



**TRIBHUVAN UNIVERSITY
INSTITUTE OF ENGINEERING
HIMALAYA COLLEGE OF ENGINEERING
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A

MAJOR PROJECT FINAL REPORT
ON

**“PADDY DISEASE DIAGNOSIS AND FERTILIZER
CALCULATION SYSTEM”**

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A MAJOR PROJECT SUBMITTED TO DEPARTMENT OF ELECTRONICS
AND COMPUTER ENGINEERING IN PARTIAL FULFILLMENT OF THE
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DEPARTMENT OF ELECTRONICS AND COMMUNICATION

Chyasal, Lalitpur

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ABSTRACT

Rice (*Oryza sativa*) is an important cereal crop worldwide. Every year, because of various pest infestations and diseases, farmers around the world are forced to fall prey to depressing losses in the annual crop yield and the consequent economic losses. Like all other crops, bacteria, fungi, and viruses are the primary causes of diseases leading to major plant damages and consequently agriculture and economic losses. Timely identification of diseases is a critical factor to minimize plant damages and make harvest as healthy and fruitful as possible. A specific class of rice plant diseases creates certain patterns on the leaves of the plant. Machine learning techniques can be employed to train a system about the association of these patterns to specific classes of rice plant diseases. In the project, Convolution Neural Network is applied to diagnosis the disease and rule-based approach is used to recommend the pesticide as preventive measures to reduce the crop losses.

Keywords: *Agriculture, Convolution Neural Network, Diseases, Economic, Machine Learning, Pest, Rice*

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ABBREVIATIONS

| | |
|----------|---|
| ANN :- | Artificial Neural Network |
| CNN :- | Convolution Neural Network |
| DNN :- | Deep Neural Network |
| FAO :- | Food and Agriculture Organisation |
| GLCM :- | Gray Level Co- Occurrence Matrix |
| HSV :- | Hue, Saturation Value |
| MoALD :- | Ministry of Agriculture and Livestock Development |
| NARI :- | National Agriculture Research Institute |
| NSSRC:- | National Soil Science Research Centre |
| RGB :- | Red Green Blue |
| SGDM :- | Study Group on Data Management |
| SVM :- | Support Vector Machine |
| TEPC :- | Trade and Export Promotion |
| USA :- | United States of America |

CHAPTER 1. INTRODUCTION

1.1 Background Theory

Rice is one of the most important crops in the world, providing sustenance and nourishment to over half of the global human population. This versatile grain is the seed of the grass species *Oryza sativa*, which is commonly referred to as Asian rice. As a cereal grain, domesticated rice has become a staple food in many cultures, and it is consumed in a variety of forms, including boiled, steamed, fried, and baked. The production of rice is a critical component of agriculture, and it is the agricultural commodity with the third-highest worldwide production. Rice is grown in many parts of the world, including Asia, Africa, Europe, and the Americas.

The cultivation of rice involves many steps, from the preparation of the land and the planting of the seeds to the harvesting, milling, and storage of the grains. In addition to being a crucial source of sustenance, rice is also an essential component of many cultural and religious practices. For example, rice is a central element of many Asian cuisines, and it is often used in religious ceremonies and rituals. In Hinduism, for example, rice is used in puja rituals and is considered a symbol of fertility and prosperity. Furthermore, rice is an excellent source of nutrition, providing more than one-fifth of the calories consumed worldwide by humans. Rice is a rich source of carbohydrates, vitamins, and minerals, and it is often used as a base for many nutritious meals. Additionally, rice can be processed into many different forms, including flour, noodles, and beverages, making it a versatile ingredient in many dishes. Overall, rice is a crucial crop that plays a significant role in the lives of millions of people worldwide. Whether consumed as a staple food, used in cultural or religious practices, or processed into various forms, rice remains a vital source of nutrition and sustenance for people of all ages and backgrounds.

Rice is an essential crop that plays a significant role in the global economy and is the primary source of sustenance for billions of people worldwide. This monocotyledonous plant is typically grown as an annual crop, but in tropical regions, it can survive as a perennial plant and produce a ratoon crop for up to 30

years. Rice cultivation is a complex process that requires significant labor and resources, making it well-suited to countries and regions with low labor costs and high rainfall. The cultivation of rice is a labor-intensive process that involves a wide range of activities, from land preparation and planting to harvesting and storage. The crop requires ample water, making it well-suited to regions with high rainfall. However, rice can be grown practically anywhere, even on steep hills or mountainous areas, with the use of water-controlling terrace systems, making it a versatile crop that can be adapted to a wide range of environments.

The production and consumption of rice have significant environmental implications, with estimates suggesting that it was responsible for 4% of global greenhouse gas emissions in 2010. Efforts to mitigate these emissions include the development of new cultivation practices and technologies that promote more sustainable rice production. Furthermore, rice plays a crucial role in many cultures and cuisines around the world. In Asia, for example, rice is a staple food that is consumed in many different forms, including steamed, fried, and boiled. It is also a key ingredient in many traditional dishes, such as sushi, biryani, and risotto. Moreover, rice is an excellent source of nutrition, providing essential carbohydrates, vitamins, and minerals that are vital for good health. Rice can be processed into many different forms, including flour, noodles, and beverages, making it a versatile ingredient in many dishes. Rice is a critical crop that is essential to the global economy and the health and wellbeing of billions of people worldwide. Whether consumed as a staple food, used in traditional dishes, or processed into various forms, rice remains a vital source of nutrition and sustenance for people of all ages and backgrounds. With ongoing efforts to improve cultivation practices and mitigate environmental impacts, rice will continue to play a vital role in the world's food supply for many years to come.

Rice, scientifically known as *Oryza sativa*, is undoubtedly one of the most important crops in the world, playing a crucial role in the sustenance of billions of people. In 2020, the global production of paddy rice reached a staggering 756.7 million metric tons (834.1 million short tons), with China and India being the leading producers,

accounting for a combined 52% of the total production. Other major producers of rice included Bangladesh, Indonesia, and Vietnam. The sheer scale of rice production around the world is truly remarkable, with the top five producers alone accounting for a massive 72% of the total production. In 2017, the top fifteen producers accounted for 91% of the world's total rice production, underscoring the crop's importance as a staple food worldwide.

It is worth noting that rice production is primarily concentrated in developing countries, with these countries accounting for a staggering 95% of the total production. This underscores the critical role of rice in providing food security and nutrition for populations in these countries. The cultivation of rice is a complex process that involves numerous steps, including land preparation, planting, harvesting, and storage. Furthermore, rice production is heavily dependent on environmental factors such as rainfall, soil quality, and temperature, making it a challenging crop to cultivate. Nonetheless, the high yields of rice per unit area make it an economically attractive crop, particularly in countries with low labor costs and high rainfall. Beyond its importance as a staple food, rice also plays a significant role in many cultural traditions around the world. In Asia, for example, rice is often used in religious ceremonies and festivals, and is a central part of many traditional dishes.

Moreover, rice is also a vital source of nutrition, providing essential vitamins, minerals, and carbohydrates that are essential for good health. Rice is undoubtedly one of the most important crops in the world, with global production reaching staggering levels in recent years. With the top fifteen producers accounting for 91% of total production, it is clear that rice plays a crucial role in food security and nutrition for populations worldwide. As efforts continue to develop more sustainable cultivation practices, rice will likely continue to be a vital source of sustenance for billions of people for many years to come.

Rice, as a staple food, holds a critical position in Nepal's food security, and its cultivation has been a significant contributor to the country's economy and cultural

heritage. With an estimated population of 29 million people, Nepal is a small landlocked country located in South Asia that has been facing various challenges, including food insecurity, poverty, and climate change. As the most important cereal crop, rice is grown on approximately 1.49 million hectares of land, accounting for more than half of the total cultivated area in Nepal. In 2018, Nepal produced a total of 5.6 million tons of rice, with an average productivity of 3.5 tons per hectare. However, despite steady progress in rice production, the country's total annual demand for milled rice is estimated to be around 4.08 million tons, which is significantly higher than the production of 3.25 million tons of milled rice in 2017. To bridge the gap between demand and supply, the country had to import 0.75 million tons of milled rice in 2019.

This highlights the importance of increasing domestic rice production to meet the country's growing demand for this essential staple food. To address the challenges faced by small-scale farmers, the government has implemented various initiatives aimed at increasing rice productivity. For example, the government provides subsidies for agricultural inputs such as seeds, fertilizers, and irrigation facilities to small-scale farmers. Additionally, the government has been working to develop and introduce new rice varieties that are more resilient to pests and diseases, require less water, and are more tolerant to climate change. These measures have contributed to increased rice productivity and improved the livelihoods of small-scale farmers.

Furthermore, rice cultivation has been a vital part of Nepal's cultural heritage and traditions. Rice festivals, rituals, and ceremonies are an integral part of the Nepalese way of life, reflecting the close relationship between Nepalese culture and rice cultivation. Rice also plays a significant role in the country's cuisine, with rice dishes such as dal-bhat-tarkari being a staple in the Nepalese diet. Nepal's unique biodiversity has resulted in the production of many unique rice varieties, with some of them being highly sought after internationally.

For example, the aromatic Basmati rice variety has gained international recognition for its distinct aroma and flavor, contributing to the country's economy through

exports. The importance of rice in Nepal extends beyond just its role as a staple food. Rice cultivation has also been a significant contributor to the country's economy, providing employment opportunities for millions of people, and contributing to the country's exports. In addition, rice farming has played a critical role in soil conservation and land management, contributing to the preservation of the country's natural resources.

In conclusion, rice plays a critical role in Nepal's food security, economy, and cultural heritage. Despite progress in increasing rice productivity, the country still faces significant challenges, including a deficit in meeting its domestic demand for milled rice, necessitating imports. To address these challenges, the government has implemented various initiatives to support small-scale farmers and increase rice productivity. Nepal's rich biodiversity has also contributed to the production of unique rice varieties that have gained international recognition. The cultural significance of rice in Nepal is reflected in its festivals, rituals, and cuisine, making it an integral part of the country's way of life.

1.2 Problem Statement

Paddy cultivation requires consistent supervision because several diseases and pests might affect the paddy crops, leading to up to 70% yield loss. Disease is a leading factor that affects the growth and development of rice. Some of the common rice disease are :Bacterial blight, Bacterial leaf streak, Blast(leaf and collar),Brown spot, Tungro, Hispa, Tungro, Downy mildew, Dead heart and so on. Rice diseases are causing a large quantity of loss in grain yield. FAO (Food and Agriculture Organization, USA) estimates that plant diseases cost the global economy around \$220 billion annually and between 20 to 40 percent of global crop production is lost to diseases and pests.

In 2020, rice, paddy production for Nepal was 5.55 million tonnes. Rice, paddy production of Nepal increased from 2.34 million tonnes in 1971 to 5.55 million

tonnes in 2020 growing at an average annual rate of 2.72%. However, Nepal's paddy harvest is expected to shrink to a five-year low to 5.13 million tonnes this fiscal year caused by unseasonal October rainfall and experts say it may cause further upward pressure on inflation and downward pressure on the economy. According to the ministry, paddy productivity or yield dropped 9.09 percent year-on-year. Farmers lose an estimated average of 37% of their rice crop to pests and diseases every year.

Identifying the plant diseases rapidly and precisely is critical to reduce the economic losses. However, disease diagnosis and treatment usually Meanwhile, machine learning, deep learning, and computer vision technologies have made image processing and disease diagnosis become feasible as shown in many studies. Pesticides treatment is used as the main methods to control crop diseases. However, the use of pesticides highly depends on diagnosis results, and unrestrained pesticides usage causes considerable environmental damage as well. Therefore, precise and timely diagnosis of the diseases is critical. Currently, the diagnosis of rice diseases is often performed manually, and the process can be extremely labour intense and time-consuming.

1.3 Objectives

- To develop the system which diagnose the disease in the paddy plant using CNN and calculate fertilizer needed.

1.4 Scope and Application

1.4.1 Project Scope

- It will assist people in diagnosis of disease in the paddy plant which is portable and less costly.
- It will assist farmer in the paddy cultivation.

1.4.2 Applications

- This system will assist people to diagnosis disease in paddy plant and take preventive measures.
- This system will introduce an approach to help the famer in paddy cultivation and increase productivity.

1.5 Report Organization

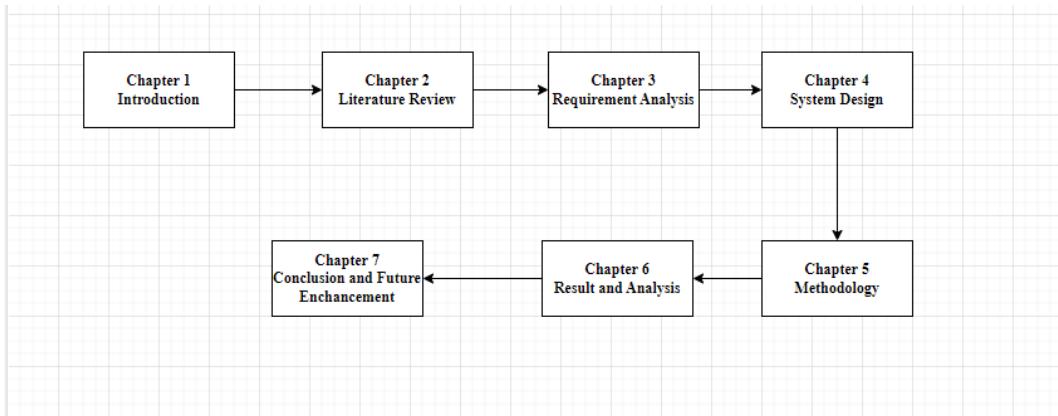


Figure 1.1: Report Organization

The project report is organized into several sections that provide a comprehensive overview of the project's objectives, methodology, and outcomes. The report begins with an introduction that outlines the project's background, significance, and research questions. The literature review section presents an in-depth analysis of relevant literature that informs the project's conceptual framework. The requirement analysis section details the project's specific requirements, including the system's functional and non-functional requirements. The system design section presents the system architecture, data modelling, and software design. The methodology section provides an overview of the research design, data collection, and analysis techniques used in the project. The results and analysis section presents the project's findings and analysis, including data visualizations and statistical analysis. Finally, the conclusion summarizes the project's key findings, contributions, and limitations, and provides recommendations for future research.

CHAPTER 2. LITERATURE REVIEW

In an attempt to overcome the problem of identifying numerous diseases in rice or paddy crop farming, various image processing techniques and machine learning algorithms have been used. Shruthi U, Nagaveni V, Raghavendra B K [4] proposed “A review on machine learning classification techniques for plant disease detection” shows different machine learning classification are used to detect the crop disease. The different classification methods are Artificial Neural Network (ANN) classification technique, K-nearest neighbour classification technique, Convolutional Neural Network classification, fuzzy classifier and Support Vector Machine (SVM) classification methods. From above mentioned techniques Convolutions Neural Network provides high accuracy compared to other methods and detect number of diseases in multiple crops.

V.Vanitha [5] proposed “Rice disease detection using deep learning” which proposes an automatic disease detection using deep neural network. The developed model can detect 3 different disease of paddy and also detect the healthy leaf image. The dataset was trained with three CNN architectures and achieved a high accuracy of 99.53%.

Shamim Mahbub, Md. Abu Nasim, Md. Jahid Hasan, Md. Shahin Alom [6] proposed “Rice disease identification and classification by integrating support vector machine with deep convolutional neural network” represents a system to identify the rice disease and help the farmers to take proper decision to control the disease and help them to increase production. They have built an AI model by integration of Support Vector Machine (SVM) with Deep Convolutional Neural Network (DCNN). Model identifies and classifies nine types of rice diseases with an accuracy of 97.5%.

Anuradha badge [7] proposed “Crop disease detection using Machine learning: Indian Agriculture” how diseases affecting the less yield and how machine learning technique will help us to detect the disease and help the farmers to take necessary

action. They used Canny edge detection algorithm for the efficient detection of crop disease by taking image of crop.

Suraksha et.al [8] proposes a technique which predicts the disease that the paddy crop is suffering by using data mining and image processing techniques. In the paper they have proposed a model for detecting diseases that the paddy plant is suffering from using feature extraction and data mining techniques.

R Rajmohan et.al [9] has proposed a technique which detects the disease that the paddy crop is suffering from by using CNN and SVM classifier. Their model uses feature extraction and SVM classifier for image processing. They have taken 250 images. They have used 50 images for testing and the rest 200 images for training the model. They have also developed a mobile app which clicks the image of the infected plant, zooms it and crops it and then uploads the image and the person receives a notification.

Lipsa Barik [10] has proposed a technique for region identification of Rice disease using image processing. The author has proposed a model which not only identifies the disease that the rice plant is suffering from but also identifies the affected region. The author has used image processing and for classification the author has used machine learning techniques like Naïve Bayes and Support Vector machines. After the prediction is done the severity of the disease is found out and then it is classified into different category.

Anuradha Badage [11] has presented a model for the detection of the disease that the plant is suffering from. The author has used canny edge detection algorithm. The author has used the canny edge detection algorithm to track the edge and get the histogram value to predict the disease that the plant is suffering from. The model also periodically monitors the cultivated field. The model detects the disease in the early stages. Then machine learning is used for training. Then the model takes proper decision and predicts the disease that plant is suffering from.

K.Jagan Mohan et.al [12] presents a model for detecting disease the paddy plant is suffering from. They have used Scale Invariant Feature Transform which extracts the features. The features are then taken and with the help of the features the model detects the disease with the help of SVM and K Nearest Neighbours classifiers.

Dhaygude S. B. et.al [13] presents a model which predicts the disease that the rice plant is suffering from. There are four steps. In the first step RGB transformed image is generated. Then HSI images are generated using the converted RGB. Then the masking of green pixels is done by taking threshold as a parameter followed by segmentation of images and useful feature extraction. At last the texture satisfied is computed from SGDM matrices. After that the evaluation of presence of disease in the leaf is calculated.

Jayanthi, G. et.al [14] proposed a model on analysis of automatic rice disease classification using Image processing techniques. Their paper has presented a detailed study of the different image classification algorithms.

S. Nithya et.al [15] proposes a model using big data. A symptom-based recommendation system has been made by them based on the paddy crop disease. The information of diseases is collected from numerous websites and blogs. The information has been analyzed through Hadoop, hive tools and HiveQ. The documents are collected and are represented in vector form using vector Space model and the weight is calculated based on the T-IDF ranking.

Arumugam, A. [16] proposes a model which follows a predictive modelling approach. This model aims to improve the paddy crop production by data mining techniques. Their work aims in providing a predictive modelling approach which will help the farmers to get high yield of paddy crops. They have used machine learning techniques like clustering and Decision trees. They have applied them to the meteorological data.

A large number of works have been done to estimate the diagnosis of paddy rice disease using digital image processing. Also, some algorithms have been implemented for feature choice. The goal of this project is to develop an Android Application Software for diagnosis of paddy rice disease and recommend pesticide to farmer.

CHAPTER 3. REQUIREMENT ANALYSIS

3.1 Functional Requirement

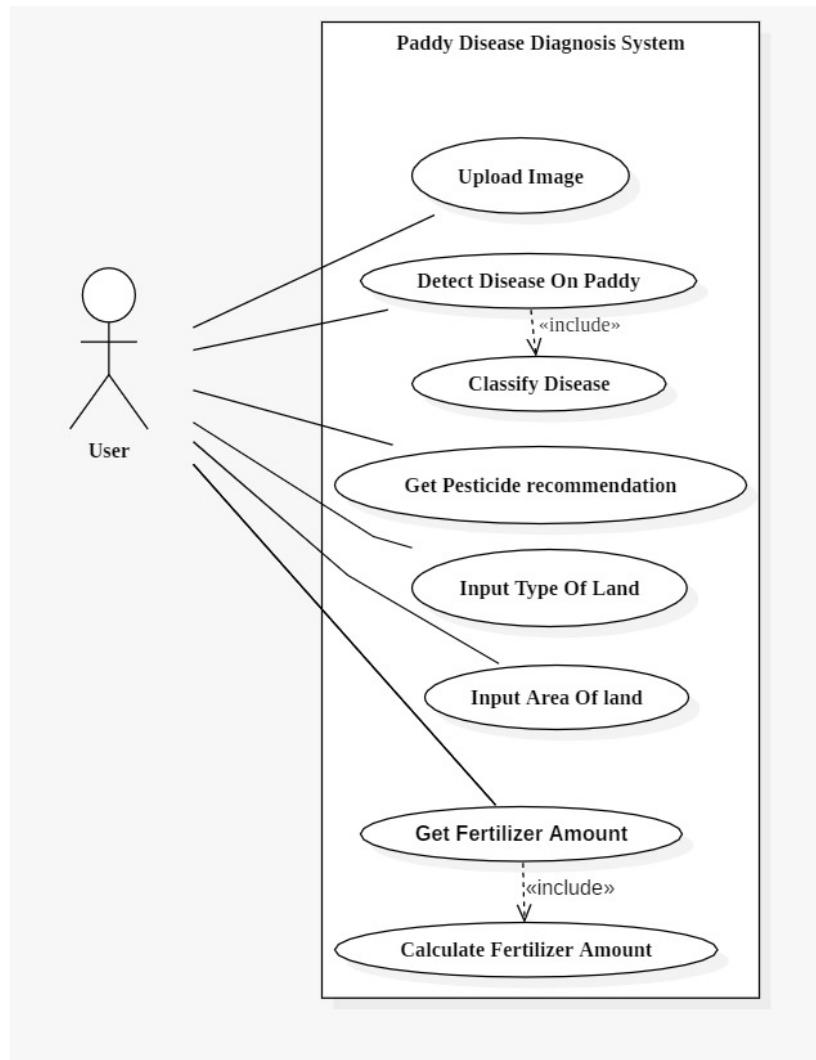


Figure 3.1: Use case diagram

3.1.1 Upload image

The system allows to upload the paddy leaf images.

3.1.2 Disease diagnosis

The system diagnosis the paddy disease in the uploaded or taken paddy rice image.

3.1.3 Classify disease

The system classifies the disease on the paddy.

3.1.4 Recommend Pesticide

The system recommends the pesticide based on the rule-based method.

3.1.5 Fertilizer calculation

The system calculates the amount of required fertilizer according to land area.

3.2 Non-Functional Requirement

3.2.1 Maintainability

The system can be easily maintained for the future purpose as the system design is simple.

3.2.2 Usability

The user-friendly nature and clear instructions on how to use it makes our system very easy to use for general public.

3.2.3 Compatibility

The system can be run easily over any PC as the system is device responsive.

3.3 Feasibility Study

A feasibility study is an analysis that considers all of a project's relevant factors, including technical, economic, operational, scheduling considerations to ascertain the likelihood of completing the project successfully. It assesses the practicality of a proposed plan or project. The study is also designed to identify potential issues and problems that could arise from pursuing the project. Thus, the feasibility of the system is evaluated in terms of the following categories:

3.3.1 Technical feasibility

The system is technically feasible, as the technologies are freely available and the technical skills required are manageable. Here the hardware component

requirement is also feasible and can run on normal mobile. Hence, it is technically capable of carrying out the project.

3.3.2 Operational feasibility

Operational feasibility includes design development parameters which checks if the final product developed is operated at client's side with an ease or not. The proposed project is operationally feasible as it provides users appropriate interface and better understandability. Farmer faces difficulty during finding the disease and providing pesticides. The system finds out the disease and recommend the required pesticides.

3.3.3 Economic feasibility

The system doesn't contain specific hardware requirement and can be run in any normal mobile. The system is app-based, all it requires is software resources which are freely available. So, the system can be easily developed and implemented in lower budget. Hence, it is economically feasible.

3.4 Software Development Approach

An iterative and incremental approach for software development using agile framework i.e Scrum is followed. Agile is an iterative approach to project management and software development that helps teams deliver value to their customers faster and with fewer headaches. Benefits of Agile include its ability to help teams in an evolving landscape while maintaining a focus on the efficient delivery of business value. The collaborative culture facilitated by Agile also improves efficiency throughout the organization as teams work together and understand their specific roles in the process.

Scrum is an agile framework within which people can address complex adaptive problems, while productively and creatively delivering products of the highest possible value. Scrum is a lightweight framework that helps people, teams and organizations generate value through adaptive solutions for complex problems. Prescribed events are used in Scrum to create regularity and to minimize the need

for meetings not defined in Scrum. All events are time-boxed. Once a Sprint begins, its duration is fixed and cannot be shortened or lengthened. The remaining events may end whenever the purpose of the event is achieved, ensuring an appropriate amount of time is spent without allowing waste in the process.

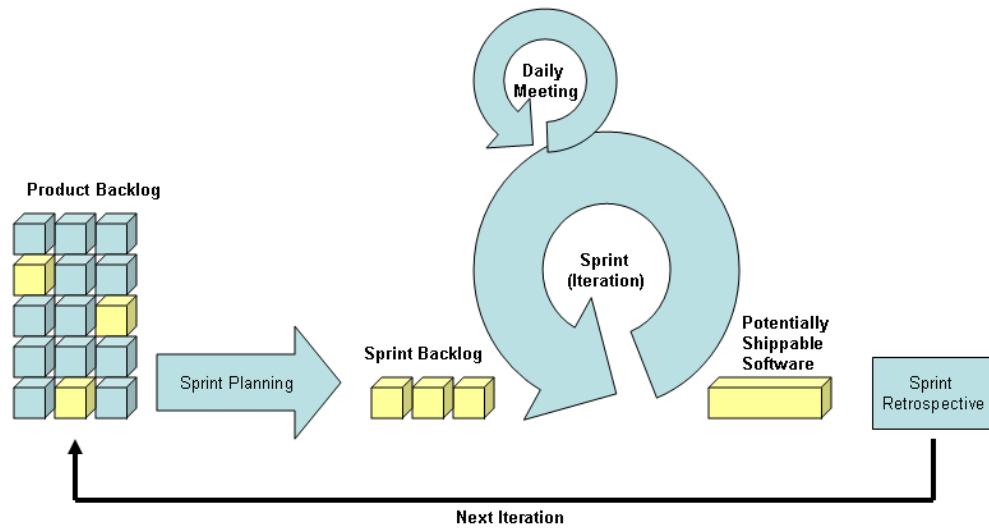


Figure 3.2: Scrum framework

CHAPTER 4. SYSTEM DESIGN

4.1 System Architecture Diagram for Disease Diagnosis

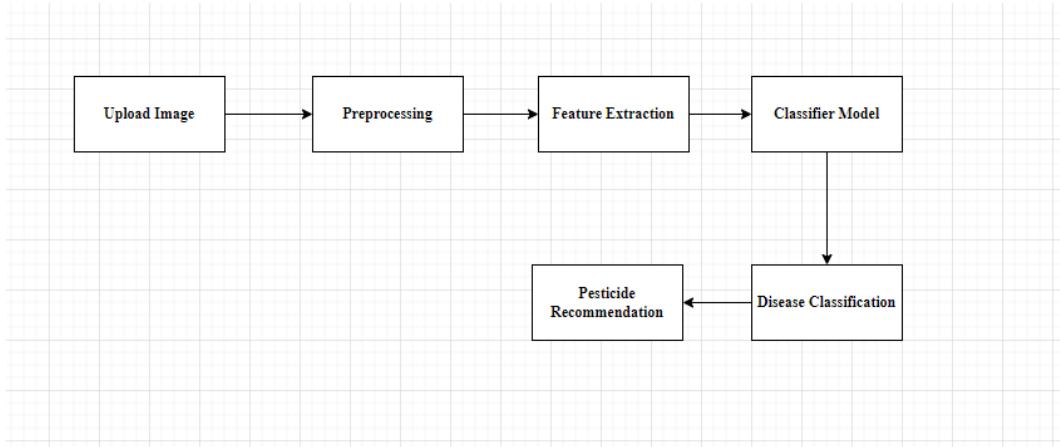


Figure 4.1: System architecture diagram for disease diagnosis

The system architecture for image classification using a Convolutional Neural Network (CNN) as a classifier involves multiple stages. First, the user uploads an image to the system. Then, the image is pre-processed to enhance its quality and make it suitable for input to the CNN. Next, the CNN extract features from the image using a series of convolutional and pooling layers. These features are then fed into fully connected layers to perform classification. The output of the CNN is a probability distribution over the different classes, which can be used to determine the most likely classification. Finally, the output is displayed to the user or used for further processing.

4.2 Flow chart for Fertilizer Calculation

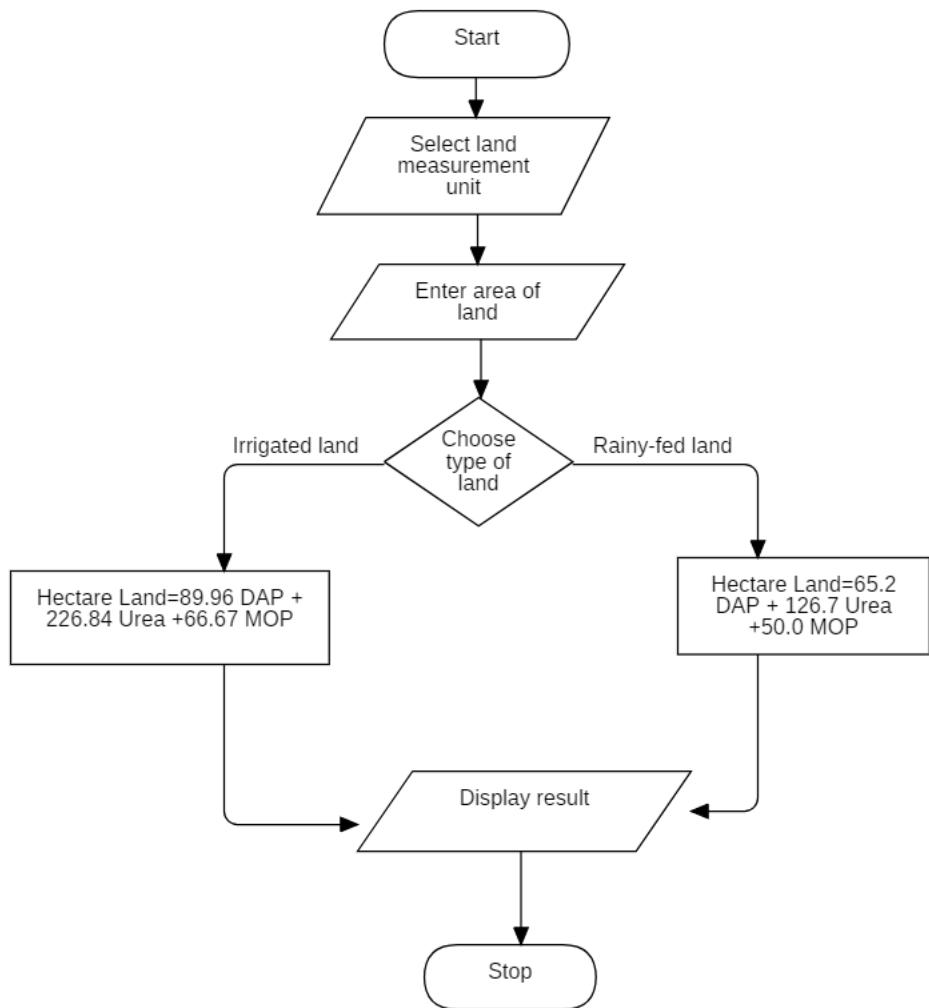


Figure 4.2: Flow chart for fertilizer calculation

Given diagram shows that at first user has to enter measurement unit and then user has to enter area of land after that user has to choose type of land. The, result will be displayed finally.

4.3 Activity Diagram for disease diagnosis

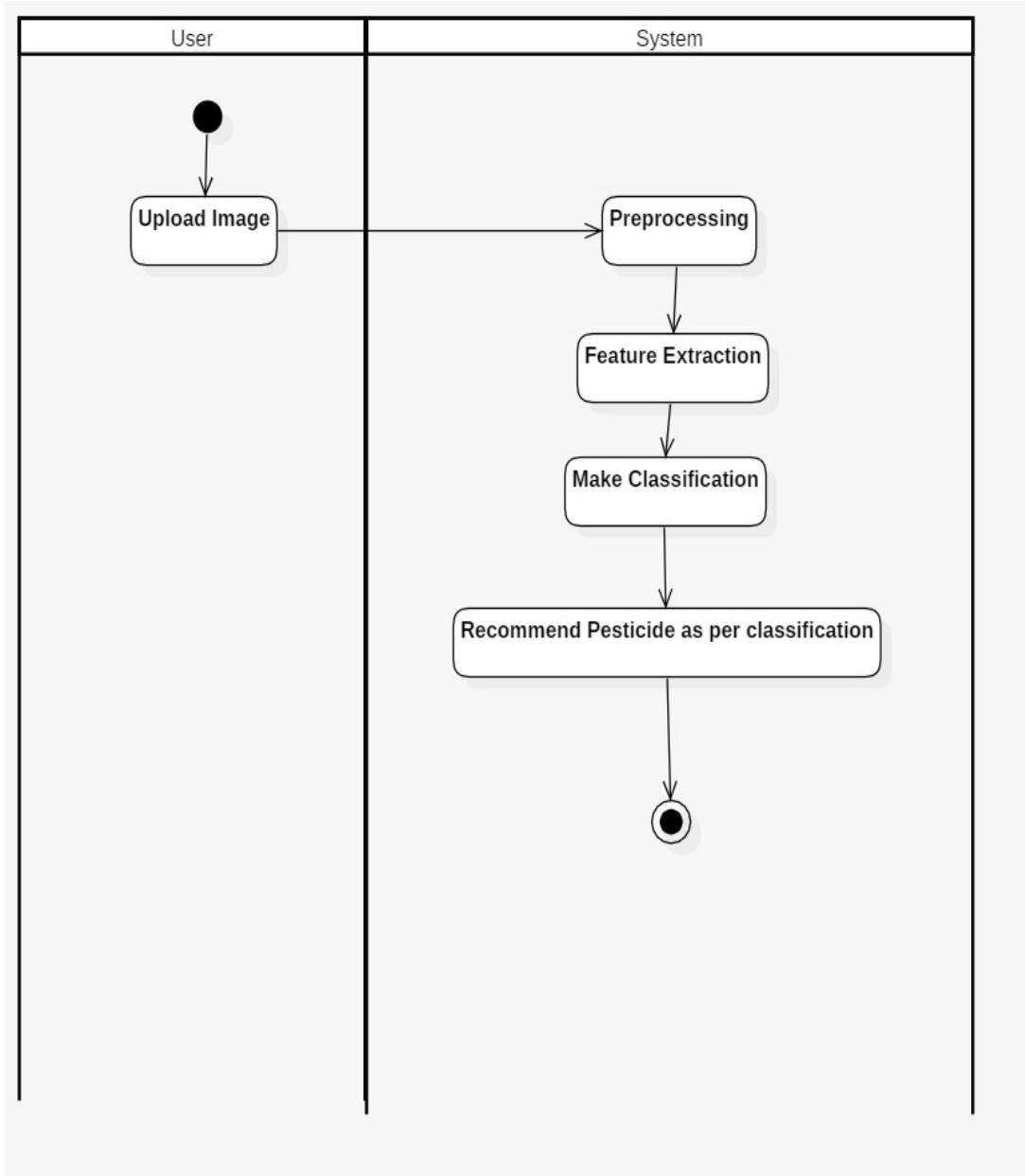


Figure 4.3: Activity diagram of the proposed system for disease diagnosis

The activity diagram for image classification using CNN as a classifier with integrated fertilizer calculation involves multiple steps. First, the user uploads an image to the system, which triggers the image preprocessing stage. The preprocessing stage involves enhancing the image quality and making it suitable for input to the CNN. After preprocessing, the image is passed to the feature extraction stage, which involves applying a set of convolutional filters to the image to extract

relevant features. The output of the feature extraction stage is then passed through one or more fully connected layers to perform classification. The output of the classification stage is a probability distribution over the different classes, which is displayed to the user.

.4.1 Activity Diagram for fertilizer calculations

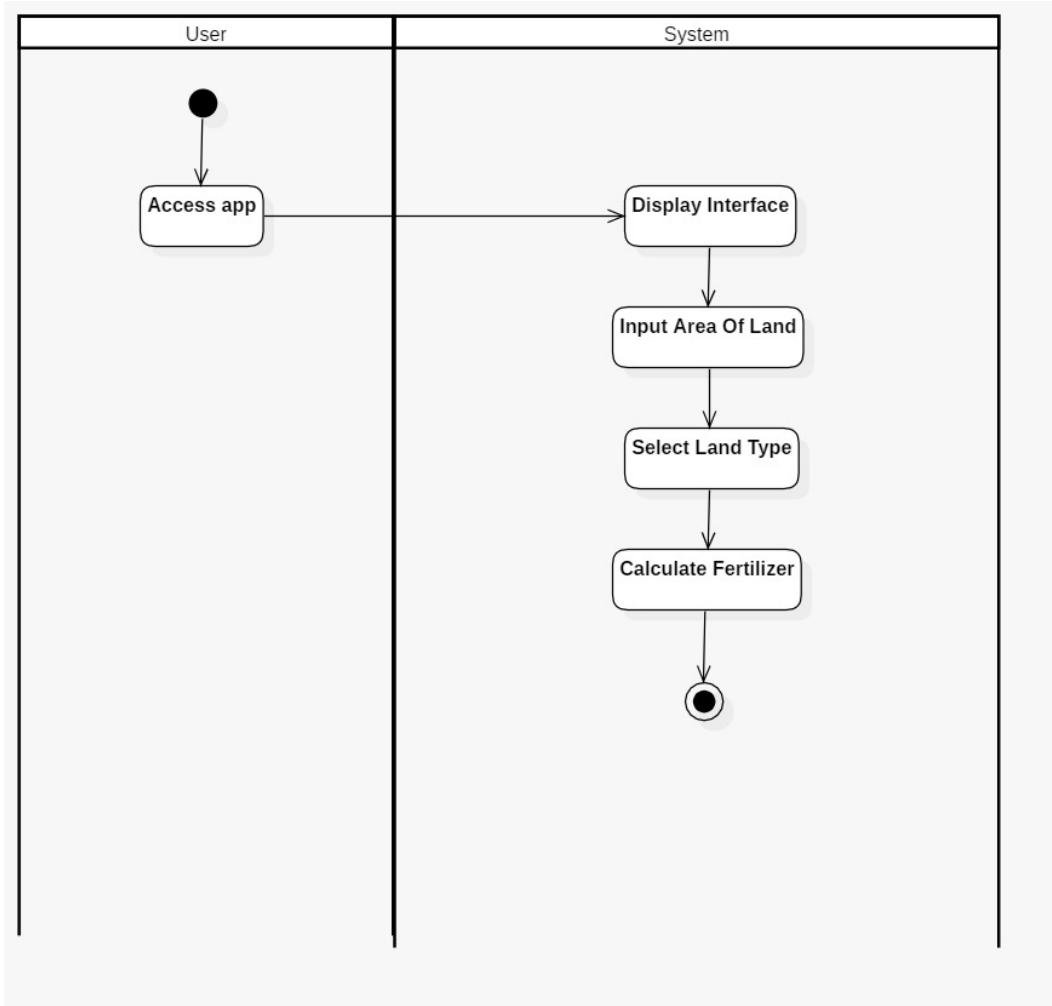


Figure 4.4: Activity diagram of the proposed system for fertilizer calculation

The system is integrated with a fertilizer calculation module. The user can choose to view the fertilizer requirements for the identified crop. The fertilizer calculation module takes into account land type and area as a factor. The output of the fertilizer calculation module is displayed to the user, along with recommendations on the type of fertilizer to use.

4.4 Data Flow Diagram

4.4.1 DFD-0

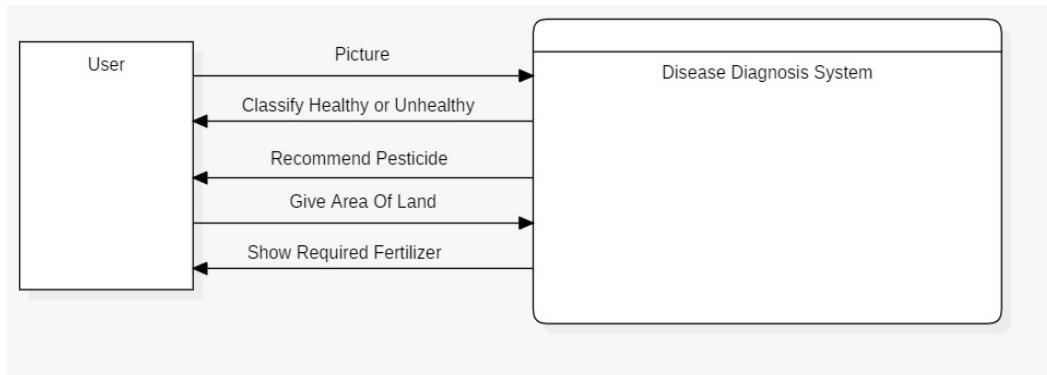


Figure 4.5: DFD-0

The level 0 data flow diagram (DFD) for paddy disease classification and fertilizer calculation with land area as input involves three main processes: input, processing, and output.

The input process involves the user entering the land area in hectares, which is then passed to the processing stage. The processing stage involves two sub-processes: disease classification and fertilizer calculation.

The disease classification sub-process involves the input of a paddy plant image, which is preprocessed and passed to a Convolutional Neural Network (CNN) for disease classification. The output of the CNN is a classification label, which is passed to the output stage.

The fertilizer calculation sub-process involves the input of the land area in hectares, as well as other relevant data such as soil type and crop history. This data is used to calculate the optimal amount of fertilizer required for the field. The output of the fertilizer calculation is then passed to the output stage.

The output process involves displaying the output of both sub-processes to the user. This includes the disease classification label and the recommended amount and type of fertilizer to use for the given land area.

Overall, the level 0 DFD for paddy disease classification and fertilizer calculation with land area as input involves three main processes: input, processing, and output. The processing stage has two sub-processes, one for disease classification and one for fertilizer calculation, both of which have inputs and outputs that are passed to the output stage for display to the user.

4.4.2 DFD-1

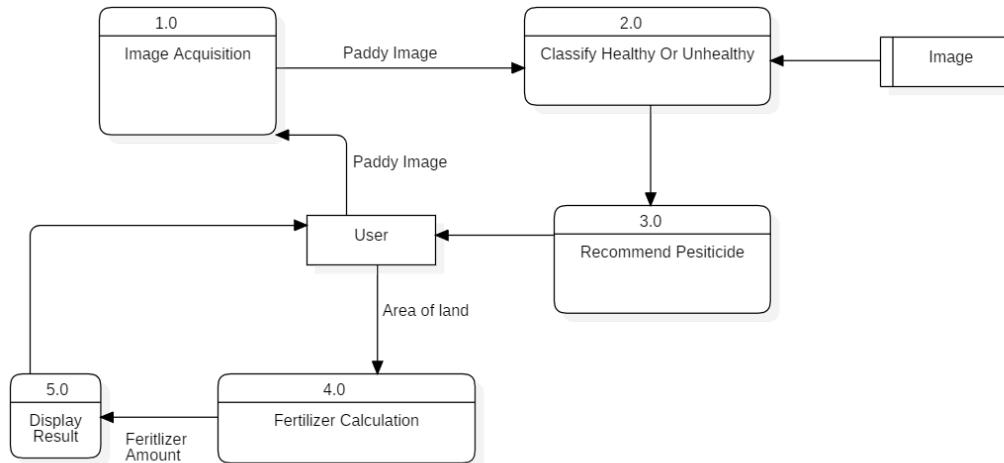


Figure 4.6: DFD-1

The Data Flow Diagram (DFD) Level 1 for the Paddy Disease Diagnosis System using CNN and Fertilizer Calculation System is a high-level representation of the system's functional components and the data flow between them. The system comprises two major components, the Paddy Disease Diagnosis System, and the Fertilizer Calculation System.

The Paddy Disease Diagnosis System uses Convolutional Neural Networks (CNN) to diagnose paddy diseases from images. The system receives input in the form of paddy plant images from farmers or users, which are then processed by the CNN

model. The output of the system is the diagnosis of the disease and the recommended treatment.

The Fertilizer Calculation System, on the other hand, calculates the appropriate amount of fertilizer needed for the paddy plants based on the soil type, plant type, and other parameters. The system takes input in the form of soil test results and plant type, and it outputs the recommended amount of fertilizer for the plants.

The two components of the system are integrated in such a way that the output of the Paddy Disease Diagnosis System is used as input for the Fertilizer Calculation System. The recommended treatment from the Paddy Disease Diagnosis System is used to determine the appropriate fertilizer to apply to the plants.

The DFD Level 1 provides a high-level overview of the system's functional components, inputs, and outputs, and the data flow between them. The system's components are interconnected to facilitate the seamless flow of data between them, which helps to ensure the accurate diagnosis of paddy diseases and the optimal application of fertilizer.

CHAPTER 5. METHODOLOGY

5.1 Methodology For Diagnosis Of Disease

The procedure involves various processes to diagnosis of paddy disease using real camera images. The various processes involved are mentioned below:

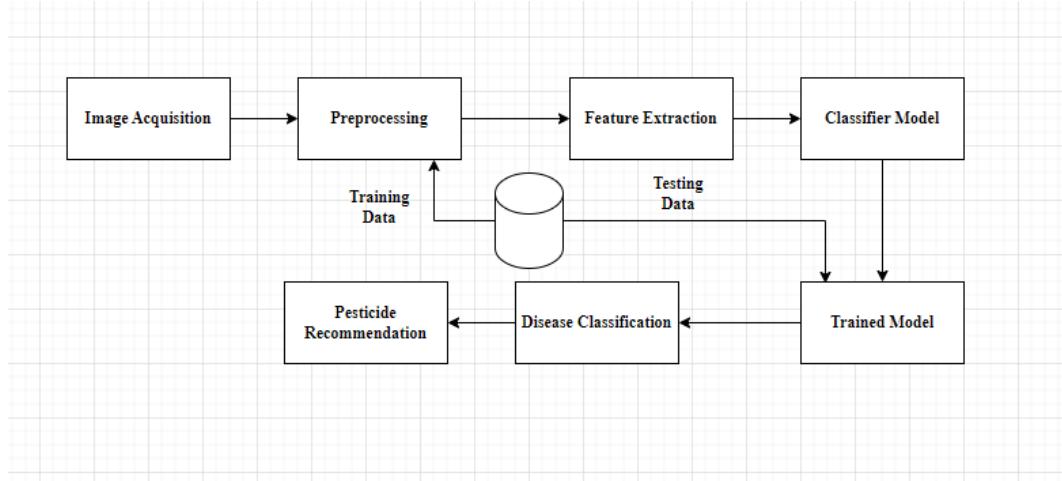


Figure 5.1: System block diagram for disease diagnosis

The system block diagram for disease diagnosis using image processing and machine learning techniques includes several key components. The process begins with acquiring images of affected plants or crops, which are then pre-processed to remove any noise or distortion. The images are then analyzed to extract relevant features, which are used as input to a classifier model. This model is trained using a set of labeled images of healthy and diseased plants, and the trained model is used to classify new images and provide a diagnosis of the disease. Finally, based on the diagnosis, the system recommends the appropriate pesticide or treatment for the affected plant or crop. Overall, this system block diagram provides a high-level overview of the various steps involved in automated disease diagnosis in plants and crops.

5.1.1 Image Acquisition

The rice images are taken from the paddy field. The data is validated by the pathologist from National Agricultural Research Institute (NARI).

Different places are visited to collect data. After the disease has been spotted, the sample and pictures are taken to the pathology lab of NARI and diagnosed by the experts. Different places visited along with disease diagnosed is mentioned below:

- i) Healthy paddy plant
Sample taken from: Sangha, Bhaktapur
GPS co-ordinate: 27.69432,85.36676
Sample Amount: 1764
- ii) Blast
Sample taken from: Bishankhunarayan, Godawari, Lalitpur
GPS co-ordinate: 27.60391,85.37507
Sample Amount: 1738
- iii) Bacterial Leaf blight
Sample taken from: Sangha, Bhaktapur
GPS co-ordinate: 27.69412, 85.37500
Sample Amount: 479
- iv) Brown-spot
Sample taken from: Kritipur, Kathmandu
GPS co-ordinate: 27.69404,85.31378
Sample Amount: 965
- v) Bacterial leaf streak
Sample taken from: Ramdhuni, Sunsari
GPS co-ordinate: 26.73447,87.21470
Sample Amount: 380
- vi) Bacterial panicle blight
Sample taken from: Itahari, Sunsari
GPS co-ordinate: 26.68570,87.27790
Sample Amount: 337

The rice images are taken for the diseases dead heart, downy mildew, hispa and tungro are taken from the online resources.

5.1.2 Image Dataset Pre-processing

Pre-processing is used for reshaping and moulding the input data. The images are all resized into the dimension of 224×224 pixels.

5.1.3 CNN based classification

Convolutional neural network (CNNs) is a deep learning neural network sketched for processing structured arrays of data. In the system, CNN image classification takes an input image and sees an input image as array of pixels and it depends on the image resolution.

Each input image is passed through a series of convolution layers with filters (Kernels), Pooling layer, fully connected layers (FC) and apply SoftMax function to classify an object with probabilistic values between 0 and 1. The below figure is a complete flow of CNN to process an input image and classifies the diseases based on values.

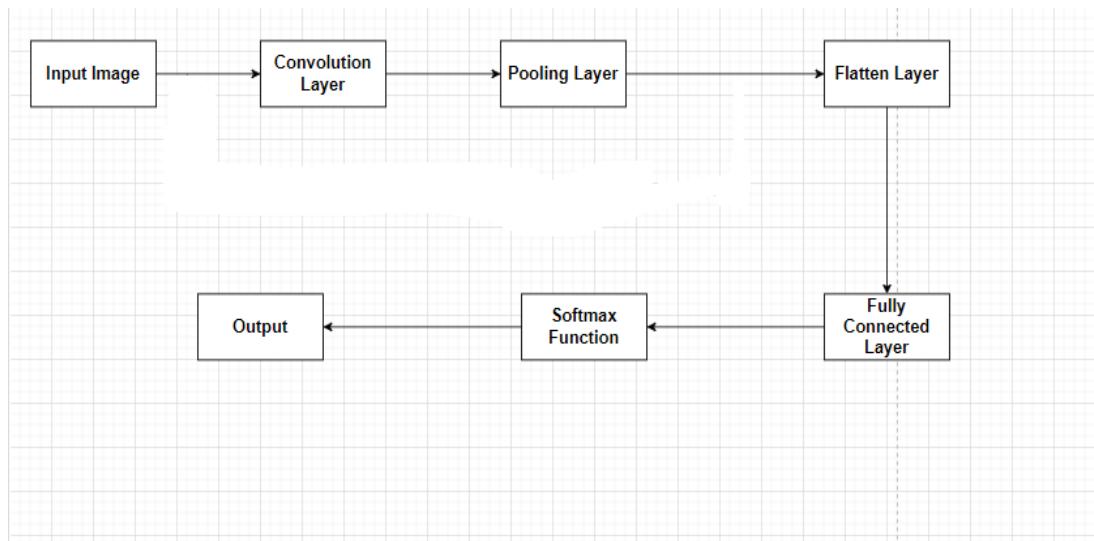


Figure 5.2: Convolution Neural Network

Convolution Layer

Convolution is the first layer to extract features from an input image. It is a mathematical operation that takes two inputs such as image matrix and a filter or kernel.

Strides

Stride is the number of pixels shifts over the input matrix.

Padding

The picture is padded with zeros (zero-padding) so that it fits or the part of the image is dropped where the filter did not fit, called valid padding which keeps only valid part of the image.

Non Linearity (ReLU)

ReLU stands for Rectified Linear Unit for a non-linear operation. The output is:

where x is the input.

Pooling Layer

Pooling layers section reduces the number of parameters when the images are too large. Spatial pooling also called subsampling or down-sampling which reduces the dimensionality of each map but retains important information. Spatial pooling can be of different types: Max Pooling, Average Pooling and Sum Pooling. Max pooling takes the largest element from the rectified feature map. Taking the largest element could also take the average pooling. Sum of all elements in the feature map call as sum pooling.

Flatten Layer

The feature map matrix is flattened into vector before feeding it into a fully connected layer like a neural network.

Fully connected layer

With the fully connected layers, all the features are combined together to create a model. Finally, an activation function such as soft-max function is used to classify the outputs.

5.1.3.1 Model building and Architecture

Stage I. Image augmentation

Image augmentation is a technique of applying different transformations to original images which results in multiple transformed copies of the same image. It is the addition of new data artificially derived from existing training data. Techniques include resizing, flipping, rotating, cropping, padding, etc. It helps to address issues like overfitting and data scarcity, and it makes the model robust with better performance.

Keras “ImageDataGenerator” class provides a quick and easy way to augment the images. It provides a host of different augmentation techniques like standardization, rotation, shifts, flips, brightness change, and many more which ensures that the model receives new variations of the images at each epoch. It requires lower memory usage.

The different augmentation technique used in the model are given below:

- Rescale=1.0/255.0,
- Validation split=0.3,
- Rotation range=5,
- Shear range=0.3,
- Zoom range=0.4,
- Width shift range=0.05,
- Height shift range=0.05,
- Horizontal flip=True,
- Vertical flip=True

Stage II. Splitting the datasets

The total dataset is divided in a 70%-30% manner which consists of 70% training set, 30% validation set.

Stage III. Mapping the labels

The labelling done in the range of the 0-9 for the different disease classes is given below:

- Healthy : 0
- Tungro : 1
- Hispa : 2
- Bacterial leaf Blight : 3
- Bacterial Leaf streak : 4
- Bacterial Panicle Blight : 5
- Blast : 6
- Brown spot : 7
- Dead Heart : 8
- Downy mildew : 9

Stage IV. Defining the Model's architecture

While creating CNN models, the different essential hyperparameter need to be determined. For this project, the layers are defined and described below for initializing the model.

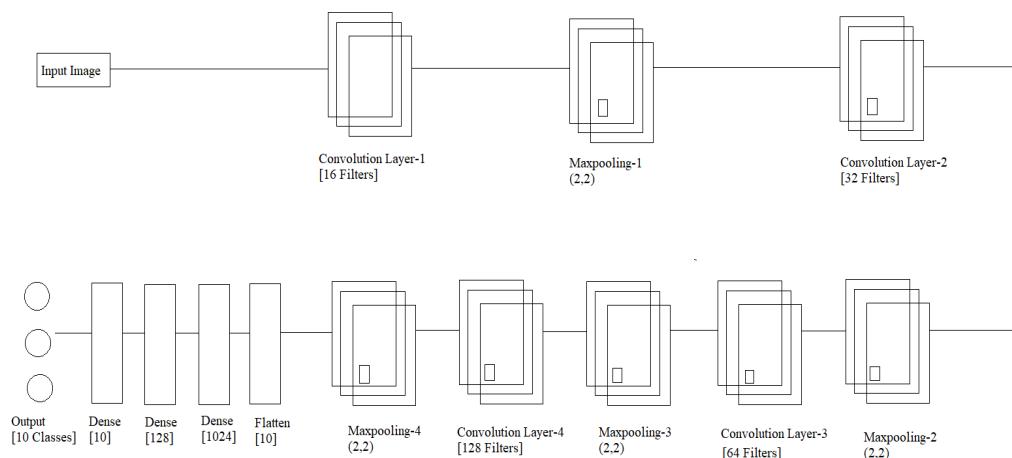


Figure 5.3: CNN architecture in the model

a) Layer 1:

Convolution was used initially on the input image of shape 224x224. Kernel size is (3, 3). 16 filters are used. The ReLu function is used as the activation function.

During max pooling, pool size = (2, 2) and strides = (2, 2).

b) Layer 2:

During 2nd convolution, Kernel size is (3, 3). 32 filters are used. The ReLu function is used as the activation function.

During max pooling, pool size = (3, 3) and strides = (3, 3).

c) Layer 3:

During 3rd convolution, Kernel size is (3, 3). 64 filters are used. The ReLu function is used as the activation function.

During max pooling, pool size = (2, 2) and strides = (2, 2).

d) Layer 4:

During 3rd convolution, Kernel size is (3, 3). 128 filters are used. The ReLu function is used as the activation function.

During max pooling, pool size = (2, 2) and strides = (2, 2).

e) Flatten layer:

The output matrix from layer 4 is initially flatten.

f) Dropout layer and dense layer:

The flatten output was passed to dense layer with filter size 1024 and 128 with activation function as ReLu respectively.

Again, the dense layer with filter size 10 and activation function as Softmax was passed for the classification of the output.

g) Optimization Layer:

An optimizer is an algorithm or function that adapts the neural network's attributes, like learning rate and weights. It assists in improving the accuracy and reduces the total loss. Adam optimizer is used with learning rate of 0.03.

The loss to be calculated is categorical cross entropy. Metrics to be evaluated by the model during training and testing is the accuracy of the model.

h) Defining checkpoint Layer:

Under the checkpoint layer, the validation accuracy is monitored. The file path was passed. This checkpoint was saved with the name callback which is necessary for back propagation.

Stage V. Training the Model

The “fit” function is used to train the model. The parameters that are passed to the function while training the model are:

- Train images and train labels.
- Validation images and validation labels.
- Epochs = 20.
- Batch size = 32.
- Verbose = 1.
- Callback = Checkpoint

Stage VI. Estimating the model's performance

The performance of the CNN algorithm is directly related to the parameters of the model. The validation image and validation labels is very essential for the evaluation of the performance of the model. Various graphs are derived while estimating model performance. The epoch vs loss graph and epoch vs accuracy graph are derived after training the model which are shown in Chapter 7.

5.1.3 Pesticide Recommendation

After the diagnosis of the paddy disease, pesticide is recommended using rule-based method as per the recommendation by the expert from the National Agricultural Research Institute (NARI). The quantity of the pesticide with respect to the land with procedure is recommended to farmer for the effectiveness of the pesticide. Pesticides is given as per the table below:

Table 5.1: Table for pesticide recommendation for different diseases

| Disease | Pesticide |
|--------------------------|--|
| Downy Mildew | Chlorothalonil and Mancozeb |
| Tungro | Fenthion 100 EC |
| Hispa | Malathion 50 EC |
| Bacterial leaf Blight | Copper oxychloride 50 WP (copper oxychloride), Nativo 75 WDG (Tebuconazole+trifloxystrobin), Gem Star Super 325 SC (azoxystrobin+difenconazole) and Bordeaux mixture |
| Bacterial leaf Streak | Terramycin 17, Brestanol, Agrimycin 500 and a combination of Agrimycin 100 + Fytolan |
| Bacterail panicle blight | Quinolone antibiotic oxolinic acid |

| | |
|------------|--|
| Blast | Tricyclazole 22% + Hexaconazole 3% SC fungicide |
| Brown spot | Iprodione, Propiconazole, Azoxystrobin, Trifloxystrobin, and carbendazim |
| Dead heart | Azadirachtin 0.03% 400 ml/ac |

5.2 Methodology For Fertilizer Calculation

The calculation of fertilizer with respect to the area of land based is implemented by adopting the following algorithm.

Algorithm:

- i. Select land measurement unit.
- ii. Enter area of the land.
- iii. Choose the type of land, either irrigated or rainy-fed.
- iv. Calculate Fertilizers quantity required as per the below formulas.

For irrigated land,

$$\begin{aligned}
 & 1 \text{ Hectare land} \\
 & = 86.96 \text{ DAP} + 226.84 \text{ Urea} \\
 & + 66.67 \text{ MOP} \dots \dots \dots \text{Equation 5.2}
 \end{aligned}$$

For rainy-fed land,

$$\begin{aligned}
 & 1 \text{ Hectare land} \\
 & = 65.2 \text{ DAP} + 126.7 \text{ Urea} \\
 & + 50.0 \text{ MOP} \dots \dots \dots \text{Equation 5.3}
 \end{aligned}$$

- v. Display result.

5.3 Tools And Technique

5.3.1 Tensorflow

TensorFlow is a free and open-source software library for machine learning and artificial intelligence. It can be used across a range of tasks but has a particular focus on training and inference of deep neural networks. We used tensorflow for training our CNN model.

5.3.2 Python

Python is a high-level, interpreted, interactive and object-oriented scripting language. Python is designed to be highly readable. It is widely used for web development, software development, mathematics, system scripting and machine learning. Its high-level built in data structures, combined with dynamic typing and dynamic binding, make it very attractive for Rapid Application Development, as well as for use as a scripting or glue language to connect existing components together.

5.3.3 Matplotlib

Matplotlib is a cross-platform, data visualization and graphical plotting library for Python and its numerical extension NumPy. It also provides an object-oriented API that enables it, in extending the functionality, to put the static plots in applications by using various Python GUI toolkits available (Tkinter, PyQt, etc.). It provides a user to visualize data using a variety of different types of plots to make data understandable. It is similar to plotting in MATLAB, as it allows users to have a full control over fonts, lines, colours, styles, and axes properties like MATLAB. It provides an excellent way to produce quality static-visualizations that can be used for publications and professional presentations.

5.3.4 Numpy

NumPy is the fundamental package for scientific computing in Python. It is a Python library that provides a multidimensional array object, various derived objects (such as masked arrays and matrices), and an assortment of routines for fast

operations on arrays, including mathematical, logical, shape manipulation, sorting, selecting, I/O, discrete Fourier transforms, basic linear algebra, basic statistical operations, random simulation and much more. At the core of the NumPy package, is the ndarray object. This encapsulates n-dimensional arrays of homogeneous data types, with many operations being performed in compiled code for performance.

5.3.5 Tkinter

Tkinter is a Python library that provides a graphical user interface (GUI) toolkit for developers to create desktop applications. It is one of the most commonly used GUI libraries for Python due to its simplicity and ease of use. Tkinter is a cross-platform library, which means that applications built using it can run on different operating systems such as Windows, macOS, and Linux. The library includes a set of tools and widgets that enable developers to create interactive and visually appealing user interfaces, such as buttons, labels, text boxes, and menus. Tkinter is an open-source library and is part of the Python standard library, which means that it comes pre-installed with Python and does not require any additional installations.

CHAPTER 6. RESULT AND ANALYSIS

6.1 Performance of the model

6.1.1 Accuracy and Loss

The accuracy and loss of the model for the 20 epoch is given below:

- Training loss: 0.3634
- Training accuracy: 0.8795
- Validation loss: 0.5702
- Validation accuracy: 0.8294

```
Epoch 13: ReduceLROnPlateau reducing learning rate to 3.000000106112566e-05.
456/456 [=====] - 781s 2s/step - loss: 0.6152 - categorical_accuracy: 0.7979 - val_loss: 0.8526 - val_categorical_accuracy: 0.7220 - lr: 3.0000e-04
Epoch 14/20
456/456 [=====] - ETA: 0s - loss: 0.4380 - categorical_accuracy: 0.8602
Epoch 14: val_categorical_accuracy improved from 0.77236 to 0.82110, saving model to /content/drive/MyDrive/keras_model_new.h5
456/456 [=====] - 794s 2s/step - loss: 0.4380 - categorical_accuracy: 0.8602 - val_loss: 0.5827 - val_categorical_accuracy: 0.8211 - lr: 3.0000e-05
Epoch 15/20
456/456 [=====] - ETA: 0s - loss: 0.4100 - categorical_accuracy: 0.8680
Epoch 15: val_categorical_accuracy improved from 0.82110 to 0.82462, saving model to /content/drive/MyDrive/keras_model_new.h5
456/456 [=====] - 803s 2s/step - loss: 0.4100 - categorical_accuracy: 0.8680 - val_loss: 0.5797 - val_categorical_accuracy: 0.8246 - lr: 3.0000e-05
Epoch 16/20
456/456 [=====] - ETA: 0s - loss: 0.3879 - categorical_accuracy: 0.8762
Epoch 16: val_categorical_accuracy did not improve from 0.82462

Epoch 16: ReduceLROnPlateau reducing learning rate to 3.000000106112566e-06.
456/456 [=====] - 784s 2s/step - loss: 0.3879 - categorical_accuracy: 0.8762 - val_loss: 0.5664 - val_categorical_accuracy: 0.8214 - lr: 3.0000e-05
Epoch 17/20
456/456 [=====] - ETA: 0s - loss: 0.3877 - categorical_accuracy: 0.8793
Epoch 17: val_categorical_accuracy improved from 0.82462 to 0.82623, saving model to /content/drive/MyDrive/keras_model_new.h5
456/456 [=====] - 766s 2s/step - loss: 0.3877 - categorical_accuracy: 0.8793 - val_loss: 0.5746 - val_categorical_accuracy: 0.8262 - lr: 3.0000e-06
Epoch 18/20
456/456 [=====] - ETA: 0s - loss: 0.3684 - categorical_accuracy: 0.8838
Epoch 18: val_categorical_accuracy improved from 0.82623 to 0.83232, saving model to /content/drive/MyDrive/keras_model_new.h5
456/456 [=====] - 795s 2s/step - loss: 0.3684 - categorical_accuracy: 0.8838 - val_loss: 0.5558 - val_categorical_accuracy: 0.8323 - lr: 3.0000e-06
Epoch 19/20
456/456 [=====] - ETA: 0s - loss: 0.3711 - categorical_accuracy: 0.8808
Epoch 19: val_categorical_accuracy did not improve from 0.83232

Epoch 19: ReduceLROnPlateau reducing learning rate to 3.000000106112566e-07.
456/456 [=====] - 786s 2s/step - loss: 0.3711 - categorical_accuracy: 0.8808 - val_loss: 0.5650 - val_categorical_accuracy: 0.8317 - lr: 3.0000e-06
Epoch 20/20
456/456 [=====] - ETA: 0s - loss: 0.3634 - categorical_accuracy: 0.8795
Epoch 20: val_categorical_accuracy did not improve from 0.83232
456/456 [=====] - 748s 2s/step - loss: 0.3634 - categorical_accuracy: 0.8795 - val_loss: 0.5702 - val_categorical_accuracy: 0.8294 - lr: 3.0000e-07
```

Figure 6.1: Screenshot of the training model at 20 Epoch

6.1.2 Epoch vs Loss Graph

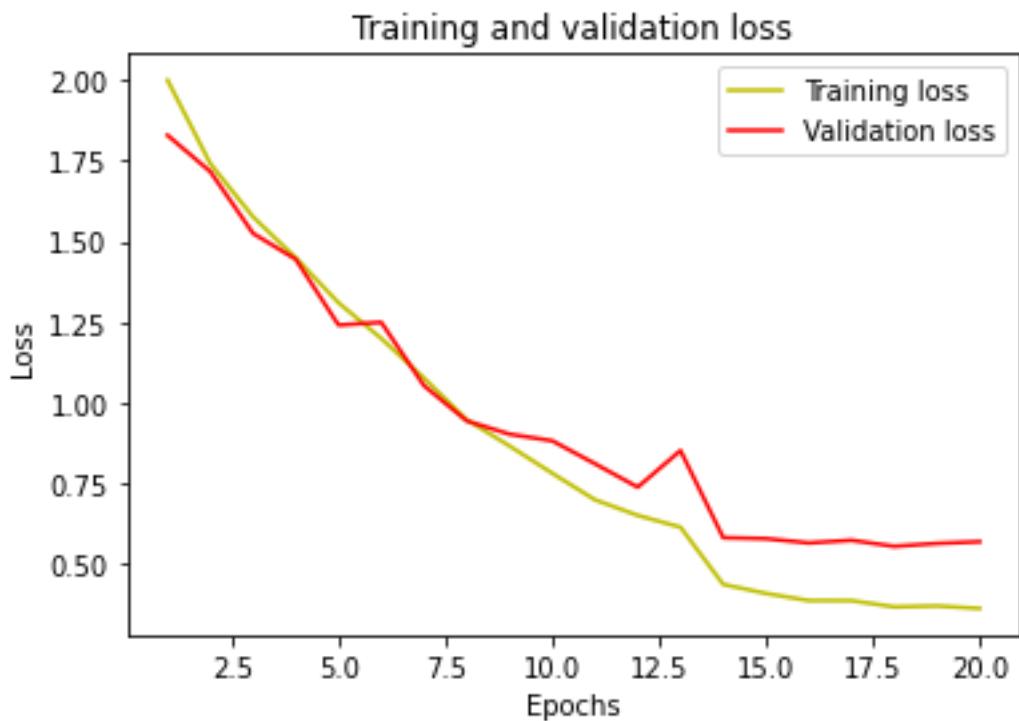


Figure 6.2: Epoch Vs Loss Graph

From graph, At the beginning of training, the loss is typically high as the model is making random predictions. As the number of epochs increases, the model gradually learns to make better predictions, and the loss decreases.

6.1.3 Epoch vs Accuracy Graph

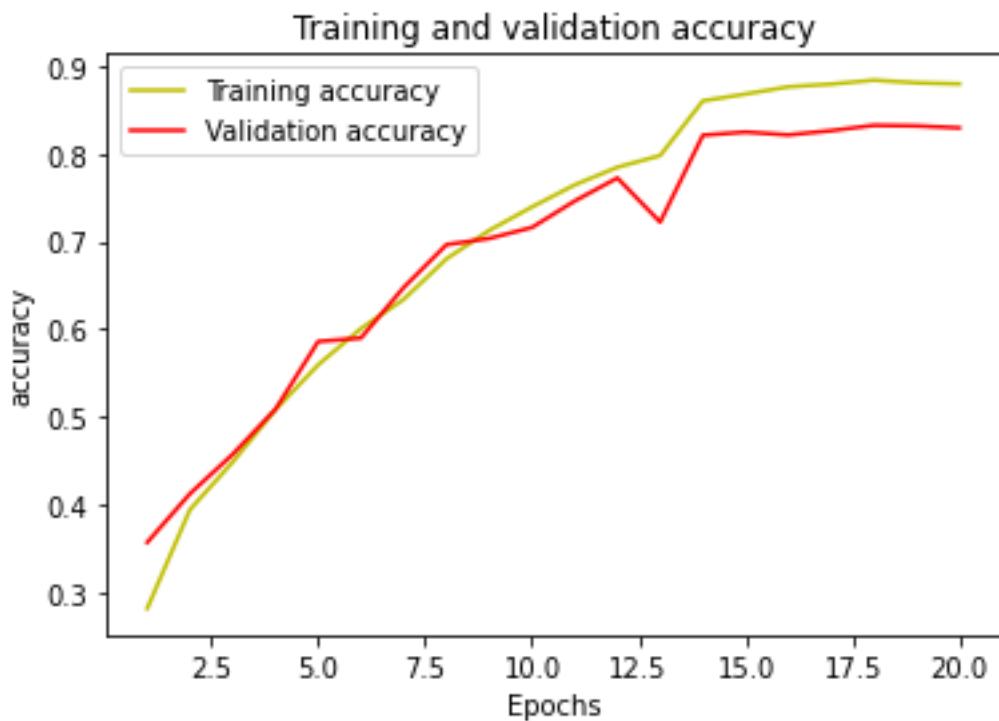


Figure 6.3: Epoch Vs Accuracy Graph

From graph, At the beginning of training, the accuracy may be relatively low as the model is making random predictions. However, as the number of epochs increases, the model gradually learns to make better predictions, resulting in an improvement in accuracy.

6.1.4 Confusion Matrix

Confusion Matrix for our model is given below:

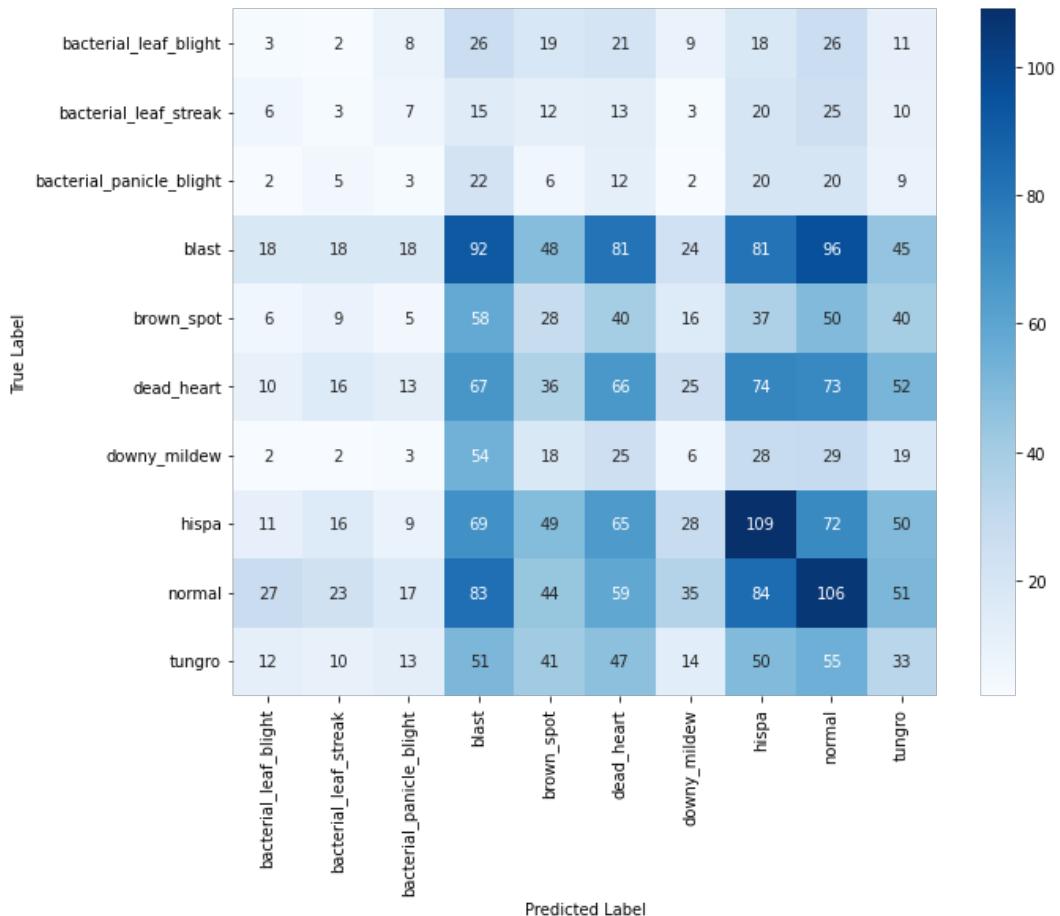


Figure 6.4: Confusion Matrix

A confusion matrix is a table that is used to evaluate the performance of a machine learning model. It is used when working with classification problems, where the goal is to predict the class label of a given input.

The matrix is organized into rows and columns, with each row representing the actual class labels and each column representing the predicted class labels. The cells of the matrix show the number of predictions made by the model that match or do not match the actual class labels.

6.1.5 Classification Report

A classification report provides a summary of the model's performance in terms of precision, recall, and F1-Score for each class, as well as overall weighted average of these measures. It is a way to evaluate the model's effectiveness in correctly predicting each class. It is usually presented alongside a confusion matrix which shows the model's performance in terms of how many instances were classified correctly or incorrectly for each class.

Precision measures the proportion of the instances predicted as positive that were actually positive, while recall measures the proportion of actual positives that were correctly identified. F1-score is the harmonic mean of precision and recall, providing a single score that balances both measures. The weighted average takes into account the number of instances in each class, so that classes with more instances have a greater influence on the overall score.

The classification report generated for the system using Scikit-learn “classification_report” is mentioned below:

Table 6.1: Table of classification report

| Class Index | Precision | Recall | F1-score | Support |
|-------------|-----------|--------|----------|---------|
| 0 | 0.05 | 0.04 | 0.05 | 143 |
| 1 | 0.04 | 0.04 | 0.04 | 114 |
| 2 | 0.04 | 0.04 | 0.04 | 101 |
| 3 | 0.15 | 0.16 | 0.15 | 521 |
| 4 | 0.09 | 0.09 | 0.09 | 289 |
| 5 | 0.15 | 0.15 | 0.15 | 432 |
| 6 | 0.03 | 0.02 | 0.02 | 186 |
| 7 | 0.20 | 0.20 | 0.20 | 478 |
| 8 | 0.18 | 0.19 | 0.19 | 526 |
| 9 | 0.10 | 0.10 | 0.10 | 326 |
| Accuracy | | | 0.14 | 3119 |

| | | | | |
|--------------|------|------|------|------|
| Macro avg | 0.10 | 0.10 | 0.10 | 3119 |
| Weighted avg | 0.13 | 0.14 | 0.13 | 3119 |

6.1.6 Prediction:

Some of the random images of paddy were given and then tested to check whether it predicts right or not. We found the following results:



Figure 6.5: Prediction of paddy disease

6.1.7 Fertilizer Calculation:

Land area was given to find out how much fertilization our system recommends. We observed the following result:

The screenshot shows a software window titled "PADDY DISEASE DIAGNOSIS AND FERTILIZER CALCULATION SYSTEM". At the top, there are standard window controls for minimize, maximize, and close. Below the title bar, a text input field says "Enter the area of the land(in HECTARE):" followed by a value of "15". To the right of the input field is a "Calculate" button. Underneath the input field, a dropdown menu is set to "Irrigated Land". At the bottom of the window, the text "Required fertilizer: 1304.3999999999999 DAP + 3402.6 UREA + 1000.0500000000001 MOP" is displayed.

Figure 6.6: Fertilizer for irrigated land

The screenshot shows a software window titled "PADDY DISEASE DIAGNOSIS AND FERTILIZER CALCULATION SYSTEM". At the top, there are standard window controls for minimize, maximize, and close. Below the title bar, a text input field says "Enter the area of the land(in HECTARE):" followed by a value of "15". To the right of the input field is a "Calculate" button. Underneath the input field, a dropdown menu is set to "Rain-fed Field". At the bottom of the window, the text "Required fertilizer: 978.0 DAP + 1900.5 UREA + 750.0 MOP" is displayed.

Figure 6.7: Fertilizer for Rain-fed land

CHAPTER 7: CONCLUSION AND FUTURE ENHANCEMENT

7.1 Conclusion

The paddy disease diagnosis system and fertilizer calculation system are valuable tools in the precision agriculture. The CNN-based disease diagnosis system can accurately classify the different diseases affecting paddy crops, enabling farmers to take timely action to prevent crop loss. Additionally, the fertilizer calculation system can help farmers optimize their use of fertilizers by recommending the appropriate amount of fertilizer based on soil conditions and crop requirements. Together, these systems can help increase crop yields, reduce wastage of resources, and improve farmers' income.

7.2 Limitations

The limitations of the project are:

- The system cannot recommend fertilizer on the basis of exact location of field.

7.3 Future Enhancement

This project can be made better in future by applying following concepts:

- Create a mobile app for portability.

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APPENDICES



Figure: Sample taken in Nepali paper



Figure: Disease being diagnosed by the Expert at NARI, Khumaltar

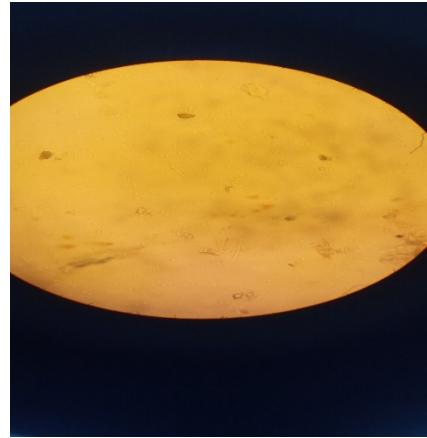


Figure: Microscopic view of disease seen at Compound Microscope

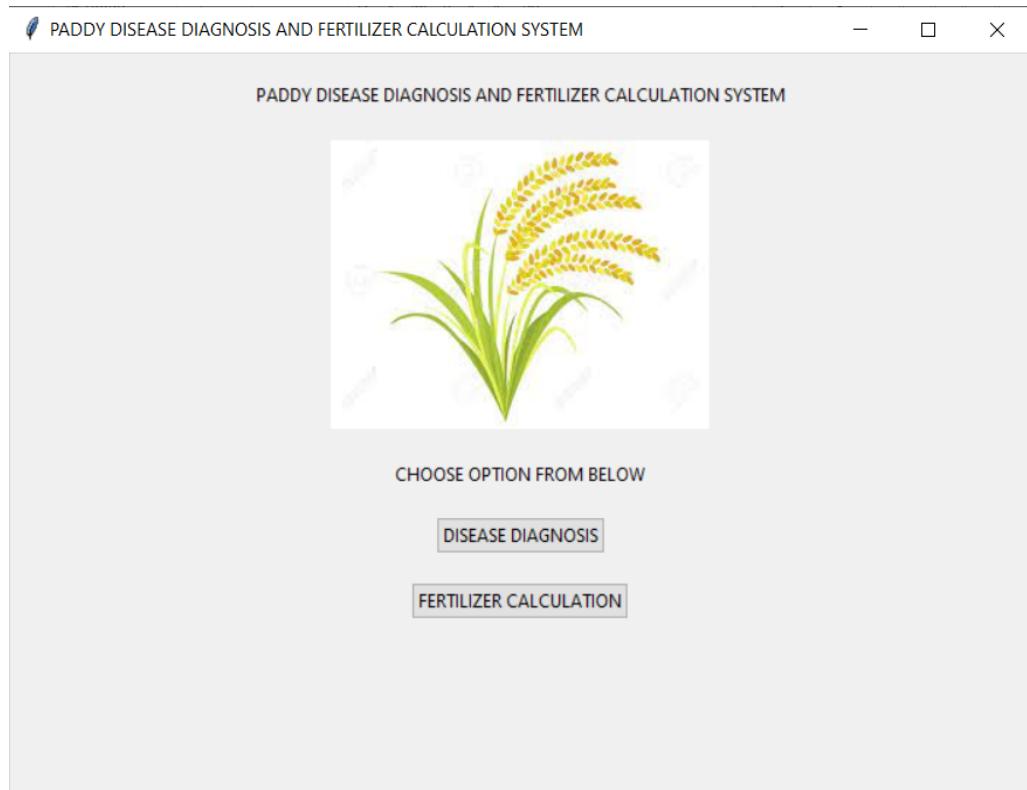


Figure: User interface of the system