters.

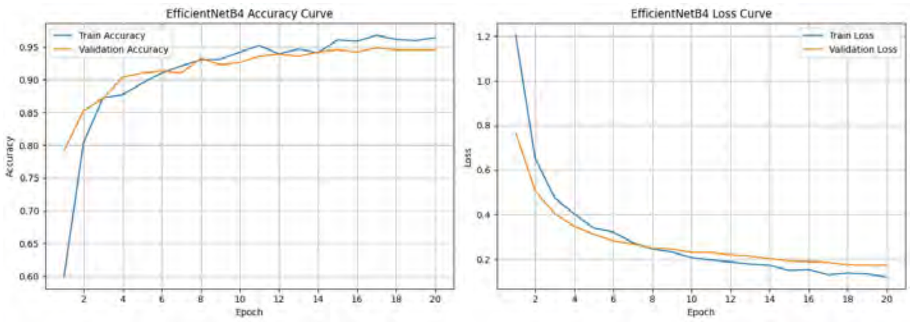


Figure 4.9: Accuracy and Loss Curve of EfficientNetB4

The in-depth understanding of the procedures through which each of the selected models learns the dataset will be feasible through the training and validation analysis of the performance described in the above section. The performance quantitative evaluation and the comparison based on the learning curves insights will be offered in the next chapter.

4.8 Summary of Proposed Methodology

The methods used to classify rice leaf disease in a broad manner are outlined in this chapter. A dataset that had been authenticated by professionals of Bangladesh Rice Research Institute (BRRI) was joined with publicly available photographs to create a diverse and balanced dataset.The dataset was further preprocessed and supplemented before being divided into training, validation and testing subsets. As the primary modeling paradigm, a customized convolutional neural network (CNN) was developed and trained from scratch to learn discriminative features for accurate rice leaf disease recognition. Also, a series of benchmark CNN architectures were provided to be compared against one another under uniform experimental conditions. The training design and the assessment technique were combined into one training unit to ensure that the tests could be uniformly tested during evaluation. This is the methodology used in the experimental results that are described in the next chapter.

4.9 Web App Implementation for Rice Disease Detection App

The Rice Disease Detection App can enable users to diagnose rice plant issues quickly through the use of images uploaded through a convenient user interface. Due to the application being developed in CSS, HTML and JavaScript the application is not heavy, and it can be used by a diverse range of users including farmers and hobbyists in the agricultural industry.

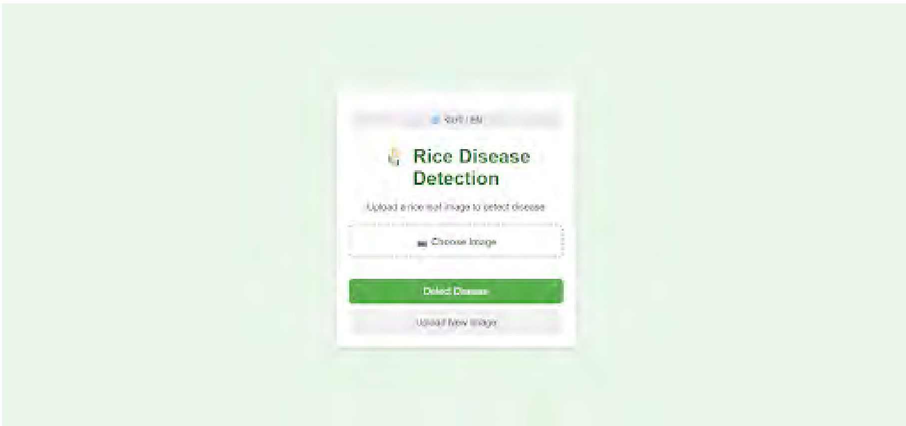


Figure 4.10: Rice Disease Detection App

Web Application Architecture:
This is due to the simplicity and user-friendly design of the app that enables users to upload a photo of a rice leaf with ease. The system analyses the image uploaded, identifies the type of disease, its cause, and preventive recommendations. It is designed in such a way that users can easily move around between the English and the Bangla language to suit the needs of the locals.The app would identify the rice disease and display the results instantly when the image has been uploaded. This provides the user with the valuable information regarding the illness and the most suitable treatment.
Limitations:
The Rice Disease Detection App has numerous disadvantages in spite of its usefulness. The performance of the present version is influenced by factors such as image quality since it has been developed mostly with frontend technologies such as HTML, CSS and JavaScript. Detection accuracy can be reduced by low-resolution images, bad lighting, angles, and so on. Also, the software does not perform well in identifying new or rare diseases that were not part of the training set. Speed of realtime processing remains an issue particularly on lower end devices when handling large volumes of the image, or in the need to generate immediate responses. This is due to the problem of insufficient diversity of the dataset that restricts its accuracy in various regions and agricultural environments since it does not present a diversity of rice types and environment. Moreover, there is no context-specific guidance in the app as there is no information regarding user behavior and historical trends of diseases, which the app may expand in the future, making it larger and giving a burden to devices with limited resources. Finally, the model cannot be adjusted to new illnesses or new scenarios since it is yet to be continuously learned through the input of users.
In spite of these challenges, the program holds potential, and its future evolution will be focused on its accuracy, expanding the scope of data, simplifying the process of real-time processing, and enabling continuous learning to respond to shifting agricultural needs.

Chapter 5

Result Analysis

5.1 Performance Evaluation

Models used in this experiment were trained on the rice disease dataset and these were VGG16, VGG19, InceptionV3, ResNet50, DenseNet121 and EfficientNetB4. They were also tested based on test accuracy, precision, recall, F1-score as well as the confusion matrix to estimate the level to which they were able to classify the rice leaf diseases.

VGG16's test accuracy was 90.38%. The model had precision and recall values of 0.893 and 0.962 respectively and the F1-score the model provided to bacterial leaf blight was 0.926. The score of the F1 of healthy leaves is 0.846 and the recall and the precision are 0.846. The accuracy of the leaf blast, along with the recall and F1-score both were 0.769 which means that VGG16 was not performing well on this disease. The precision, recall and F1-score of Neck Blast were 1.000 and failed. The results were found to have a precision value of rice fake smut of 1.000 and a memory of 0.962 and F1-score of 0.980 and sheath blight had a precision value of 0.920, recall value of 0.885 and F1-score value of 0.902. VGG16 was a fairly successful model in the classification of leaf blast, albeit not very successful.

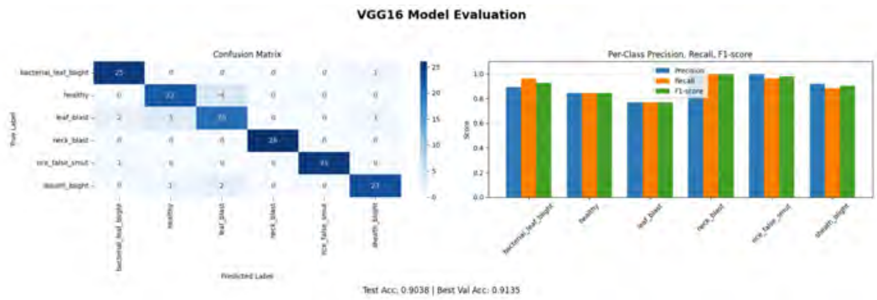


Figure 5.1: Confusion Matrix and Precision, Recall, F1-score for VGG16

VGG19 has an 89.74% test accuracy. The F1-score, recall and accuracy of bacterial leaf blight were 0.960, 0.923 and 0.941 respectively. Healthy leaves did not perform better than VGG16 with precision of 0.852, recall of 0.885 and F1-score of 0.868. The accuracy, the recall, and the F1-score of the leaf blast were 0.850, 0.654 and 0.739, respectively, which implies that leaf blast is a rather challenging disease to identify. On the other hand, the position of neck blast has 1.000 scores in all measures (accuracy, recall and F1-score) compared to rice false smut where it has been correct (0.963), recalls (1.000) and F1-score (0.981). Sheath blight was not totally eliminated and its precision is 0.774, recall is 0.923 and F1-score is 0.842 can be narrowed down specifically on the case of leaf blast and sheath blight.

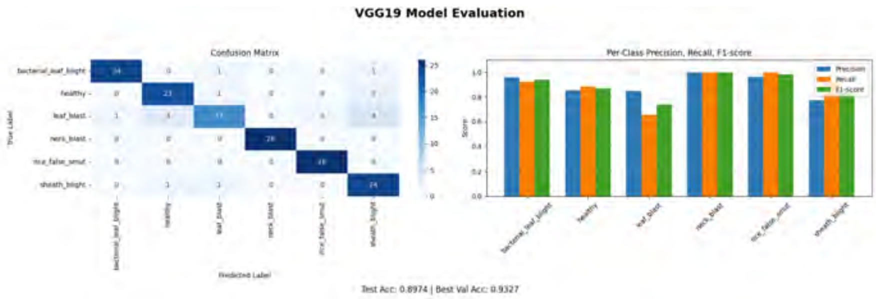


Figure 5.2: Confusion Matrix and Precision, Recall, F1-score for VGG19

InceptionV3 scored higher regarding test accuracy (92.31). The precision, recall and F1-score were 0.917, 0.846, and 0.880 in the instance of bacterial leaf blight. The accuracy, recall of healthy leaves were 0.889, 0.923 and F1-score of 0.906, and the accuracy and recall of leaf blasts were similar with 0.885 and F1-score of 0.885. Neck blast received a flawless rating of 1.000 F1-score and rice fake smut received 1.000 precision, 0.962 recall and 0.980 F1-score. InceptionV3 had sheath blight precision of 0.857, recall of 0.923 and F1-score of 0.889 which turned out to be better than VGG16 and VGG19 in general and had fewer misclassification errors.

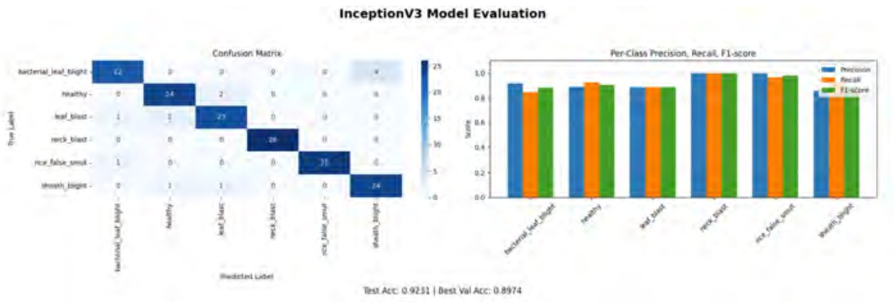


Figure 5.3: Confusion Matrix and Precision, Recall, F1-score for InceptionV3

ResNet50 The highest accuracy rate of 97.44 was experienced in a test using the ResNet50. This was a very high performance of this class with the bacterial leaf blight precision of 1.000, recall of 0.962 and F1-score was 0.980. The accuracy, recall and F1-score of healthy leaves were found to be 0.963, 1.000 and 0.981 respectively. Whereas neck blast remained in operation with accuracy of 1.000, recall and F1-score stood at 1.000, the precision, recall and F1-score of the leaf blast stood at 0.893, 0.962 and 0.926 respectively. Sheath blight had the best average of 1.000, 0.923 and 0.960 in precision, recall and F1-score respectively and rice fake smut had the best score of 1.000 in all three categories. The ResNet50 performed well in general performance with few cases of misclassifications.

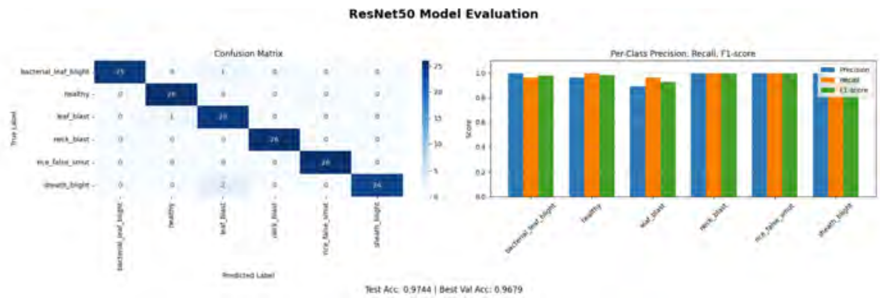


Figure 5.4: Confusion Matrix and Precision, Recall, F1-score for ResNet50

DenseNet121 gave a test accuracy of 92.31%. The accuracy, the recall, and the F1-score of bacterial leaf blight were compared to ResNet50 and were 0.960, 0.923, and 0.941, respectively. The accuracy of 0.926, recall 0.962 and F1-score of healthy leaves was 0.943, which is strong performance. This illness was identified with the help of leaf blast with the precision of 0.826, a recall of 0.731, and an F1-score of 0.776. The neck blast had the three values of 1.000 as compared to the rice false smut which had a precision of 1.000, recall of 0.962 and F1-score of 0.980. Sheath blight had the best and yet not adequate precision of 0.833, recall of 0.962, and F1-score of 0.893. In general, ResNet50 was more competitive than DenseNet121.

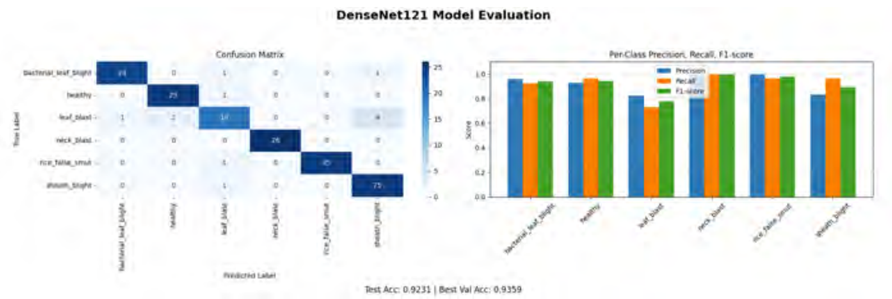


Figure 5.5: Confusion Matrix and Precision, Recall, F1-score for DenseNet121

Finally, **EfficientNetB4** as compared to ResNet50, was the closest model with the highest test accuracy of 97.44. The precision of bacterial leaf blight was 0.963, recall 1.000 and F1-score 0.981 which indicated good results. Healthy leaves with the F1-score 1.000 are characterized with perfect recall and accuracy. Leaf Blast had balanced measures with an F1-score of 0.923 and a precision and recall are equal to 0.923. Neck blast was perfect with all the values being 1.000 in terms of precision, recall, and F1-score and rice false smut with 1.000 precision, 0.962 recall, and 0.980 F1-score. Sheath blight was known to have a precision of 0.962, recall of 0.962 and F 1 score of 0.962 and also did the same without being classified as sick. EfficientNetB4 was the most reliable model that works well in all classes.

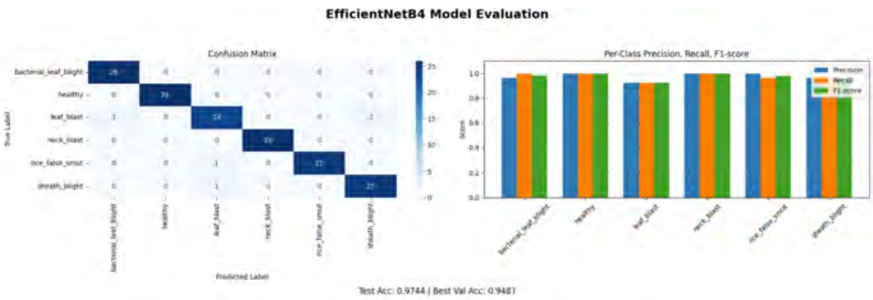


Figure 5.6: Confusion Matrix and Precision, Recall, F1-score for EfficientNetB4

5.1.1 Evaluation of Custom CNN Model:

The six types of rice leaf disease which covered bacteria leaf blight, healthy, leaf blast, neck blast, rice fake smut, and sheath blight were applied as six categories in the validation, and testing with 70%, 20%, and 10% of the data respectively. The error rates and the accuracy of the model at the end of 80 training epochs were 96.52 and 93.59 respectively. The learning and generalization of the dataset by this training model is demonstrated by this performance. The model offers classifications reports giving detailed statistics of each class. The model achieved a perfect score of 1.0000 with a precision, recall and F1-score in the score of all leaf blast and this indicates that the model can identify this disease accurately with no errors. Likewise, neck blast with an F1- score of 0.9905 and precision and recall of 1.0000 were perfectly identified by the model and this indicates that the model has high precision but it declines slightly in comparison to leaf blast and neck blast. The model was comparatively accurate (0.8070), remembered (0.8846), and the F1-score was 0.8440, indicating that the healthy leaves were identified with the model correctly with a higher percentage of false positives of the healthy category than the ill classes.The model was useful in the classification of sheath blight as it had the F1-score of 0.9804, high precision (1.0000) and recall (0.9615). The inability to distinguish this disease among others was also shown by the fact that the precision and recall of the leaf blast class were slightly lower (0.769), which led to the overall effectiveness of the model across the classes (0.769). The only exception was the leaf blast, the F1-score of this model was negatively affected since it was not able to get high accuracy and recall.The report on training mentioned that the model was trained with 80 epochs. The accuracy of the test of the model was 96.52 and the test validation accuracy was 93.59. The maximum Epoch of the model was Epoch 67 where maximum validation accuracy of 94.87 is attained. The convergence of the model was realized very slightly overfitted as observed by the training loss of 0.6507 and validation loss of 0.6612. The model appeared to be overfitting to the unknown data, as the mean error difference in the training set and the validation set were 0.1051. Overall, the model demonstrated a good performance; the best ones to detect rice diseases were ResNet50 and EfficientNetB4. This model is a valid tool employed in diagnosing of diseases as it can identify various diseases, particularly, the neck blast and sheath blight with almost hundred percent precision although in some cases it has been affected with leaf blast. The balancing feature of the model between recollection and accuracy is reflected in high F1-scores of most disease classes. The model used has 80 training epochs and is appropriate to apply in real life scenarios of rice disease detection.

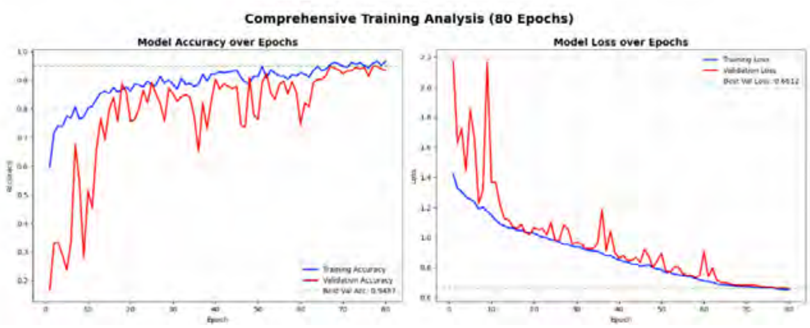


Figure 5.7: Custom CNN Model Accuracy and Loss Curve

5.1.2 Grad-CAM Visualization:

Grad-CAM(Gradient-weighted Class Activation Mapping) is a technique that can be used to visualize the areas of an image that a model pays attention to in order to make a prediction. It does this by generating a heat map that shows areas within the image that are important and which informs the choice made by the model. Analysis: The heatmap in the Grad-CAM picture of the rice leaf, shows areas of the leaf that the model found significant to the classification of the disease. The black space (e.g. green and red) points out parts of the rice leaf that played a major role in the choice of the model. High importance areas are usually bright such that, where the model concentrated its more attention, it made more emphasis when drawing its prediction.

Figure 5.8: Grad-CAM Visualization

In this specific picture, the model appears to be concentrated on spots of leaves or discoloration which is presumably associated with a particular illness. The focus points are the edges of the leaf and the discolored parts, and this makes sense as far as a disease classification task is concerned, where color characteristics such as yellowing or spotting are major attributes. Interpretation: The Grad-CAM output indicates that the model is targeting the right locations on the leaf which are signs of diseases such as brown spot or leaf blight. With these areas of interest, the model will be basing its decision on visual information that correlates with disease. Such a visualization can be used to demystify the behavior of the model making it more transparent and understandable. This makes us certain that the model is examining meaningful aspects and not making blind guesses.

5.1.3 LIME Explanation:

LIME (Local Interpretable Model-agnostic Explanations), is a technique employed to provide explanations of single predictions of a black-box model. It operates by inferring the interpretation of a model that is easier to follow at a certain prediction. The LIME explanation picture indicates the portions of the picture that led to the ultimate decision that appears as the highlighted points. Analysis: The LIME image uses the highlighted areas on the rice leaf to indicate the areas that had the most significant influence on the decision of the model. The superpixels are used by LIME to approximate the decision of the model in the local area and in addition identify the most significant parts that influenced the classification.

Figure 5.9: LIME Explanation

The LIME areas correspond to the areas we see in the Grad-CAM picture and this shows that the model is targeting the diseased areas of the leaf, especially regions covered by spots or are discolored. In contrast to Grad-CAM, which relies on the gradient values, LIME is implemented by modifying the image and monitoring the variations of the model response. The output of the visual output shows the most informative parts of the leaf that will be used in the model, and this validates its decision. Interpretation: LIME also provides an additional level of explainability, indicating that the model is targeting areas that are reasonable to the disease classification. This assists us to know the reason why the model classified the leaf as a particular disease. The boxes of LIME imply that the model is not targeting random parts of the leaf but on areas of interest that are visually related to the symptoms of the diseases, as the areas may be yellowing or have blotchy spots.

5.2 Analysis of Design Solutions

In this section, the usefulness of the deep learning design solutions, presented in Chapter 4, will be analyzed with a specific focus made on transfer learning-based convolutional neural networks and a designed CNN architecture. Several pretrained models such as VGG16, ResNet50 and EfficientNetB4 were compared in the same experimental context to provide fair and significant comparison. The models vary widely in terms of depth, number of parameters and ways of extracting features, directly affecting their performance as well as the amount of computation they need. The metrics used during the evaluation were based on accuracy in classification, efficiency, feasibility of implementation, cost, and performance stability. The deeper architectures as having residual connections were observed to have better feature learning capacity thus higher classification accuracy. EfficientNetB4, specifically, demonstrated good results and had a comparatively balanced number of parameters since it relies on compound scaling. Nevertheless, these trained models are more computationally intensive and cannot be used in the scarce resource agricultural setting. Conversely, the traditional CNN model that was trained using the default CNN model only used the training data at hand to learn the features. Despite a slight decrease in its classification accuracy when compared to pretrained models, it exhibited much lower computational complexity and a lower training time. Table 5.1 presents the comparisons and correlations between the considered models and shows the trade-offs between performance, complexity, and feasibility.

Model	Accuracy	Computational Complexity	Feasibility	Strengths	Weakness
VGG16	Moderate	High	Medium	Simple Architecture	Overfitting tendency
ResNet50	High	High	Medium	Strong generalization	High resource usage
EfficientNetB4	Very High	Moderate	High	Accuracy-efficiency balance	GPU dependency
Custom CNN Model	Moderate	Low	Very High	Lightweight, fast	Lower Accuracy

Table 5.1: Comparative Design Solution

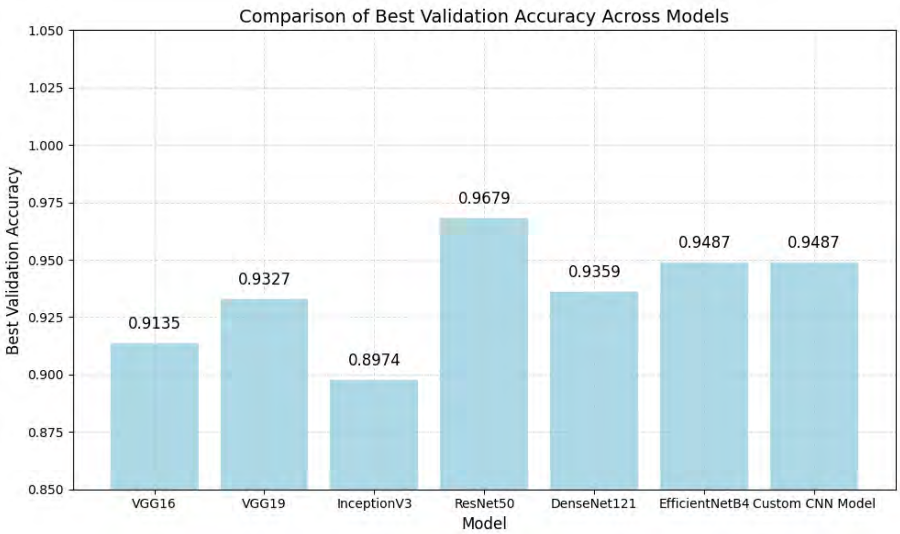


Figure 5.10: Bar Chart of Best Validation Accuracy of All Models

The bar chart refers to the best validation accuracy among seven models VGG16, VGG19, InceptionV3, ResNet50, DenseNet121, EfficientNetB4 and the Custom CNN Model. A breakdown of the graph is as follows:
X-axis (Model Names): This axis displays the names of the models under comparison which are both pretrained models and the custom CNN. Y-axis (Validation Accuracy): This demonstrates the validation accuracy of the individual models with a range of 0.85 to 1.0.

- ResNet50 achieved the best validation accuracy of 0.9679 which means that it has good generalization capacity on the validation data.
- EfficientNetB4 followed closely with a validation accuracy of 0.9487 demonstrating its accuracy and performance in computational efficiency.
- VGG16 and VGG19 had a little lower performance with validation of 0.9135 and 0.9327 respectively. These models, despite their effectiveness, performed worse than more sophisticated ones such as ResNet50 and EfficientNetB4 did.
- The Custom CNN model achieved 0.9487 which stands at the same level as EfficientNetB4 and provides a more viable trade-off in terms of calculation and implementation of the model.

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5.3 Final Design Adjustments

The final changes done to the architecture of the rice disease detection model were aimed at finding a balance between the performance of the computation and cost-effectiveness. All said and done, these design changes ensured that the final product was not only correct but also computationally viable as it provided the product with a viable alternative in its early detection of the rice disease in farming, especially where advanced computational facilities were limited. The reason why CNN model was selected was the similarity of the model in terms of performance in matters of validation accuracy and reduced cost in terms of computation. This choice made this model to be more suitable in working in agricultural environments that possess limited resources and in most cases power to process is limited. To achieve an optimum output of the model, various modifications have been done within the training period. Special care was observed with regard to overfitting wherein the custom CNN model was trained and 80 epochs were considered. The other loss function employed was Categorical Focal Crossentropy to make sure that it is able to accommodate class imbalance. This had the benefit of concentrating more on the more difficult to categorise samples and decreased the strength of the more identifiable classes. This had to be altered in making sure that the model could identify such diseases as sheath blight, bacterial leaf blight and healthy rice leaves. Moreover, to speed up convergence and lessen overfitting, the AdamW optimizer was used with a learning rate of 2×10^{-4} and weight decay. Furthermore, the Squeeze-and-Excitation (SE) block was included to improve the model's performance in properly diagnosing rice leaf diseases by strengthening its capacity to prioritize useful information. In the comparison of the results in the validation, the custom CNN model with a validation accuracy of 94.87% was comparable to more computationally intensive models like EfficientNetB4. The custom CNN was more practical in a low-resource setting in real-time application since it used fewer parameters with possibly equivalent accuracy. This enabled it to be trained at less time and using minimal hardware so that it would be put to practical use in real life applications without necessarily having to use a large amount of processing power. Further fine-tuning also solved the misclassification problems especially in cases of similar diseases including sheath blight as well as rice fake smut. Greater accuracy and diversity of examples to the dataset increased the precision and recall of the model on these challenging classes. These series of changes made the end model strong and stable, and allowed the end model to identify the various diseases found on rice leaves effectively, even in the realistic setting of the agricultural system. Everything considered, such design adjustments made sure that the end result was not only accurate but also computationally efficient, which would give it a viable solution in terms of identifying early rice diseases in the agricultural industry particularly in those regions with low access to sophisticated computational capabilities.

5.4 Statistical Analysis

The results of classification were statistically analyzed to confirm the consistency and reliability of the results in the form of numbers and visual representation tools. The confusion matrix is an important method used to evaluate the performance of the model as it shows the abilities of the model to distinguish the different classes of rice leaf diseases. The model is in good operation, and it is able to recognize most of the data as indicated by the high level of diagonal dominance in the matrix. Misidentifications are, however, present and more so between the sexually similar diseases as in the case of rice fake smut and healthy leaves, and sheath blight falsely identified as healthy. These errors are typical in picture classification tasks when some of the diseases have similar visual features such as yellowing or spots diagnostic of multiple types of diseases. similar symptoms. The confusion matrix demonstrates that the model is generally very effective, yet it still requires some additional refinements that will help it differentiate among the given types of diseases more accurately.
The capability of the model to classify rice leaf diseases is graphically presented in the confusion matrix (Figure 5.11). The off-diagonal values present inaccurate classifications whereas the diagonal values (highlighted in dark blue) represent true positives, or correct predictions of each illness classification. An example is sheath blight and rice fake smut which are falsely labeled as healthy. This terminates that the model is not able to distinguish between different illnesses that share similar visuals. The heatmap shows the overall performance of the model as well as the majority of the diseases being identified successfully. The intensity of colors of the heatmap is proportional to the quantity of samples in each category, which reveals the strong aspects and problems of the model. The matrix provides a good visual illustration of the strengths and weaknesses of the model particularly where mistakes are being occasioned by visual similarities among types of illnesses.

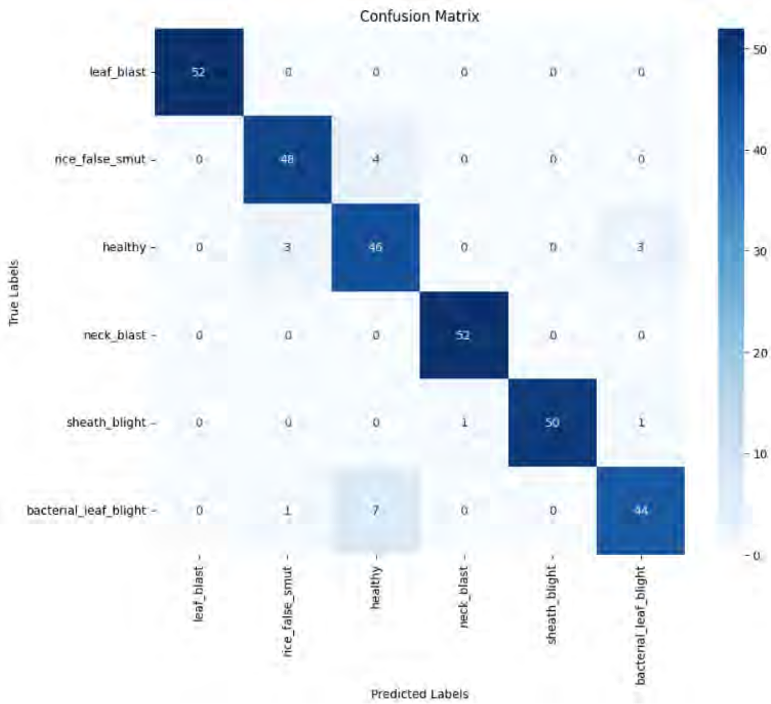

Figure 5.11: Confusion Matrix of Custom CNN Model

5.5 Comparisons and Relationships

The parameters of the pretrain models and the Custom CNN model are compared in this table. In the table, there are the following metrics in every model:

- Total Parameters (Size): This is a total number of the trainable and nontrainable parameters of the model. Big data models may have more parameters, which may be better at discovering complex patterns, but also require more processing power.

- Trainable Parameters: Parameters that are selected by the model when training it are referred to as trainable parameters. Models with larger trainable parameters also require larger memories and processing power, although they also tend to have larger capacity.

- Non-Trainable Parameters: The parameters stay constant in the process of training. These settings are not updated in backpropagation. Models that contain pretrained layers that do not require careful fine-tuning have larger non-trainable parameters.

VGG16 and VGG19 are observed to have the largest memory size with VGG19 being the largest at 125.40 MB. It means that these models are more advanced and they require large computer resources to train and make inferences since these are deeper structures. ResNet50 and EfficientNetB4 are relatively more efficient (around 94 MB and 71 MB, respectively) in terms of parameters or memory size, however, they also require considerable amounts of resources, particularly in the training process.There are 12,848,646 trainable parameters of the VGG16 model and total of 27,563,334. Parameters 14,714,688 are non trainable .VGG19 model has 12,848,646 parameters which all are trainable and total 32,873,030. This model has 20,024,384 nontrainable parameters.The number of trainable parameters of the ResNet50 model is 1,052,166, total parameters is 24,639,878.It does possess 23,587,712 non-trainable parameters. EfficientNetB4 is very light having 921,094 parameters that can be trained and there are total 18,594,917 parameters. There are 17,673,823 non-trainable parameters with this model. DenseNet121 contains a total 7,565,382 parameters and 527,878 trainable parameters. This model has 7,037,504 non-trainable parameters. InceptionV3 has total 22,854,950 and trainable parameters of 1,052,166. 21,802,784 non-trainable parameters of this architecture. Due to the residual connections and scaling of compounds used in these models, their trainable parameters are much lower compared to VGG16 and VGG19 which can potentially indicate higher generalization ability. Custom CNN model is set to have less complexity of computation but at the cost of performance of having the best validation accuracy with total 11,547,774 parameters and 11,537,150 parameters that are trainable. The non trainable parameters are 10,624. This model is especially appropriately suitable in resource-constrained environments in real-time deployment.

Model Name	**Total Parameters (Memory Size)**	**Trainable Parameters (Memory Size)**	**Non-Trainable Parameters (Memory Size)**
VGG16	105.15 MB	49.01 MB	56.13 MB
VGG19	125.40 MB	49.01 MB	76.39 MB
InceptionV3	87.18 MB	4.01 MB	83.17 MB
ResNet50	93.99 MB	4.01 MB	89.98 MB
DenseNet121	28.86 MB	2.01 MB	26.85 MB
EfficientNetB4	70.93 MB	3.51 MB	67.42 MB
Proposed Custom CNN Model	44.05 MB	44.01 MB	41.50 KB

Table 5.2: Correlation between the Level of the Model and the Number of Parameters and the Use of Data

Comparison of Model Parametric:
Larger models (e.g. VGG16 and VGG19) are the most expensive to compute because they have more parameters. Though these models require a lot of memory and processing power, they are ideal in activities that demand high accuracy. Smaller models including Custom CNN model and DenseNet121 offer a better trade-off between performance and processing economy. Custom CNN can be compared to EfficientNetB4 in terms of validation accuracy, however, it is more appropriate in a low-resource environment due to its smaller trainable parameters. The major indicators between the pretrained models and the Custom CNN model are captured in this table. The models are compared by best validation accuracy, test accuracy, and the computational complexity. The most accurate are ResNet50 and EfficientNetB4, which are also quite power-consuming. Custom CNN model however offers a better solution though it shows slightly lower test accuracy compared to pretrained models.

Model Name	**Best Validation Accuracy**	**Test Accuracy**	**Computational Complexity**
VGG16	0.9135	0.9038	High
VGG19	0.9327	0.8974	High
InceptionV3	0.8974	0.9231	High
ResNet50	0.9679	0.9744	Very High
DenseNet121	0.9359	0.9231	High
EfficientNetB4	0.9487	0.9744	Very High
Custom CNN Model	0.9487	0.9167	Low

Table 5.3: Comparison of Pretrained Models and Custom CNN

- Best Validation Accuracy: ResNet50 had the largest validation accuracy at 0.9679, then EfficientNetB4 with an accuracy of 0.9487. Both of these models are very performance-intensive although their performance is exceptional.

- Test Accuracy: ResNet50 and EfficientNetB4 achieved excellent test accuracy, the highest test accuracy of 0.9744 being achieved by ResNet50. The Custom CNN model is closely competing with pretrained models in terms of best validation accuracy, although with a slightly lower test accuracy.

- Computational Complexity: ResNet50 and EfficientNetB4 require a lot of resources, making them not the most suitable options in the case of limited resources. Due to the low computational cost, the Custom CNN model is ideal to implement in real-time in low resource settings.

5.6 Discussions

The experiment results support the effectiveness of methodological decisions described in Chapter 4 to classify rice leaf disease. Using expert-verified BRRI data enhanced the accuracy of labeling, whereas the diversification of data was achieved with online sources, increasing the accuracy of generalization. Despite the fact that the proposed system has been shown to be quite effective under the conditions of controlled experiments, there are still certain limitations associated with the sensitivity to the extreme environmental changes, and the lack of large-scale field validation. These limitations will need to be addressed to be used in the real world.

Chapter 6

Conclusion

6.1 Summary of Findings

In this paper, it was able to show that deep learning methods and, in particular, convolutional neural networks (CNNs) are applicable to the task of rice leaf disease classification. The CNN model that was customized provided a good trade-off between accuracy and computation speed and could therefore be used in real-time farming conditions, where resources were limited.

6.2 Contributions to the Field

The thesis is a meaningful addition to the body of knowledge on the topic of precision agriculture since it offers a lightweight, deep learning-based rice leaf disease classification model. The model is highly classifiable and also computationally efficient, which is important in real-time applications since it operates in low resource conditions.
A combination of focal loss and Squeeze-and-Excitation attention modules is a new strategy of enhancing the capacity of the model to handle the imbalance of classification and the ability to produce desired features.

6.3 Recommendations for Future Work

Further development of the rice leaf disease detection system should focus on the aspects of scalability so that the system could address a diverse range of agricultural data such as the extension of the rice leaf disease detection system to other crops and stages of the disease. The precision of the prediction and tailor-made recommendations of the diseases will be highly enhanced through the incorporation of IoT devices that would gather real-time environmental variables including soil conditions, weather, and humidity. Collaboration with agricultural experts could also enhance the ability of the system to differentiate a nutritional deficit and a disease leading to better diagnosis. This will be possible through further adoption should the system be tailored to cost-effective devices especially in the rural places where resources are limited.
The backend infrastructure should be implemented to give the necessary functionality to the app development. The app can contain huge amounts of information, 47

be updated in real-time, as well as can offer personalized recommendations aided by a database management system or a cloud-based application. The integration with the IoT devices would provide useful insights to farmers by real-time information gathering in the field. The app would become more useful when it has some features added to it, such as since it is multilingual, it has illness alarm push notifications and can easily connect to agricultural specialists. An automated feedback system that is developed by the detection of the disease will make the system more useful in the real-life agricultural conditions since farmers will be able to make timely and informed decisions. The sustainability of the app in the long run will be determined by its capacity to grow successfully, remain affordable, and promote additional upgrades.

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