IDENTIFICATION OF RICE LEAF DISEASES USING CNN WITH TRANSFER LEARNING

BY

MD. KAWSAR HOSSAIN
ID: 191-15-12759

SHAMIM SHIKDER
ID: 191-15-12693
AND

MOHAMMAD FATTAH SAMIT
ID: 191-15-12876

This Report Presented in Partial Fulfillment of the Requirements for the Degree of Bachelor of Science in Computer Science and Engineering

Supervised By

Asma Mariam
Lecturer
Department of CSE
Daffodil International University

Co-Supervised By

Sharun Akter Khushbu
Lecturer
Department of CSE
Daffodil International University

DAFFODIL INTERNATIONAL UNIVERSITY

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APPROVAL

This Project titled **"IDENTIFICATION OF RICE LEAF DISEASES USING CNN WITH TRANSFER LEARNING"**, submitted by Md. Kawsar Hossain, ID No: 191-15-12759, Shamim Shikder, ID No: 191-15-12693, and Mohammad Fattah Samit, ID No: 191-15-12876 to the Department of Computer Science and Engineering, Daffodil International University, has been accepted as satisfactory for the partial fulfillment of the requirements for the degree of B.Sc. in Computer Science and Engineering and approved as to its style and contents. The presentation was held on 24 January 2023.

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Daffodil International University

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Department of Computer Science and Engineering
Faculty of Science & Information Technology
Daffodil International University

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Internal Examiner

Md. Sabab Zulfiker
Senior Lecturer
Department of Computer Science and Engineering
Faculty of Science & Information Technology
Daffodil International University

24.1.2023

External Examiner

Dr. Ahmed Wasif Reza
Associate Professor
Department of Computer Science and Engineering
East West University

DECLARATION

We hereby declare that this project has been done by us under the supervision of **Asma Mariam, Lecturer, Department of CSE** Daffodil International University. We also declare that neither this project nor any part of this project has been submitted elsewhere for the award of any degree or diploma.

Supervised by:

Asma

Asma Mariam
Lecturer
Department of CSE
Daffodil International University

Co-Supervised by:

Khushbu
25.01.23

Sharun Akter Khushbu
Lecturer
Department of CSE
Daffodil International University

Submitted by:

Kawsar Hossain

Md. Kawsar Hossain
ID: 191-15-12759
Department of CSE
Daffodil International University

Shamim

Shamim Shikder
ID: 191-15-12693
Department of CSE
Daffodil International University

Samit

Mohammad Fattah Samit
ID: 191-15-12876
Department of CSE
Daffodil International University

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ABSTRACT

The damage done by rice leaf diseases is detrimental to our food safety and economic growth. Farmlands are being reduced day by day due to urbanization. Therefore it is highly essential to have the maximum harvest within limited space. But rice leaf diseases make it difficult to maximize the harvest. In Bangladesh brown spot, leaf scaled, rice tungro, sheath blight, and leaf blasts are the main diseases that are commonly seen in rice leaves. Detection of such diseases at an early stage can save a lot of crops and increase productivity. But this cannot be achieved manually within a short time in an accurate way. This paper comes up with a solution using CNN and transfer learning to identify the diseases before they can spread any further. The dataset was collected and modified from Kaggle and Mendeley Data. Our objective is to detect rice disease quickly and accurately to aid the agricultural sector and save a lot of time and effort for the farmers. InceptionV3, Xception, Resnet50V2, NasNetLarge and VGG16 were five transfer learning models that we applied. CNN without transfer learning,Xception, Resnet50V2, NasNetLarge and VGG16 accuracies are respectively 79.32%, 84%, 88%, 82%, and 81%. Whereas the InceptionV3 model achieved better results with an accuracy of 95%.

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Introduction

1.1 Introduction

At the present time, climate change, industrialization, and urbanization have become a major letdown in the agricultural sector. As the population growth rate is increasing at an alarming rate, especially in developing countries, the demand for food is escalating. It affects countries that rely on agriculture for development, especially south Asian countries. These countries (e.g. Bangladesh, Vietnam, India, Indonesia, etc.) mostly depend on rice as their main agricultural product. Increasing demand for rice is not sufficient for the supply due to decreasing per capita arable land. The annual shortage of rice is estimated to increase from 400,000 tons in 2016 to 800,000 tons by 2030 [1]. Rice leaf disease adds a new dimension to all these problems. These diseases cause the farmers to lose most of their harvest as they spread very fast across the whole land and infect the healthy crops. So, these diseases decrease production even further. Hence, rice leaf diseases can cause a disastrous situation even going as far as creating food shortages and starvation. The most common rice leaf diseases are sheath blight, leaf scaled, rice tungro, brown spot, leaf blast, etc. These diseases are often caused by bacteria, viruses or fungi. The most effective way of minimizing the consequences of these diseases is to identify the diseased plant as soon as possible. Otherwise, the disease would spread across the whole land affecting other healthy rice plants as well. Manual detection of leaf diseases is quite time-consuming and also takes a lot of effort. Moreover, it is extremely difficult to differentiate between these rice leaf diseases with the naked eye. This paper gives a modern approach to overcoming this situation. In this work, we have used 970 images (laterly augmented to 1914 images) from several existing datasets on the internet.

In this modern era, technology can provide solutions to almost anything. Using one of the most practiced aspects of the modern world, Deep Learning, our work proposes a method to identify rice leaves diseases more accurately and quickly to aid the farmers and benefit the agricultural sector to achieve efficient production.

1.2 Motivation

Rice is the staple food for almost half of the world's population. The people from the southern and eastern regions of Asia mostly depend on rice for the supply of most of the calories their body needs. In the 2021/2022 crop year, about 509.87 million metric tons of rice was consumed worldwide, up from 437.18 million metric tons in the 2008/2009 crop year [2].

As the world population is proliferating and arable lands are decreasing, the agriculture sector needs to produce crops with much more efficiency than ever. With the issues already on the table, diseases of rice add an additional dimension to the scenario. Rice can be subjected to various diseases caused by bacteria, viruses, and fungi. Farmers lose an average of 37% of their rice yields to pests and diseases, with losses ranging from 24% to 41% depending on the production circumstances [3].

To minimize the losses caused by rice diseases, the affected plant needs to be detected early and accurately so that the disease doesn't spread to healthy crops. Fast and accurate detection of the affected crops can save a lot of crops on that particular land. Manual detection of these diseases is not quite feasible as there are lots of crops on the land and checking each plant manually for signs of infection is not really achievable.

Image Processing can be a modern and efficient solution to these problems. Such a technique can be carried out to deliver quick and precise identification of rice leaf diseases. As rice is one of the most consumed food sources, the data required to perform such processing is quite manageable. There are many platforms on the internet where such datasets on rice leaf diseases are available. These datasets can be used to perform image processing and build a model that can be capable of differentiating these diseases and able to identify infected diseases accurately.

1.3 Rationale of the Study

Distinguishing between different types of diseases requires complex reasoning like humans. In order to overcome such challenges, the implementation of Deep Learning techniques is required. Empowering machines with the ability to learn how to recognize and extract features from the given images. In order to overcome the challenges that are generally imposed in Rice Leaf Disease identification, Convolutional Neural Network (CNN) with transfer learning was utilized to attain optimal performance more quickly than conventional Machine Learning models.

We used various CNN architectures for transfer learning such as InceptionV3, Xception, Resnet50V2, NasNetLarge, and Vgg16. The InceptionV3 model outperformed the rest with an outstanding accuracy of 95%. Analyzing and classifying diseases with accurate prediction allows us to effectively distinguish between rice leaf diseases. Hence, improving the ongoing research on this topic. Furthermore, farmers would be able to use solution applications based on this research and weed out infected crops. Removal of diseased crops would stop the injection from spreading any further. Resulting in better yield results.

1.4 Research Question

- What are the benefits of rice disease detection?
- What are the problems with traditional rice disease detection?
- How are the images of Rice Disease preprocessed in CNN?
- Why is rice disease detection important?
- Why is transfer learning used in the thesis?
- How will this thesis help our country?
- What is the motivation behind this thesis?

1.5 Expected Outcome

The goal of this thesis is to give better disease detection results than the previous work. The work would identify healthy and infected leaves as well as it could classify the diseases. Our work focuses on finding the optimal method to provide better disease detection results. The benefit of the work would increase agricultural productivity at a large scale by assisting farmers to take measures against the infected crops. The work would also benefit other people who would be conducting research in these fields in understanding the approach to this kind of issue.

1.6 Report Layout

Chapter One contains introductory information related to the research work such as introduction, motivation, the rationale of the study, research questions, expected outcome, and report layout.

Chapter Two discusses the background of the conducted research including the introduction, related works, research summary, the scope of the problems, and challenges.

Chapter Three contains the methodology of the research. In this chapter, the research subject and instrumentation, data collection procedure, statistical analysis, proposed methodology and implementation requirements were covered.

Chapter Four presents the experimental results and discussions. Experimental setup, experimental results and analysis and discussion were described in this section.

Chapter Five describes the research's impact on society and the environment along with ethical aspects and sustainability plans.

Chapter Six includes the summary and conclusions of the research.

CHAPTER 2

Background Studies

2.1 Introduction

Rice diseases are stumbling blocks between healthy rice and efficient production. These diseases cause a 10-15 percent reduction in yield. Rice diseases can be caused by bacteria, viruses, or fungi. The work covered 5 rice leaf diseases: Sheath Blight, Leaf Scaled, Rice Tungro, Leaf Blast, and Brown Spot. The characteristics of these diseases were studied and analyzed for this research purpose.

Rhizoctonia solani is responsible for Sheath Blight disease which is caused by fungus. The prevalence of this disease is high in high temperatures and humidity. Extreme use of Uria. frequent rain and waterlogging are some reasons for this disease. The spots that occur due to Sheath blight are gray in the center and brown at the edges. The spots coalesce and spread on the leaf sheaths and leaves, which look like rattlesnakes. Figure 2.1.1 shows a leaf infected with sheath blight.

Figure 2.1.1: Sheath blight

Leaf scaled is a disease caused by a fungus named Microdochium oryzae. The disease can spread because of wet weather and a high amount of nitrogen. When a crop is infected with leaf scaled, scaled appearances of the leaves are observed (shown in Figure 2.1.2).

Figure 2.1.2: Leaf Scaled

Leaf Blast occurs in rice plants due to Pyricularia grisea fungus. It can attack any rice plant at any stage. It spreads through seeds, air, insects and weather. It is observed that the disease spreads out quickly if it is cold at night, and hot during the day and dew drops pile up in the morning. If the land remains dry for a long time the rice plants are attacked by Leafblast. At first, oval shaped white/gray spots are found on the leaves. Dark brown colors are spotted around the white/gray spots. When these spots enlarge, they start looking like eyes. A leaf infected with leaf blast is shown in Figure 2.1.3.

Figure 2.1.3: Leaf Blast

Rice Tungro is caused by viruses. The disease can spread from the infected plant even through grasshoppers flying from one plant to another. Leaves of tungro-affected plants initially show light green and light yellow streaks along the veins (as shown in Figure 2.1.4). Later all the leaves gradually turn yellow or orange-yellow. Affected young leaves are pale in color and curl. Affected plants are shorter than healthy plants when infected at the seedling/bud stage but not as much as in older plants.

Figure 2.1.4: Rice Tungro

Brown Spot is caused by fungi named “Bipolaris oryzae”. This disease can be found even in saplings. Brown spot often occurs when there is inadequate nutrition and water in the soil. When a leaf is infected with Brown Spot, small spots like sesame grains are found in the leaves. The centers become white and brown at the edge when the spot expands. Multiple spots can form large spots and kill the leaf. Figure 2.1.5 displays a leaf with Brown Spot disease.

Figure 2.1.5: Brown Spot

Healthy specimens of Rice (Oryza sativa) leaves were also used to differentiate between healthy and diseased rice leaves. Figure 2.1.6 shows a healthy leaf of rice. Due to the presence of the healthy class in the dataset, it becomes easier for the model to determine the infected leaves,

Figure 2.1.6: Healthy Rice Leaf

All these different characteristics of each disease were observed and the proposed model differentiates between these diseases using these different characteristic features of the infected leaves.

2.2 Related Work

Kawcher Ahmed et. al. proposed an automated system for rice leaf disease detection using machine learning [4]. They obtained the data they needed from UCI's machine-learning repository. They dealt with three different diseases: Brown spot, leaf smut, and bacterial leaf blight. Each illness type has 40 images in the dataset they used. They used WEKA to train their model with several machine-learning algorithms. They used ColorLayoutFilter to convert the images into features. From the 35 attributes, they extracted 5 of those features using CorrelationAttributeEval. 90% of the data was utilized for training and the remaining 10% for testing. 4 algorithms (Naive Bayes Classifier, Decision Tree, Logistic Regression, K-Nearest Neighbour) were used to attain the goal. Their attained accuracy for these algorithms was 70.8%, 91.7%, 97.9%, and 50%

respectively. So, among the four algorithms, they have used, the Decision tree outperforms the other algorithms in terms of accuracy.

S.Ramesh et. al. described an approach to detect blast diseases in rice using machine learning algorithms [5]. They took 300 photos of the rice leaf from a village named panpoli in Tamilnadu using the camera of Redmi Note 5. Later they resize the photo into 256 X 256 pixels and also converted the RGB images to HSV images. For image segmentation, they've used K-Means clustering. GLCM, the standard deviation, and the mean value were determined while features were extracted. For classification, artificial neural networks were used. If the ANN predicted value was greater than 0.5 the leaf was labeled as healthy or defective. As training images, they used 180 images and the rest as testing images. Their training accuracy for blast leaf and normal leaf were 99% and 100% respectively. They had 90% accuracy in test images finding blast leaf and 86% in predicting normal leaf. The strong suit of their work is that it took only 3 minutes to train the ANN model with a quite low-end PC.

Minu Eliz Pothen et. al. proposed a system capable of detecting rice leaf disease better than the previous techniques [6]. The data for their analysis came from the UC Irvine Machine Learning Repository. The database contains a total of 120 photos, with 40 images for each disease. For further processing, they resize the images], which improves the image. While only 30% of the data is used for testing, 70% is used for training. The test data was once more separated into 15% for validation. For classification using the SVM approach, the data is trained using three kernel functions: polynomial, linear, and radial basis function (RBF). Each SVM kernel function is coupled with the LBP and HOG feature descriptors to achieve classification accuracy. After everything was said and done, they discovered that using SVM with LBP, the accuracy for linear, polynomial, and RBF functions as kernels is 89%, 90.23%, and 86.21%, while using SVM with HOG, the accuracy is 92.01%, 94.6%, and 89.0%. Both the SVM with LBP and HOG for Polynomials kernels gave the best accuracy (90.23% and 94.6%).

Prabira Kumar Sethy et. al. proposed an innovative approach to identify defective diseased leaves of rice crops by using K-Means clustering or the 3-Means clustering method. [7]. Using Image Processing to determine the defective area of rice crop leaves and clearly differentiate it between three clusters for image segmentation. Images of Leaves infected with brown spots and leaf scaled disease have been taken as input. The RGB images were converted to L*a*b color space to apply the K-Means algorithm to separate the defected area segment in MATLAB software. Images with brown spots contain 15.4302% of the infected area. Images with leaf scaled disease contain 15.013% of the infected area. According to this paper, we need to adjust the value of K proportional to the infected area. This framework produces more accurate results with rapid computing speed compared to the direct K-Means algorithm. However, this technique will face complications if the leaf is infected with multiple diseases where more clusters would be required.

Santanu Phadikar et. al. introduced a Computer-Vision-based Weed Identification under Field Conditions using Controlled Lighting [8]. The study provides a software prototype technique based on diseased photos of different rice fields for identifying rice diseases. Using a neural network to differentiate the infected region of the leaf that was used for classification. Rice plants with Leaf Blast and Brown Spot were selected for this work.. On the segmented images, a boundary identification technique based on the 8-connectivity approach was used. For classification, an approach to unsupervised learning An SOM neural network, or self-organizing map, was employed, with input coming from the gray value of the pixels in spot photos. For fractional zooming, the interpolation method was employed to equalize the spots' size. The RGB of the spots for classification has a 92% accuracy rate, while the spot's Fourier transform is 84%, its Arbitrary rotation is 82%, and its Fourier transform of the 50% spinning spots is 70%.

Shreya Ghosal et. al proposed a system to detect rice leaf diseases using CNN with Transfer learning [9]. They acquired the 1649 rice leaf images from the villages of Madarat in Baruipur, Dharinda in Tamluk, and Basirhat, and the internet. Mobile devices such as Redmi 5A and Motorola E4 Plus cameras were used to take these photos. The dataset contains images of Rice Leaf Blast, Rice Leaf Blight, Brown Spot, and healthy leaf. For increasing images, a few augmentation techniques were used. They used CNN which was based on a pre-trained VGG-16 model and also used transfer learning. The accuracy for their proposed model was 92.4% with 70% of data (20% of these data were used in validation) used in training and the rest in testing. They also conducted their model without transfer learning and got only 74% accuracy. Their dataset was quite small although they used transfer learning well enough to make up for the small dataset. But if they are to manage more images, it would have been possible to achieve more accuracy.

Krishnamoorthy N and et. al proposed an approach to identify rice leaf diseases using CNN with transfer learning [10]. Their dataset consists of 5200 images. They collected the images from Kaggle and other sources on the internet. The dataset contains images of three rice leaf diseases(brown spot, leaf blast, and bacterial blight) and also healthy leaves. They resized all the images. A few augmentation techniques (shearing, Rotation, zooming vertical and horizontal flip) were used to expand the dataset. They used CNN while using RELU as their activation function. They used a simple CNN model and also fine-tuned some parameters and achieved an accuracy of 84.75%. They used the InceptionResNetV2 model with transfer learning. The training and test set consisted of 4000 and 3000 instances respectively. Their acquired accuracy was 95.67%.

Amrita A. Joshi et. al. introduced an image-processing technique for monitoring and controlling rice diseases [11]. They collected the images from the Agricultural Research Station, Lonavala, Maharashtra, and some from the internet as well. In this study, they focused on four diseases: rice sheath rot, rice blast, rice brown spot, and rice bacterial blight. They collected 115 images of diseased rice leaves. The photos were normalized after being downsized to 200x200 pixels. Each image went through pre-processing, segmentation, and feature extraction. They used two classifiers for this work, which are the k-Nearest Neighbor classifier (k-NN) and Minimum Distance Classifier (MDC). For training, 70% of the data was used and the rest 30% was used for test purposes. The proposed method is implemented using the MATLAB R2012a version. They attained 87.02% and 89.23% accuracy for k-NN and MDC respectively. The accuracy was the same for some particular diseases and also deviated in some diseases where MDC gave better accuracy. Their work lacks a sufficient number of images. They have used only 115 images. Their model could have performed better if was introduced more data.

Shreyashi Bhattacharya et. al. proposed a deep-learning approach for the classification of rice leaf disease [12]. They took the pictures at a rice field in West Bengal's Nadia district. the Canon EOS 1300D camera was used to take the pictures. They dealt with the three illnesses brown mark, blast, and bacterial blight. After a few augmentation techniques were applied the final number of images was 2000, where 500 images were in each class. Their designed CNN model only implemented two hidden layers. The train set consisted of 70% data and the rest was in the test set. The first filter weight was 9,9,3,16 and the second filter weight were 5,5,16,32. Their research successfully distinguished between healthy and sick rice leaves with an accuracy of 94% and correctly identified various diseased leaves with an accuracy of 78.44%. Their dataset was quite small. Thus, their work faced some errors in detecting different diseased leaves.

Prabira Kumar Sethy et. al. proposed a deep feature-based approach for rice leaf disease identification using a support vector machine [13]. In this study, a deep CNN-based system was used to classify four different rice leaf diseases. From several rice fields in western Odisha, 5932 photos of damaged rice leaves with bacterial blasts, brown spots, blight, and tungro were gathered. High-resolution pictures were captured with a DSLR camera and collected from some online database, resized and augmented to increase the image count 6 times. 11 CNN models' performance was evaluated using a deep feature plus support vector machine (SVM) and transfer learning technique. Among the deep feature approaches, the F1 score of resnet50 plus SVM was 0.984 and it was their best classification method with a training time of mere 69s.

2.3 Research Summary

In this research paper, an optimal way to detect rice diseases was introduced. While initiating the research we enriched our knowledge of rice diseases and learned about the symptoms of each disease then we started looking for datasets. The datasets for this research were collected from online resources. Several rice leaf diseases are present in the dataset, including leaf scales, sheath blight, brown spots, and rice tungro. Infected leaf images as well as some healthy leaf images were also in the dataset. The images needed to be filtered. Some images were even dropped due to their poor quality and some augmentation was done to increase the chances of higher accuracy. Then for identifying the diseases transfer learning was implemented and several architectures were used to find the accuracy of each model. Each architecture had a different number of layers and provided various accuracy. Hence, the paper presented an accurate and faster way to recognize the diseases of rice and correctly classify those crops by differentiating them from healthy crops.

2.4 Scope of the Problem

The dataset and the research outcome are interconnected. Some issues in the dataset would also reflect on the overall result of our conducted work. Some of those problems are:

- The dataset contained some images there were quite similar to the images of the other class. Some of the images of Brown spot were quite similar to some images of the leaf blast.
- Some of the leaves had so tiny spots in them that they were not quite detectable and the machine could mistake them for healthy leaves.

2.5 Challenges

The difficult part of the research was collecting the data. Because for conducting successful research the data needs to be accurate and of good quality. But most of the image datasets available online do not have good-quality images. So, a thorough search for the dataset was carried out for finding the appropriate dataset for the research. After gathering the data, the next challenge was augmenting the images for increasing accuracy. Then training the model was quite challenging as it was necessary to study various algorithms to determine the appropriate approach for our dataset. Several layers were added to train the model more accurately and a better model for predicting the diseases was obtained after a lot of effort.

CHAPTER 3

Research Methodology

3.1 Introduction

The specific methodology and approach used to perform the research will be covered in this chapter. The chapter will describe the method used to successfully complete the research. The core objective of this research was to accomplish the precise identification of rice diseases. A detailed overview of each step followed to achieve the desired goal shall be covered in this section. The steps are shown in Figure 3.1.1.

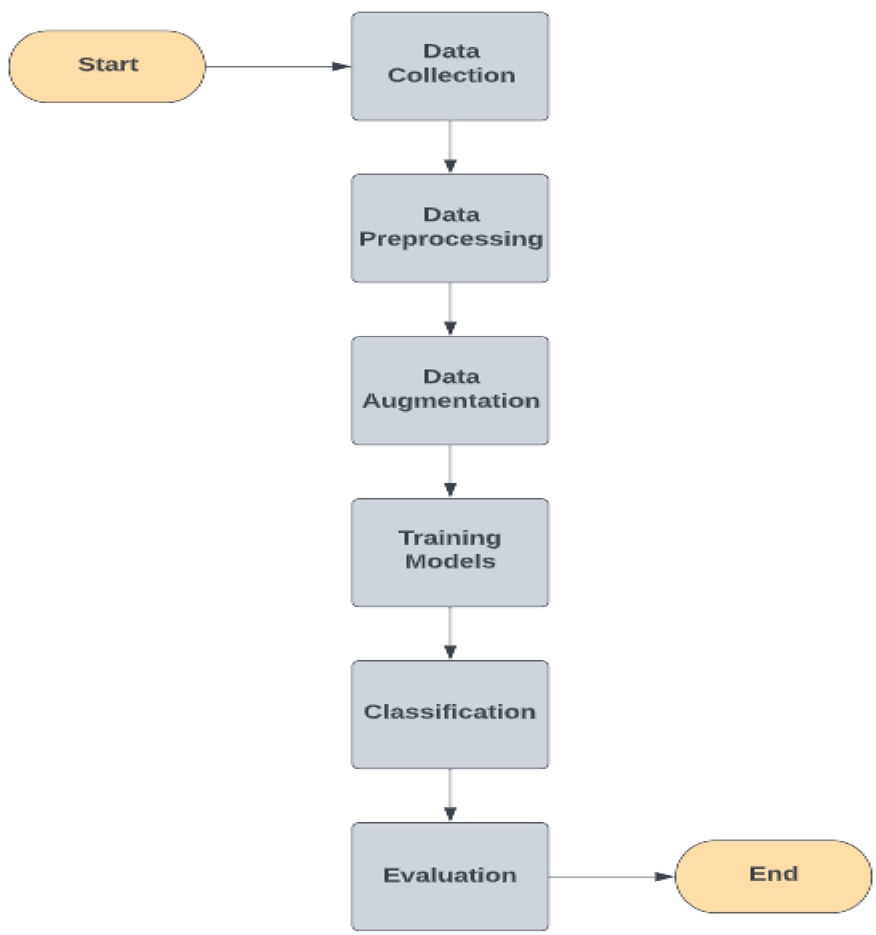

Figure 3.1.1: Classification Steps

As shown in Figure 3.1.1, several steps were followed to reach the desired objective. The first part was data collection. Once the dataset for the research was collected, and then those data went through preprocessing and augmentation for generating better results. Then they were trained with CNN without transfer learning as well as CNN with transfer learning. Hence they became capable of classifying all the six classes that we used in this study and finally, the evaluation of these models was done to determine the capabilities of those models. These steps will be covered in detail later on in this report.

3.2 Research Subject and Instrumentation

The aim of this thesis is to categorize various rice diseases. For achieving the target, a deep learning algorithm was used for image classification. In our work, a model capable of differentiating between diseases and identifying healthy leaves was created. To do this, a high-configuration PC was needed for work.
The following instruments were used to complete the process,

Hardware and Software:

- CPU: Intel Core i3-10110U
- SSD: 256 GB
- RAM: 8 GB

Tools used:

- Tensorflow 2
- Keras
- Python 3.8
- Scikit-learn
- NumPy

3.3 Data Collection and Data Preprocessing

The work consists of image processing which is based on a dataset of rice leaf disease. The effectiveness of the model mostly depends on the dataset. An ideal dataset would increase the chances of better accuracy. Hence, it is essential to put emphasis on the dataset.

3.3.1 Data Collection

The dataset was obtained from Mendeley Data, where the dataset was named as Dhan-Shomadhan: A Dataset of Rice Leaf Disease Classification for Bangladeshi Local Rice [14]. From this dataset, the data for Brown Spot, Leaf Scaled, Rice Tungro, and Sheath Blight was used. We collected another dataset from Kaggle named Rice Leafs [15]. From this dataset, we used Healthy and Leaf Blast images. For our work, we used 6 classes named: Brown Spot, Leaf Scaled, Rice Tungro, Sheath Blight, Leaf Blast and Healthy. So, the proposed model would detect 5 types of diseases and would identify healthy leaves. The dataset consists of 970 images.

3.3.2 Data Preprocessing

The dataset modified by us for the research contained some blurry images and low-resolution images. We conducted a thorough analysis of the dataset and removed those images that were not up to the quality standard. We did some resizing on the images.

3.3.3 Data Augmentation

The dataset we worked with does not have many images. To overcome the shortage some augmentation was done. The augmentation provided the model with a variety of inputs to work with hence increasing the number of inputs. We performed some augmentation like zoom, rotation, horizontal flip, vertical flip, and shear. As a result of augmentation our total data became 1914. A sample of an augmented image is shown below in Figure 3.3.3.1.

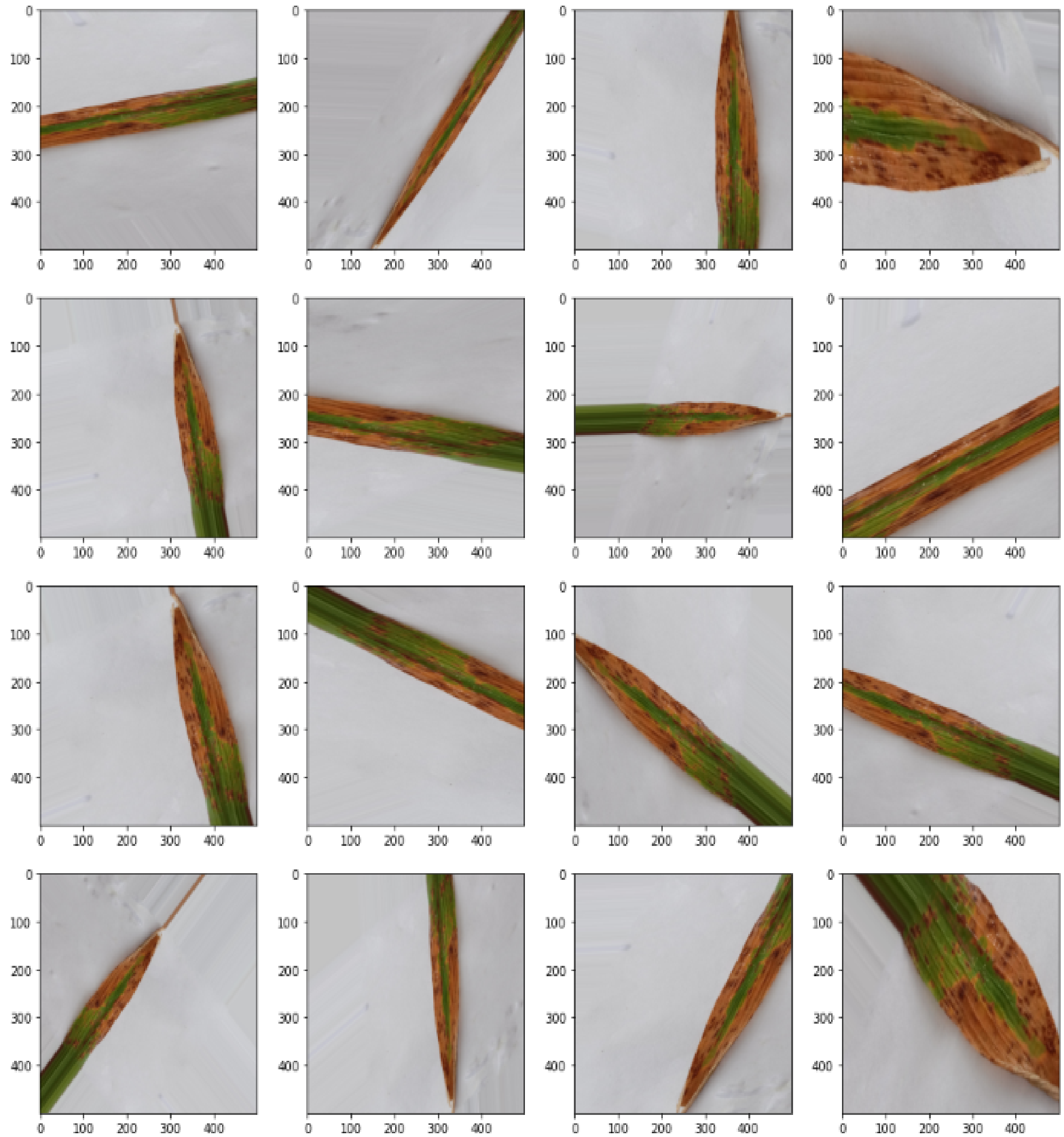

Figure 3.3.3.1: Sample of an Augmented Image

3.4 Statistical Analysis

Our dataset had 970 images belonging to 6 classes. Then we augmented the images and got a total of 1914 images. The Class index of those 6 classes are shown below along with a number of images before augmentation in Table 3.4.1 and after augmentation are shown in Table 3.4.2.

Table 3.4.1: Number of Images Per Class Before Augmentation

Class Name	Class Index	No. of Images
Brown Spot	0	90
Healthy	1	297
Leaf Blast	2	102
Leaf Scaled	3	143
Rice Tungro	4	119
Sheath Blight	5	219

Table 3.4.1: Number of Images Per Class After Augmentation

Class Name	Class Index	No. of Images
Brown Spot	0	291
Healthy	1	331
Leaf Blast	2	315
Leaf Scaled	3	336
Rice Tungro	4	318
Sheath Blight	5	323

3.5 Proposed Methodologies

The research was implemented on both CNN without transfer learning and CNN with transfer learning. We used inceptionV3, Xception, Resnet50V2, NasNetLarge, and Vgg16 for transfer learning. We used separate training and test files for each model.The validation set and training set were created from the training dataset. Then the models were prepared and trained for the classification.

3.5.1 CNN without Transfer Learning

The convolutional neural network is a deep learning architecture that learns directly from the image data. It is highly effective to detect patterns in pictures that represent the entities within the images. Therefore, making it very efficient regarding the classification of non-image data. The CNN architecture has three layers: convolutional, pooling and fully connected layers(shown in Figure 3,5,1,1).

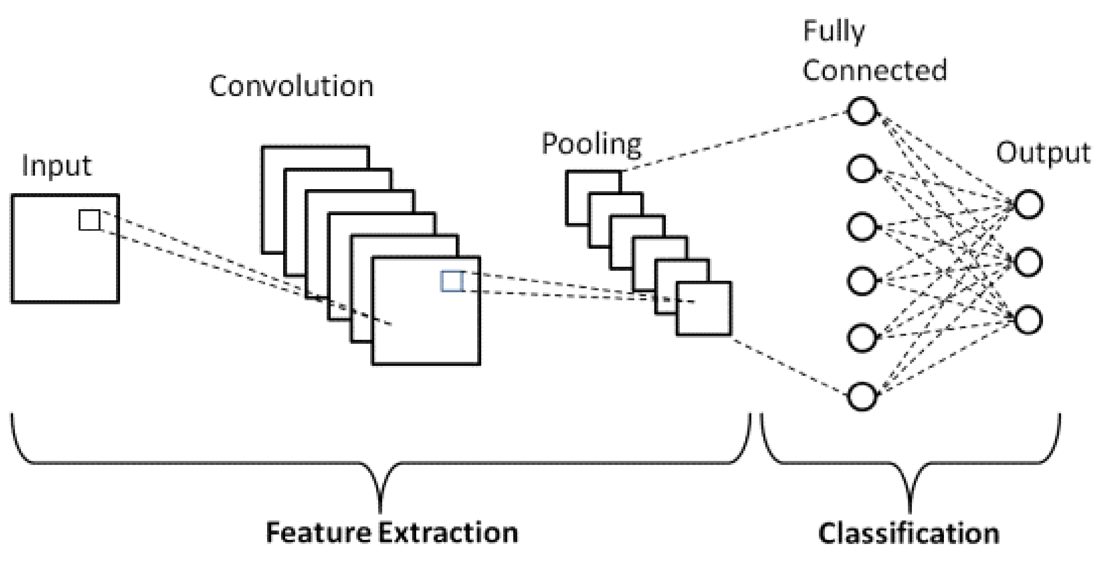

Figure 3.5.1.1: Basic Layers of CNN Model

For preparing our CNN model we used 20 training batches, 12 validation and 8 test batches where the batch size was 32. Our model was prepared using the following layers shown in Figure 3.5.1.2.

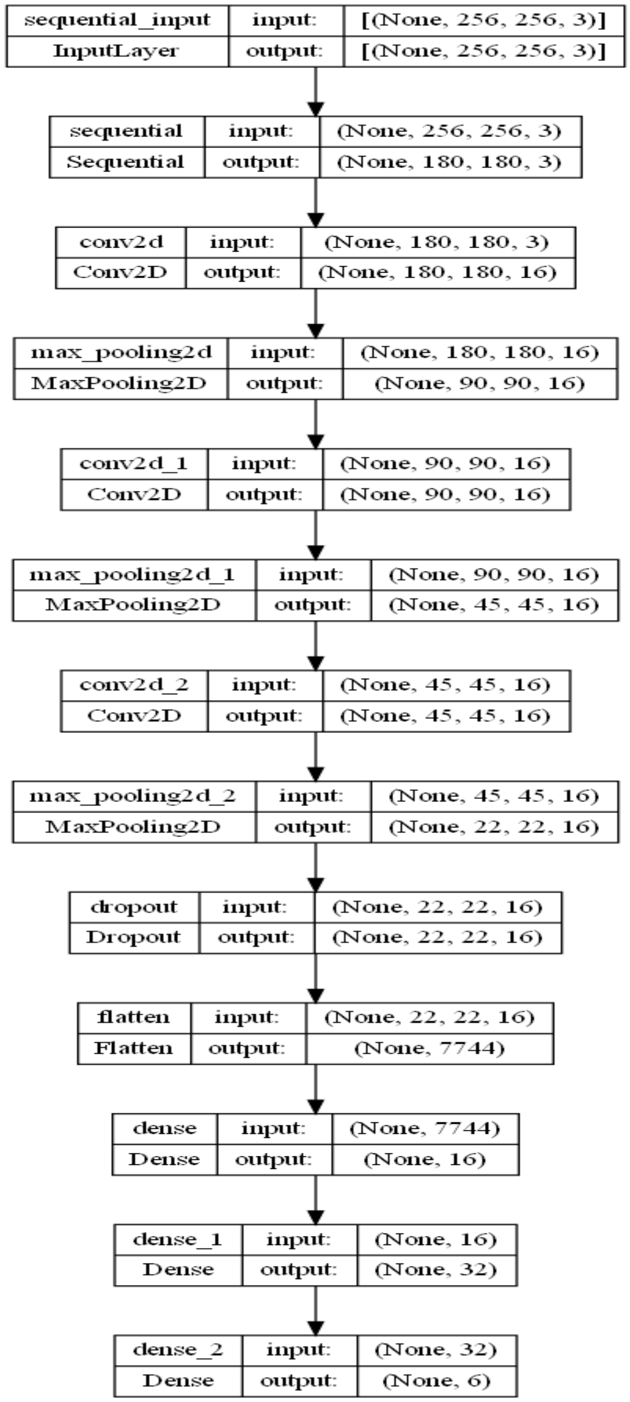

Figure 3.5.1.2: CNN Model

For compiling the model we used ‘adam’ as the optimizer, sparse categorial crossentropy as the loss function as shown in Figure 3.5.1.3.

```
model_1.compile(
    optimizer = 'adam',
    loss = tf.keras.losses.SparseCategoricalCrossentropy(from_logits = False),
    metrics = ["accuracy"]
)
```

Figure 3.5.1.3: Compiling CNN model

3.5.2 InceptionV3

InceptionV3 is a robust pre-trained model which is basically an enhanced and optimized version of the previous InceptionV1, previously known as GoogLeNet. Highly efficient with deeper networks compared to previous versions with a total of 48 layers. Moreover, it is computationally inexpensive and adaptive to achieve greater accuracy.

Split our data into train and test data then we split the train data into train and validation sets. We added the following layers (in Figure 3.5.2.1) with the InceptionV3 base model.

```
inputs3 = pretrained_model3.input
x3 = tf.keras.layers.Flatten()(pretrained_model3.output)
x3 = tf.keras.layers.Dense(1024, activation='relu')(x3)
x3 = tf.keras.layers.BatchNormalization()(x3)
x3 = tf.keras.layers.Dropout(0.2)(x3)

outputs3 = tf.keras.layers.Dense(6, activation='softmax')(x3)
model = tf.keras.Model(inputs=inputs3, outputs=outputs3)
```

Figure 3.5.2.1: Added Layers to InceptionV3 Model

We used categorical_crossentropy as the loss function and Adam as the optimizer. The learning rate was 0.0001 as shown in Figure 3.5.2.2.

```
from tensorflow.keras.optimizers import Adam
optimizer = Adam(learning_rate = 0.0001)
model.compile(optimizer=optimizer,loss='categorical_crossentropy',metrics=['accuracy'])
```

Figure 3.5.2.2: Compiling InceptionV3 Model

3.5.3 Xception

The Inception architecture is expanded in Xception, which uses depthwise detachable convolutions in place of the normal Inception modules. The feature extraction basis of the network in the Xception architecture is composed of 36 convolutional layers.

For the model we have kept 15% data for validation and 15% data for test and the rest for training. The following layers shown in Figure 3.5.3.1 was added to the base model of Xception.

```
x = xception.output
x = tf.keras.layers.GlobalMaxPooling2D()(x)
x = tf.keras.layers.Dense(1024, activation='relu')(x)
x = tf.keras.layers.Dense(512, activation='relu')(x)
output = tf.keras.layers.Dense(6, activation='softmax')(x)
```

Figure 3.5.3.1: Added Layers to Xception Model

We used categorical_crossentropy as the loss function and Adam as the optimizer for compiling the model.

3.5.4 ResNet50V2

Residual Network is abbreviated as ResNet. As the network's name suggests, the new word it adds is residual learning. Resnet50 has 50 layers. The propagated structure of the links between blocks was altered in ResNet50V2. ResNet50V2 performs well on the ImageNet dataset as well.

In this model we used 15% data for testing and 15% for validation and the rest of the data for training. We added some additional layers to the base model of ResNet50V2(Figure 3.5.4.1).

```
x = Flatten()(resent_model.output)
x = Dense(1024,activation='relu')(x)
x = Dense(1024,activation='relu')(x)
x = Dense(512,activation='relu')(x)
x = tf.keras.layers.BatchNormalization()(x)
x = tf.keras.layers.Dropout(0.2)(x)
x = Dense(6,activation='softmax')(x)
```

Figure 3.5.4.1: Added Layers to ResNet50V2 Model

In this model adam was used as optimizer and categorical_crossentropy was the loss function where the learning rate was 0.0001.

3.5.5 NasNetLarge

NASNet-Large was developed using more than a million photos from the ImageNet collection. The NASNetLarge model's default input dimension is 331x331.

In this model, for training, validation, and testing we used 70%, 15%, and 15% of data respectively. The layers we added with the base model of NasNetLarge in displayed in Figure 3.5.5.1.

```
X = tf.keras.layers.Dense(2048, activation='relu')(x)
X = tf.keras.layers.Dropout(0.25)(X)
X = tf.keras.layers.Dense(1024, activation='relu')(X)
X = tf.keras.layers.Dropout(0.25)(X)
X = tf.keras.layers.Dense(512, activation='relu')(X)
X = tf.keras.layers.Dropout(0.25)(X)
X = tf.keras.layers.Dense(256, activation='relu')(X)
X = tf.keras.layers.Dropout(0.25)(X)
X = tf.keras.layers.Dense(128, activation='relu')(X)
```

Figure 3.5.5.1: Added Layers to NasNetLarge Model

Like the previous models, in this model we used adam as the optimizer and categorical_crossentropy as the loss function for compiling the model.

3.5.6 VGG16

The CNN architecture known as vgg16 is one of the finest computer vision models currently available. It exhibited a considerable improvement over the advanced setups, examining the networks and increasing the complexity of the structure with small-scale convolution filters (3 x 3). Totaling about 138 trainable parameters with weight layers in the depth between 16 and 19. VGG16 requires an input tensor with 3 RGB channels with a size of 224, 244.

We split the data into train, and test data. Afterwards, splitting the train data into train, validation sets. The following layers were added to the vgg16 base model(shown in Figure 3.5.6.1).

```
x = Flatten()(vgg_conv.output)
x = Dense(1024,activation='relu')(x)
x = tf.keras.layers.BatchNormalization()(x)
x = tf.keras.layers.Dropout(0.2)(x)
x = Dense(6,activation='softmax')(x)
```

Figure 3.5.6.1: Added Layers to VGG16 Model

We chose adam as the optimizer and categorical_crossentropy as the loss function. In vgg16 the learning rate was 0.0001.

```
from tensorflow.keras.optimizers import Adam
model.compile(
    optimizer = Adam(learning_rate = 0.0001),
    loss='categorical_crossentropy',
    metrics = ['accuracy']
)
```

Figure 3.5.2.2: Compiling VGG16 Model

3.6 Implementation Requirements

We implemented our work on both Google Colab and Jupyter Notebook. We used python 3.8 as the main language with the help of TensorFlow 2 and Keras libraries to complete our task. It gave a comparatively better performance on the Jupyter notebook depending on the CPU performance. The implementation required a low-end GPU and ran quite efficiently on our machines.

CHAPTER 4
EXPERIMENTAL RESULTS AND DISCUSSION

4.1 Introduction

The identification of rice leaf diseases requires a neural network to process the image and perform classification. We used several models for the classification and selected a few models suitable for rice leaf disease identification. We used Jupyter notebook for the task and tried to make the model as optimal as possible so that it doesn't require much training time and can identify diseases quickly. We used Convolution neural networks and as well implemented transfer learning. Our dataset went through some preprocessing and augmentation before training those data into a model. The model was built considering minimal usage of the GPU. Hence the model could be trained on low-end machines as well.

4.2 Experimental Results and Analysis

We used CNN without Transfer learning and also with Transfer learning using InceptionV3 Xception, ResNet50V2, NasNetLarge, and Vgg16 for classifying the diseases. We added some additional layers to these pre-trained models. The dataset we used for transfer learning had a total of 1914 images consisting of 6 classes: Brown Spot, Leaf blast, Sheath Blight, Leaf scaled, Rice Tungro, and Healthy. Among all the model, InceptionV3 provided highest accuracy which is 95%.The accuracy for the used models are given below in Table 4.2.1.

Table 4.2.1: Accuracy of Different Models

Model	Accuracy
CNN without Transfer Learning	79.32%
Inceptionv3	95%
Xception	84%
ResNet50V2	88%
NasNetLarge	82%
Vgg16	81%

4.2.1 CNN without Transfer Learning

After the preprocessing is done, the CNN model is used to classify the diseases. The classification was done for 6 classes. We used 20 batches of data for the training dataset, 12 batches for validation, and 6 batches for the test dataset, where the batch size was 32. The epoch size was set to 50.

Next, we used Adam as the optimizer and sparse categorical cross-entropy as the loss function. Then we compiled our model, which had an 79.32% accuracy.

```
9/9 [==============================] - 6s 56ms/step - loss: 0.5352 - accuracy: 0.7932
[0.5352249145507812, 0.7932330965995789]
```

Figure 4.2.1.1: Test Accuracy for CNN without Transfer Learning

The training and validation accuracy and loss for each epoch are demonstrated in Figure 4.2.1.2 and Figure 4.2.1.3 respectively.

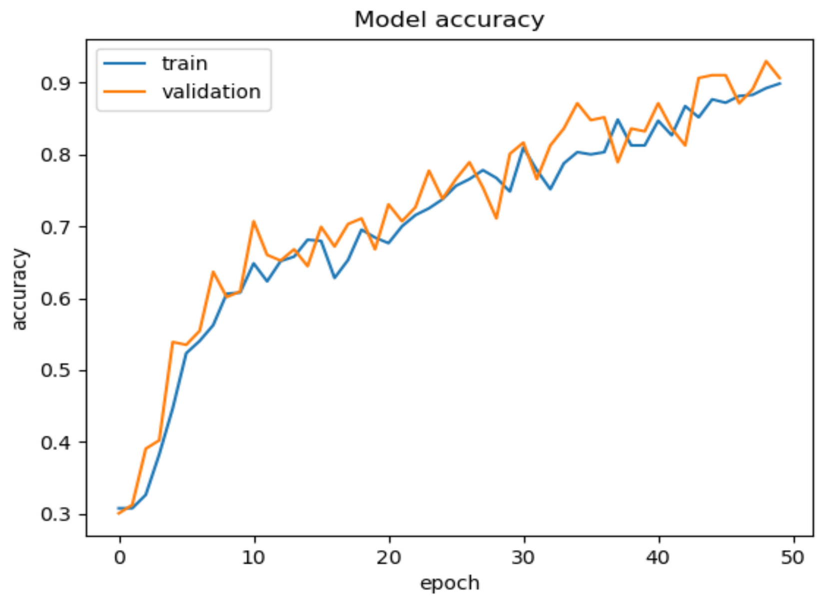

Figure 4.2.1.2: Training vs Validation Accuracy for CNN

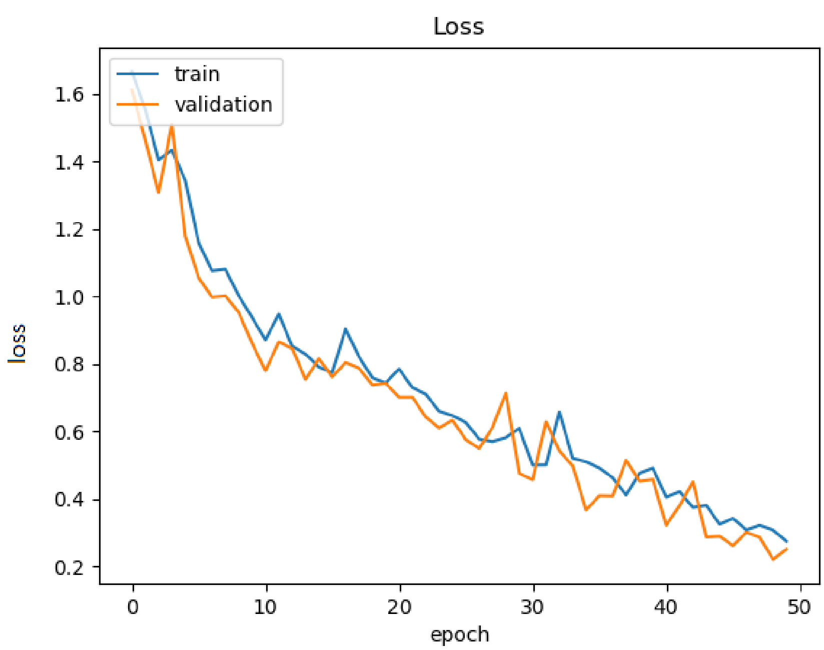

Figure 4.2.1.3: Training vs Validation Loss for CNN

Here are some predicted results of the CNN model in Figure 4.2.1.4.

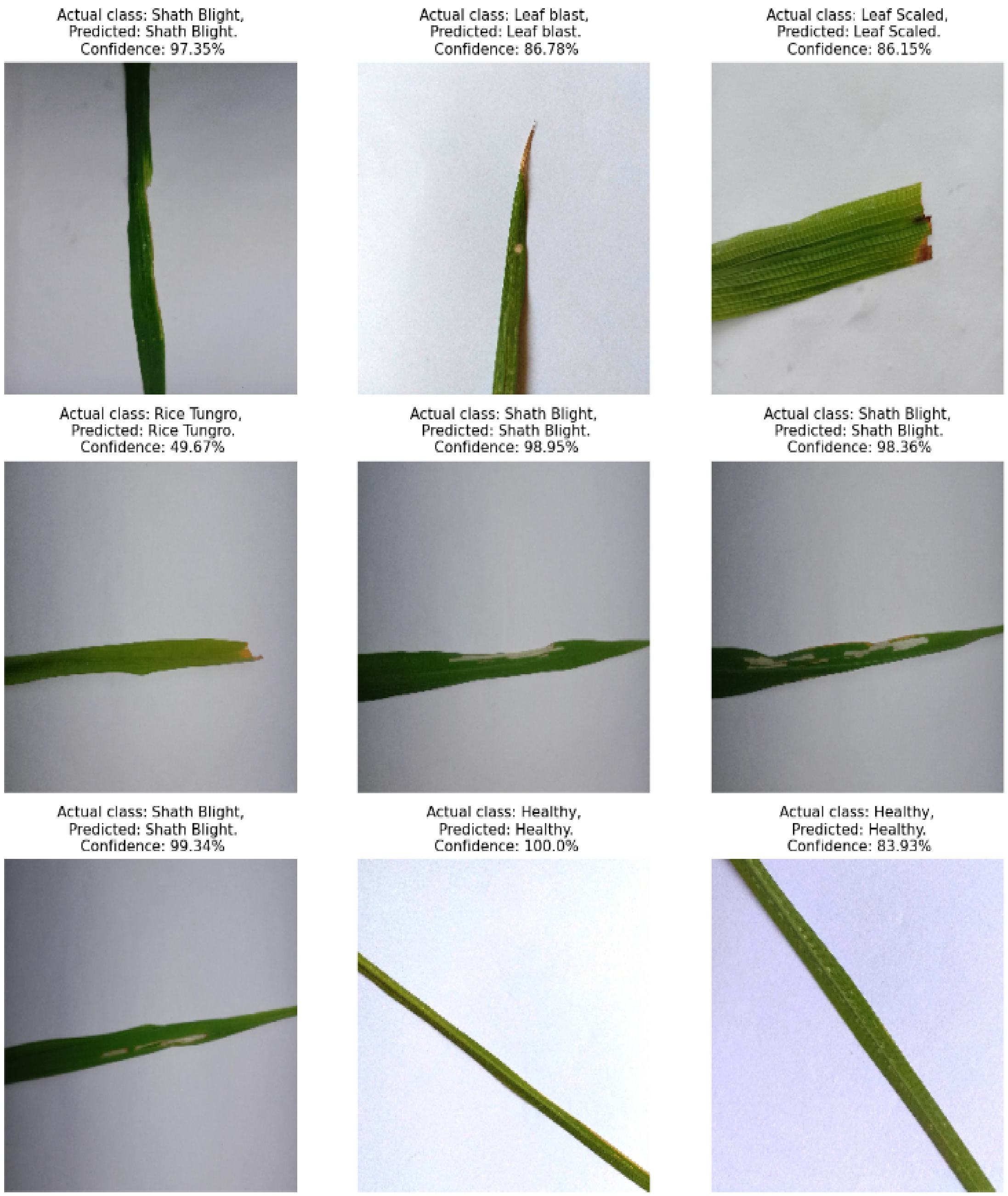

Figure 4.2.1.4: Predicted Results for CNN

4.2.2 Transfer Learning:

Several pre-trained models were used to train the Convolutional Neural Network during the experimentations. The pre-trained models are basically saved networks previously trained on a subset of the ImageNet dataset. It is a large-scale dataset used for image classification. Modifications were made to the pre-trained models to implement Transfer Learning effectively. Each of these models required different configurations to achieve optimal results.

4.2.2.1 InceptionV3:

After the preprocessing section is completed, the Pre-trained CNN architecture, inceptionV3 was applied to classify the diseases. We used 1914 images in total among which 70% for training 15% for validation and the remaining 15% to test in these models. The batch size was set to 32.

Our data went through 20 epochs and the training and validation accuracy for those epochs are given below in Figure 4.2.2.1.1 and 4.2.2.1.2 respectively.

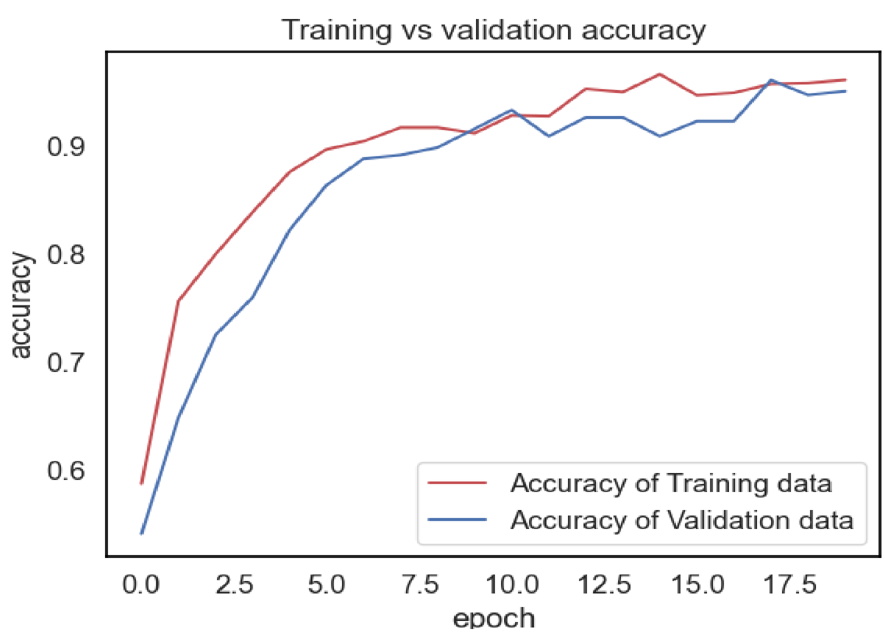

Figure 4.2.2.1.1: Training vs Validation Accuracy for InceptionV3

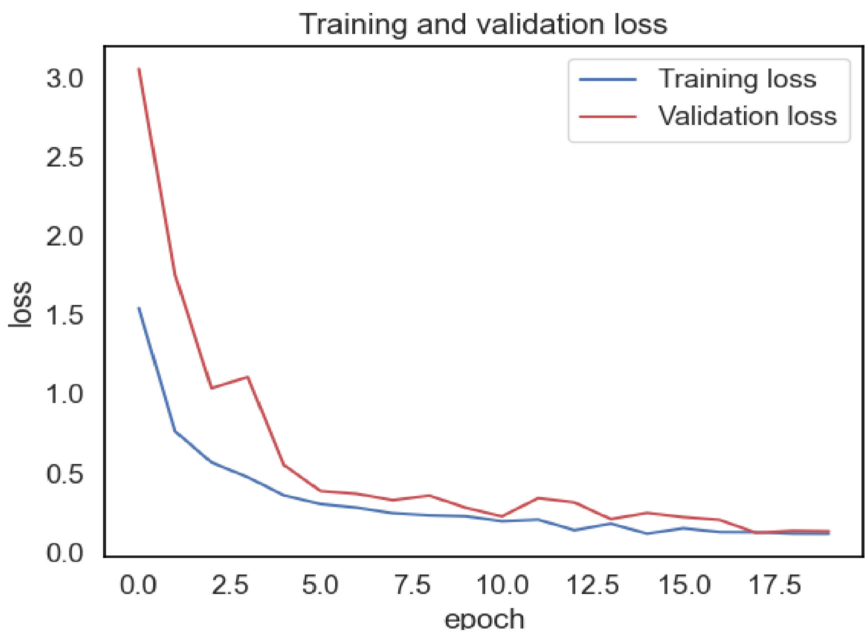

Figure 4.2.2.1.2: Training vs Validation Loss for InceptionV3

We compiled our model, which scored 95% accuracy for the test data. The accuracy is shown below in Figure 4.2.2.1.3 with the precision and recall values for all 6 classes.

```
9/9 [==============================] - 9s 742ms/step
              precision    recall  f1-score   support

           0       0.90      0.91      0.91        47
           1       1.00      0.95      0.98        43
           2       0.96      0.98      0.97        46
           3       0.98      0.88      0.92        48
           4       0.86      1.00      0.92        43
           5       1.00      0.97      0.98        61

    accuracy                           0.95       288
   macro avg       0.95      0.95      0.95       288
weighted avg       0.95      0.95      0.95       288
```

Figure 4.2.2.1.3: Classification Result for InceptionV3

Figure 4.2.2.1.4 displays the accuracy for each class in a heatmap.

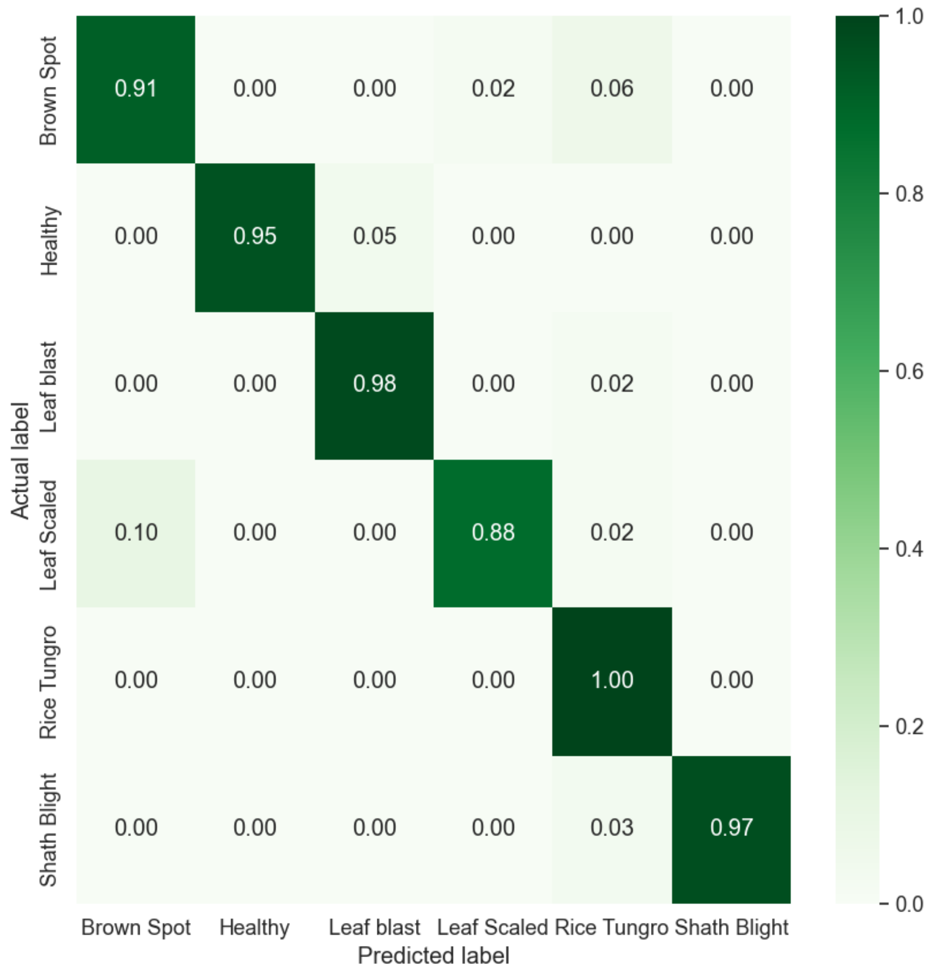

Figure 4.2.2.1.4: Class Wise Accuracy for InceptionV3 using Heat-map

4.2.2.2 Xception:

The pre-trained Xception model was used along with some additional layers where we took 70% for training, 15% for validation, and 15% for testing. The data went through 20 epoch. And the achieved training and validation accuracy as well as training vs validation loss is shown in Figure 4.2.2.2.1 and Figure 4.2.2.2.2 respectively.

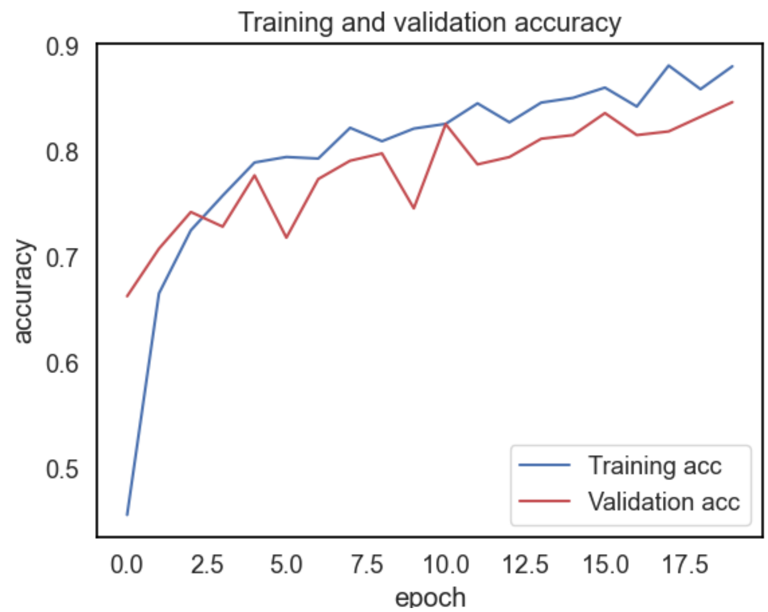

Figure 4.2.2.2.1: Training vs Validation Accuracy for Xception

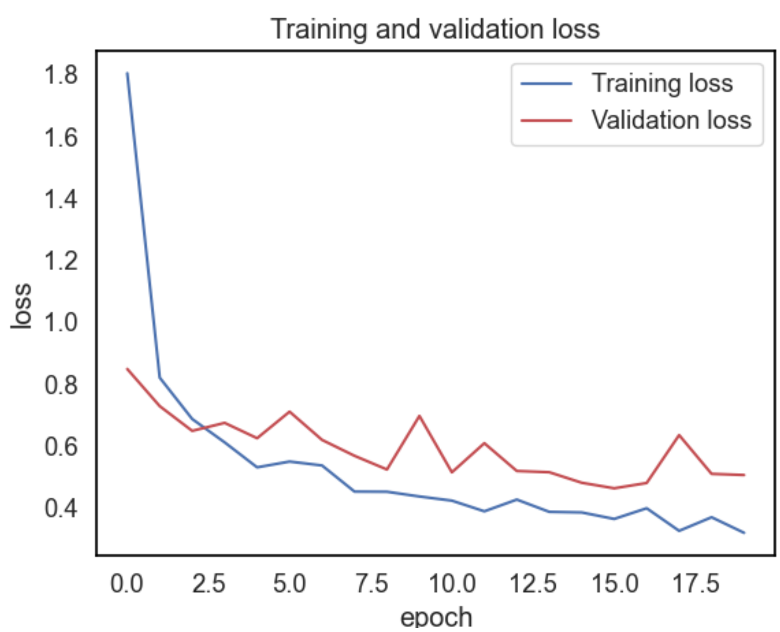

Figure 4.2.2.2.2: Training vs Validation Loss for Xception

The Xception model provided 84% accuracy for the test data. The accuracy is shown below in Figure 4.2.2.2.3 with the precision and recall value for all 6 classes.

```
9/9 [==============================] - 40s 4s/step
              precision    recall  f1-score   support

           0       0.92      0.77      0.84        43
           1       0.91      0.94      0.92        51
           2       0.93      0.90      0.91        48
           3       0.75      0.67      0.71        45
           4       0.63      0.91      0.75        44
           5       0.94      0.82      0.88        57

    accuracy                           0.84       288
   macro avg       0.85      0.83      0.83       288
weighted avg       0.85      0.84      0.84       288
```

Figure 4.2.2.2.3: Classification Result for Xception

4.2.2.3 ResNet50V2:

This model was fed with the same amount of train, validation, and test data as the previous models which are 70%, 15%, and 15% respectively. These data went through 20 epochs as well as augmentation. The accuracy and loss results for each epoch are displayed in Figure 4.2.2.3.1 and 4.2.2.3.2 respectively.

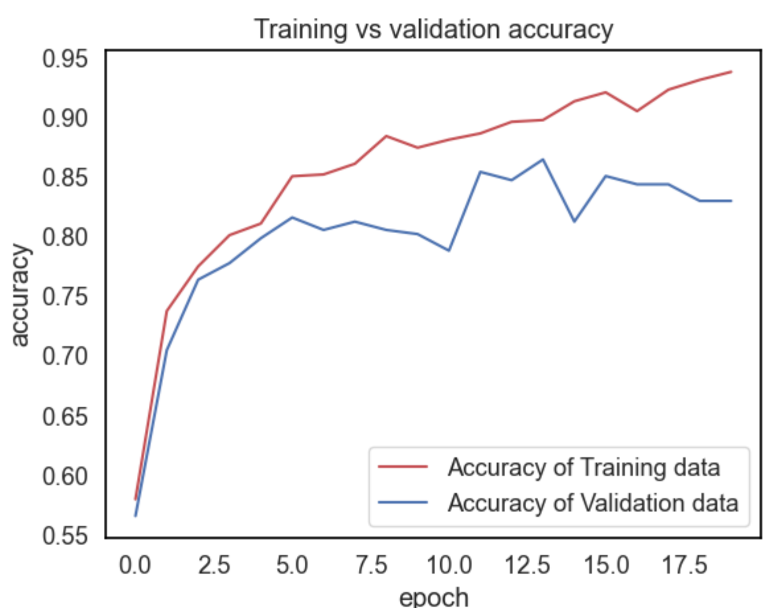

Figure 4.2.2.3.1: Training vs Validation Accuracy for ResNet50V2

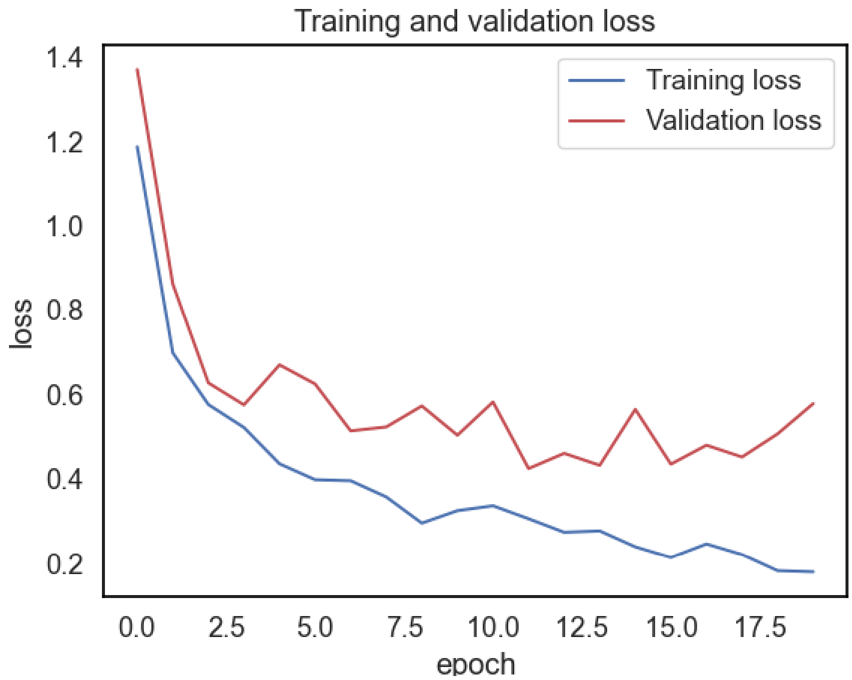

Figure 4.2.2.3.2: Training vs Validation Loss for ResNet50V2

The ResNet50V2 model provided 88% accuracy for the test data. The accuracy is shown below in Figure 4.2.2.3.3 with the precision and recall value for all 6 classes.

```
9/9 [==============================] - 10s 974ms/step
              precision    recall  f1-score   support

           0       0.89      0.74      0.81        46
           1       0.97      0.90      0.94        40
           2       0.93      0.98      0.95        53
           3       0.81      0.71      0.75        41
           4       0.75      1.00      0.86        54
           5       0.96      0.87      0.91        54

    accuracy                           0.88       288
   macro avg       0.89      0.87      0.87       288
weighted avg       0.88      0.88      0.87       288
```

Figure 4.2.2.3.3: Classification Result for ResNet50V2

4.2.2.4 NasNetLarge:

This model was supplied with the train, validation, and test data as the previous models which are 70%, 15%, and 15% respectively. These data went through 20 epochs as well as augmentation. The accuracy and loss results for each epoch are displayed in Figure 4.2.2.4.1 and 4.2.2.4.2 respectively.

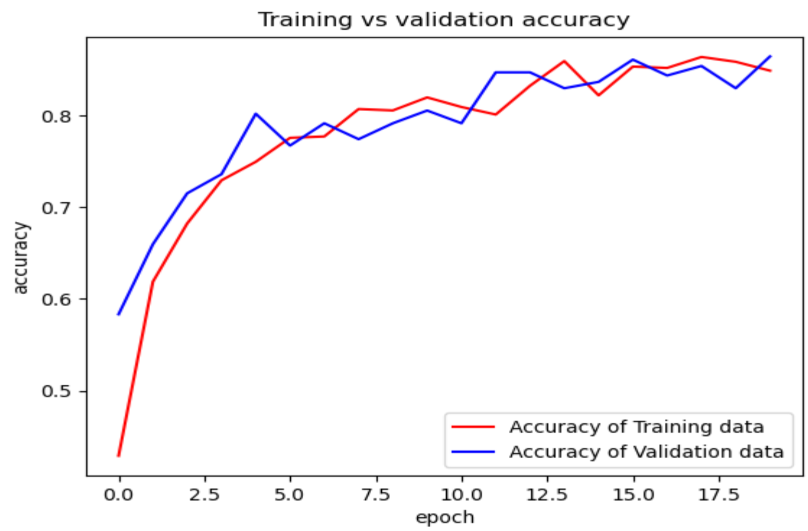

Figure 4.2.2.4.1: Training vs Validation Accuracy for NasNetLarge

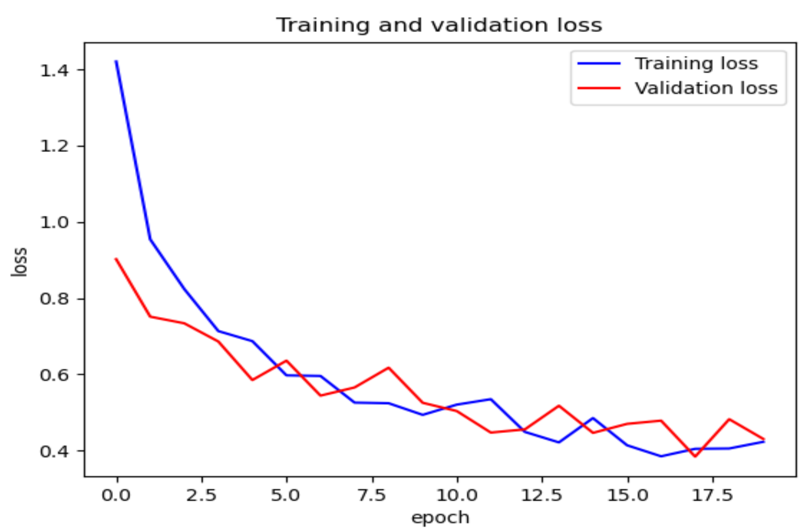

Figure 4.2.2.4.2: Training vs Validation Loss for NasNetLarge

The NasNetLarge model provided 82% accuracy for the test data. The accuracy is shown below in Figure 4.2.2.4.3 with the precision and recall value for all 6 classes.

9/9 [==============================] - 45s 4s/step

	precision	recall	f1-score	support
0	0.80	0.90	0.85	41
1	0.81	1.00	0.90	39
2	0.94	0.88	0.91	56
3	0.74	0.81	0.77	53
4	0.81	0.54	0.65	46
5	0.83	0.83	0.83	53
accuracy			0.82	288
macro avg	0.82	0.83	0.82	288
weighted avg	0.83	0.82	0.82	288

Figure 4.2.2.4.3: Classification Result for NasNetLarge

4.2.2.5 VGG16:

We used Pretrained VGG16 for the classification. A total of 970 images were used. We split the data into 70%, 15%, and 15% for training, validation, and testing respectively for predicting the 6 classes. Our data went through 20 epochs and the training and validation accuracy for those epochs are given below respectively in Figure 4.2.2.5.1 and Figure 4.2.2.5.2.

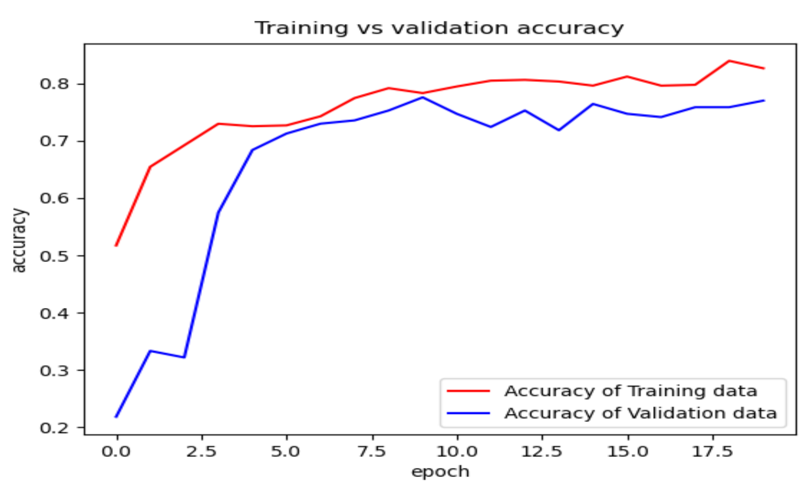

Figure 4.2.2.5.1: Training vs Validation Accuracy for VGG16

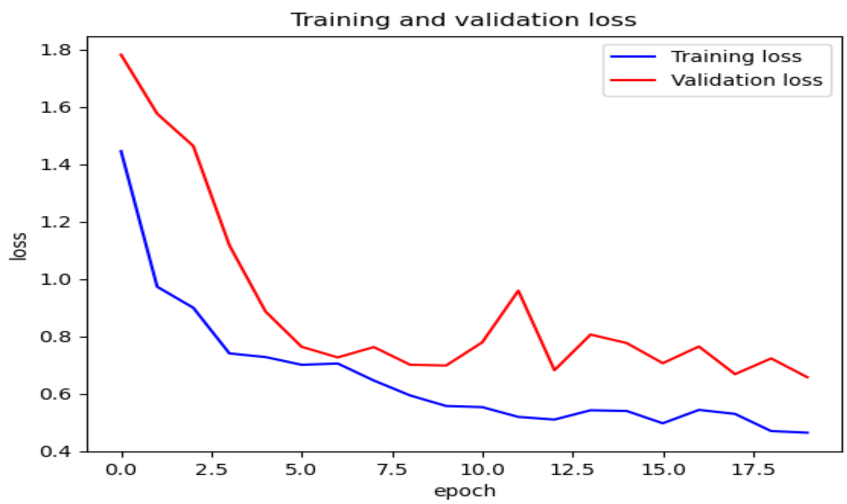

Figure 4.2.2.5.2: Training vs Validation Loss for VGG16

Furthermore, the vgg16 model provided 81% accuracy for the test data. The accuracy is shown below with the precision and recall value for all 6 classes.

```
4/4 [==============================] - 8s 2s/step
              precision    recall  f1-score   support

           0       0.60      0.67      0.63         9
           1       0.91      0.97      0.94        30
           2       0.91      0.77      0.83        13
           3       0.58      0.47      0.52        15
           4       0.65      1.00      0.79        13
           5       1.00      0.79      0.88        24

    accuracy                           0.81       104
   macro avg       0.77      0.78      0.77       104
weighted avg       0.82      0.81      0.81       104
```

Figure 4.2.2.5.3: Classification Result for VGG16

4.3 Discussion

In our thesis, we successfully classified 5 types of rice leaf diseases: Leaf blast, Rice Tungro, Leaf Scaled, Sheath Blight, and Brown Spot, and differentiated healthy rice leaves from infected leaves. For our study, we collected two different datasets online and then modified them into a single dataset. The dataset contained 970 images and 6 classes. Then we performed some preprocessing and image augmentation which increased our dataset size to 1914 images. Then we built the model and trained the model by specifying train and test data size for both CNN and transfer learning. Our CNN model provided 79.32% accuracy for the test data and our Transfer Learning model: inceptionV3 provided 95% accuracy whereas our other model Xception, ResNet50V2, NasNetLarge, and VGG16 provided 84%, 88%, 82%, and 81% accuracy respectively.

CHAPTER 5

Impact on Society, Environment and Sustainability

5.1 Impact on Society

Rice is the most consumed food for the people of the southern and eastern regions of Asia. Rice is the most common source of carbohydrates and other nutrients. Most people in these Asian regions keep their bodies active by consuming rice. Rice provides 21% of global human per capita energy and 15% of per capita protein [16].

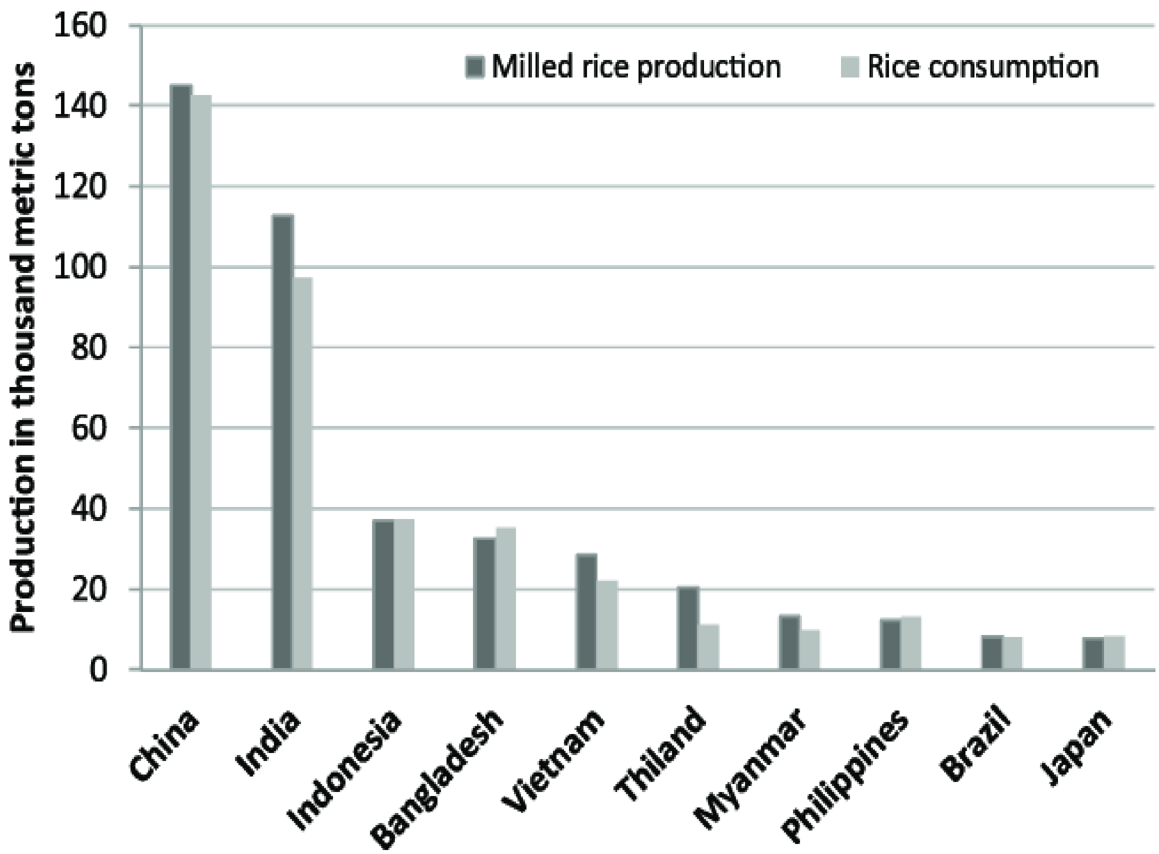

Figure 5.1.1: Bar chart of rice production and rice consumption in different countries

The Figure 5.1.1 visualizes the countries directly concerned with the production of rice. Any disease of rice would directly or indirectly affect society. Spreading out these diseases would lead to a great reduction in the production of rice resulting in a negative impact on the supply chain. Because once these kinds of diseases infect rice plants, they spread out to the entire field attacking even the healthy plants. The inability to properly detect these diseases will lead to great loss for the farmers and also the people in society. Farmers will lose their yield and people will fall victim to the shortage of rice which fulfills their major share of carbohydrates. Large scale implementation of our proposed work would reduce the damage caused by these diseases by correctly identifying the infected plants quickly. Hence, it would save the farmers from their losses and ensure that the enhanced production of rice is maintained. The work would also introduce society to automation and encourage the implementation of automation on a large scale.

5.2 Impact on Environment

Food shortage hinders the economy of any country, especially an agricultural country. If such a problem persists long enough, there would be a high chance of famine and economic collapse.

On average, farmers lose a vast majority of the rice they produce due to pests and diseases. These losses can be detrimental to the environment. Figure 5.2.1 shows the damage done by diseases and pests in several regions.

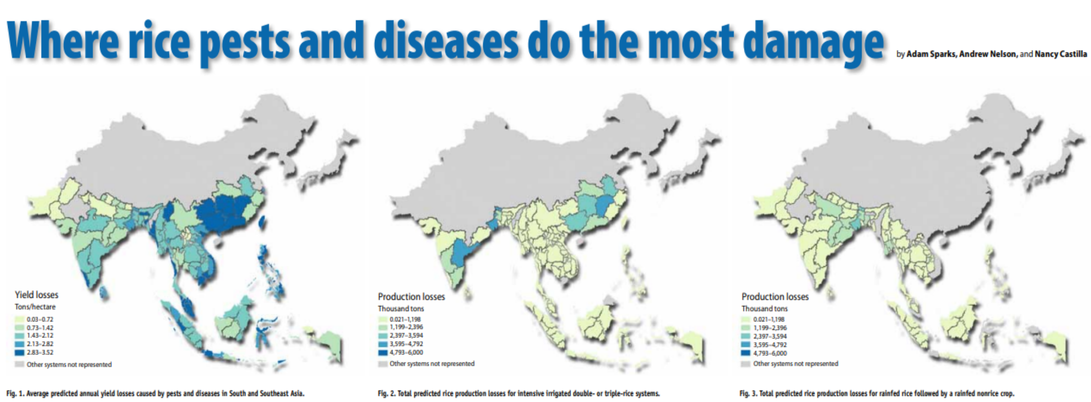

Figure 5.2.1: Global rice production loss index

Increasing production will minimize the gap between the supply and the demand for food. In order to do that, proper rice leaf disease management needs to be carried out. Our research will enable people to determine infected crops efficiently to eradicate them effectively. Suppressing the yield loss due to diseases to a minimum. Fewer resources will be wasted, decreasing emissions. Consequently, reducing the food shortage problem. Reinforcing the socio-economic status of a country will assure the safety and health of the citizens. Moreover, if there is a surplus of production then it can be used for export, resulting in economic growth. Further research can be done using and comparing the methodologies used in this paper for a better outcome.

5.3 Ethical Aspects

The proposed work of the paper is solely for the benefit of society and for the betterment of the agriculture sector by ensuring quality production. Our proposed work follows all ethical bindings to ensure that it doesn't cause any harm to society. The dataset used for the research was public data hence the paper doesn't intrude into confidential data.

5.4 Sustainability Plan

In today's world, climate change, industrialization, and automation influence how we will move forward. Therefore, proper planning needs to take all the factors into consideration to operate in the long run. Setting feasible goals such as improving upon the existing training models through deep learning implementation. Collecting more high-quality images to the dataset to train our model more effectively. Thus, upgrading our hardware and software appropriately. These plans will require time and funding. Large-scale development projects can be done using this research. As a result, gaining the attention of the government, numerous organizations, and institutes to fund our research.

CHAPTER 6
CONCLUSION AND FUTURE WORK

6.1 Summary of the Study

The study focuses on the purpose of identifying rice leaf diseases with the purpose of increasing rice production and providing a faster and more accurate disease detection system. In our study, we suggested a model for quickly and accurately identifying rice leaf disease and recognizing healthy rice leaves. The proposed method uses a convolutional neural network and also transfer learning models such as InceptionV3, Xception, ResNet50V2, NasNetLarge, and Vgg16. Our dataset was made using two different datasets by modifying them then some removal of images was necessary as they had low resolution or blurred images. We performed some augmentation such as resizing, zooming, rotation, and horizontal and vertical flips to increase the number of images. We are quite satisfied with our model. Because it is not only capable of providing higher accuracy but also efficient. The work has enriched our knowledge of neural networks and would contribute to the agricultural sector by boosting their production, saving lots of crops and time as well.

6.2 Conclusion

In our study, we presented a deep learning approach using Convolutional Neural Network architecture as the key to the multi-class classification issue regarding Rice Leaf diseases. Initially we collected 970 images of 6 classes of rice leaves and then augmented those images to get a total of 1914 images. Furthermore, implementing Transfer Learning involves fine-tuning the preset InceptionV3, and Vgg16 to compare results with the previous Simple CNN architecture. The InceptionV3 model outperformed the rest of the models with an accuracy of 95% where Xception, ResNet50V2, NasNetLarge, and VGG16 provided 84%, 88%, 82%, and 81% accuracy respectively. Therefore, effectively distinguishing between rice leaf disease images by analyzing and classifying between the disease classes with accurate prediction.

6.3 Implication for Further Study

There are various complications associated with the prediction of rice leaf diseases classified from image data. These issues are caused by internal and extrinsic variables, both of which have a significant impact on the performance of the training models and overall accuracy.

Concerning the performance of existing research, we would like to implement deep learning techniques and explore additional pre-trained models with transfer learning. Further hyperparameter tuning would require us to gain more knowledge and experience in this field. A simple yet robust web application based on this research is planned for future development.

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