# DOCTOR PADDY: AN AI-POWERED RICE CROP DISEASES IDENTIFICATION AND MANAGEMENT SYSTEM

A thesis submitted by


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Submitted in the partial fulfillment of the requirements for the degree of Bachelor of Science in Computer Science


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November 2023

# CERTIFICATE

This is to certify that “**PROJECT/THESIS REPORT ON DOCTOR PADDY: AN AI-POWERED RICE DISEASES IDENTIFICATION AND MANAGEMENT SYSTEM** is submitted in partial fulfillment of the requirement for the degree of Bachelor of Science in Computer Science by the following students:

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ACKNOWLEDGEMENT

First of all, we are very much thankful to the Almighty Allah for giving us strength and showing us the righteous paths to conduct the study and to develop the project which is in the best interests of the betterment of humanity.

Our whole hearted gratitude goes to our project supervisor **Dr. Sammer Zai**, for her significant guidance, encouragement, appreciation and inspiration. In particular, we are very much thankful for the greatest counseling and the precious time she devoted for the supervision of our project.

Our greatest thanks go to **Prof. Dr. Shahnawaz Talpur**, Chairman Computer Systems Engineering, Mehran University of Engineering and Technology, Jamshoro, who always remained cooperative and supportive. his encouragement and appreciation made us able to work effectively and efficiently.

Special Thanks to **Department of Crop Production, SAU, Tandojam** and **Rice research center Tandojam**, for without their fruitful guidance towards understanding rice crop diseases and helpful insights over current issues faced by the regional farmers and field assistants, the success of this project was not possible.

Last, but not the least, we are grateful to our teachers, family and friends for their cooperation and help in all respects during study period which enabled us to progress expeditiously.

# ABSTRACT

Rice, one of Pakistan's main crops, is essential to the country's agricultural system, rice is grown on millions of hectares and produces about 7 million tons of grain year; it is an essential source of nutrition for Pakistan's expanding population as well as a means of living for many farmers. Despite its significance, this sector's development has failed in many places, which has led to yield losses. The primary causes of this problem are diseases and natural disasters that impact paddy leaves, especially when these diseases strike the plant at an early stage of growth. But technological developments could completely change how diseases are identified and treated in rice fields. This thesis introduces "Doctor Paddy: An AI-Powered Rice Crop Diseases Identification and Management System." A technology which provides real-time disease diagnostics by analyzing photos of rice crops using cutting-edge machine learning algorithms. Our goal is to improve the sustainability of Pakistani rice production by providing a simple and easy-to-use tool for disease management. Our strategy is centered on increasing the accuracy and efficiency of disease diagnosis, giving farmers the tools, they need to manage their crops, and eventually enhancing their standard of living.

Its methodology includes gathering data of various paddy leaves that are infected with diseases, preparing the data to standardize datasets, training and testing ML models, evaluating the models with various metrics, optimization, creating an intuitive web application, and doing real-world testing to get feedback.

The project's results show an amazing 80–85% accuracy rate of our ResNet-50 model in recognizing and classifying diseases affecting rice crops, providing farmers in Pakistan's agricultural industry with substantial improvements.

# Table of Contents

# List of figures

# List of Abbreviations

| | |
|---|---|
| AI | Artificial Intelligence |
| ANNs | Artificial Neural Networks |
| API | Application Programming Interface |
| CEP | Complexity |
| CNNs | Convolutional Neural Networks |
| CSS | Cascading Style Sheets |
| FE | Feature Extraction |
| FS | Feature Scaling |
| HTML | Hyper Text Markup Language |
| IOT | Internet Of Things |
| IPM | Integrated Pest Management |
| JS | Java Script |
| KNN | K-Nearest Neighbors |
| LGBM | Light Gradient Boosting Machine |
| ML | Machine Learning |
| MLMs | Machine Learning Models |
| ResNet | Residual Neural Network |
| SDGs | Sustainable Development Goals |
| SVM | Support Vector Machine |
| VGG | Visual Geometry Group |

# Chapter 1

## INTRODUCTION

Rice is a staple and a major source of income for Pakistan. It makes up fifteen percent of the foreign exchange profits. Its productivity, yield per hectare, and area under cultivation all demonstrate its significance. This crop thrives in areas where it is impossible to cultivate other crops or where there is a plenty of water available for irrigation during the summer, or Kharif. Rice prefers a soil pH of 5.0–6.5, and Cheema et al. (1991) report that rice is moderately tolerant of an exchangeable sodium percentage (ESP) of 20–40% [1]. Additionally, according to the 1961 WAPDA report, this crop may withstand soil containing up to 0.40-0.60 percent white alkali and 0.10-0.20 percent black alkali [2]. Because rice needs a steady supply of water, it is often planted on thick clay soils with an impermeable subsurface layer (hard pan) that restricts drainage. Because flooding removes salts from the soil, rice production can be utilized to recover salty soils.

One reason for the low rice yields worldwide (including in Pakistan) is the over forty diseases that affect the rice crop. Diseases can strike a plant at any point during its growth and development, targeting the seed planted, root system, leaves, stalk, leaf sheath, inflorescence, and even the grain that is still growing. Different infectious diseases are caused by bacteria, viruses, nematodes, and fungi. Non-infectious diseases can be brought on by extremes in temperature as well as variations in the levels of various nutrients that are vital to the crop [3]. Although there may be numerous other reasons for variations in output, illnesses cannot be disregarded, overlooked, or regretted since they also gradually reduce crop yield. All of these diseases can harm certain plant parts, certain years, and certain regions. Diseases can affect any portion of these illnesses can harm certain plant parts, certain years, plant, and almost any plant in any field can contract one or more diseases. All are of major concern due to their effects on the amount and/or quality of plants, straw, or grain, and they attract attention due to their symptoms or indicators [4].

Towards addressing these issues, we introduce "Doctor Paddy: An AI-powered Rice Crop Diseases Identification and Management System." This creative approach uses ML algorithms to quickly diagnose problems by analyzing photos of rice crops. Its goal is to give farmers an easy-to-use and accessible tool for managing and identifying diseases, therefore improving the sustainability of Pakistan's rice production. Our method uses artificial intelligence to increase the efficiency and accuracy of disease diagnostics, giving farmers more control over their crops and, consequently, better livelihoods.

## 1.1. BACKGROUND INFORMATION

Early It is extremely important to understand a few fundamental concepts before moving forward to understand the proposed method.

Here are some of the rice diseases outbreaks in Pakistan.

**Brown Spot:** Small, oval to spindle-shaped lesions on the leaves are the hallmark of this common rice disease, In Pakistan, brown spot is a persistent problem in rice production. It is more common in areas with a lot of rainfall and humidity. The disease mostly affects rice leaves, which lowers photosynthesis and can result in yield losses if left untreated. [5]

**Dead Heart:** Bacteria and fungus are among the several pathogens that cause this serious infection in rice. It is strongly associated with unfavorable soil conditions and environmental factors. Pakistani rice farmers have long struggled with dead heart, which is frequently brought on by insects that bore holes in stems. Early in the rice crop's life, infestations usually cause the center leaves to wither and eventually die.

**Downy Mildew:** Downy Mildew is a disease that affects the upper surface of leaves. It is brought on by the pathogen Peronosclerospora oryzae and is identified by the emergence of pale green to yellow lesions. Downy mildew has been reported in Pakistani areas that grow rice. It affects grain quality and yield and is linked to damp, humid weather. It causes gray to white lesions on the undersides of leaves. [6]

**Hispa:** Often referred to as the Rice Hispa (Dicladispa armigera), Hispa is a significant pest that harms rice harvests. A major pest in Pakistani rice fields, Hispa is a leaf-rolling insect. It rolls and holes rice leaves in a way that is characteristic of the harm it does. Reports of Hispa infestations have been made in areas where the pest's circumstances are ideal.

**Tungro:** Reports of the viral disease, which is spread by leafhoppers, have been made in Pakistan's rice-growing regions. It is a serious danger to rice production, especially in areas where leafhopper populations are large. A concoction of the rice tungro bacilliform virus (RTBV) and the rice tungro spherical virus (RTSV) causes rice tungro, a viral illness. Plants that are infected display symptoms like reduced grain size, yellowing of the leaves, and stunting. The disease is especially dangerous since it can cause large crop losses in rice fields and is spread by the green leafhopper bug. [7]

**Bacterial Leaf Blight:** This bacterial disease is persistent in Pakistani rice crops, particularly in areas with high levels of humidity and precipitation. It may result in yield losses by causing water-soaked lesions on rice plants. The disease is especially dangerous since it can cause large crop losses in rice fields and is spread by the green leafhopper bug. raw-colored and waxy-looking. Rice yields can be drastically reduced by bacterial leaf blight, which is mostly transmitted by wind, water, and contaminated agricultural equipment.

**Bacterial Leaf Streak:** Another bacterial disease that affects rice, bacterial leaf streak is similarly caused by Xanthomonas oryzae pathovar oryzicola. Long, thin, water-soaked lesions on the leaves that subsequently become pale yellow and create erratic streaks are its defining feature. Since the bacteria that cause bacterial leaf streak are mainly waterborne, they might cause yield losses, particularly in regions that receive a lot of rain and irrigation. [8]

**Bacterial Panicle Blight:** Rice panicles are susceptible to this bacterial disease, which is brought on by Burkholderia glumae. Infected panicles discolor from brown to black, and the grains may turn chalky and smell bad. The spread of bacterial panicle blight is linked to contaminated seeds and rain splashes, and it can cause severe losses in rice grain quality and yield. In certain Pakistani rice-growing regions, reports of bacterial panicle blight have been made. This disease can cause problems with grain yield and quality, affecting rice panicles. [9]

**Blast:** One of the deadliest rice diseases, blast is brought on by the fungus Magnaporthe oryzae. Every portion of the plant is impacted, including the panicles, nodes, and leaves. Small, water-soaked lesions on infected plants eventually enlarge to form circular or spindle-shaped lesions with a brown border and a gray center. Blast is mostly disseminated by wind, rain, and fungal spores, which can result in significant production losses. In areas with high humidity and frequent rains, it is a serious concern. In Pakistan, blast poses a serious threat to rice farming. There have been reports of occasional outbreaks that seriously harm rice fields. Lesions on leaves, stems, and panicles are the outcome of the disease, which affects grain quality and yield.

**Traditional methods of treating these diseases.**

Pakistani farmers utilize a variety of conventional techniques to control pests and diseases related to rice. These techniques include the use of resistant rice varieties, sanitation measures to stop the spread of diseases like Downy Mildew, biological and mechanical control for pests causing Dead Heart, crop rotation and proper field drainage to prevent diseases like Brown Spot, and the application of natural substances like neem oil or sticky traps to prevent pests like Hispa and Tungro. Although these methods are available and reasonably priced, their efficacy may vary. Integrated pest management (IPM) plans frequently use contemporary methods and technologies to enhance their effectiveness. [10]

## 1.2. MOTIVATION

Our project is driven by the basic importance of rice to the food security and economic stability of our country. Diseases like Brown Spot, Dead Heart, Downy Mildew, Hispa, Tungro, Bacterial Leaf Blight, Bacterial Leaf Streak, Bacterial Panicle Blight, and Blast are a constant threat to our farmers' livelihoods and the safety of our food supply. These diseases dominate our agricultural landscape.

To give our farmers the resources they need to protect their rice crops, increase productivity, and maintain their livelihoods in the face of these obstacles, we must make the most of technology. The goal of our project is to present a ground-breaking method for quickly and precisely diagnosing and treating rice crop illnesses by utilizing artificial intelligence (AI). By means of this initiative, we hope to strengthen the farming communities' capacity to manage their crops and improve the sustainability of rice production.

The driving force behind this initiative is the conviction that "Doctor Paddy" is a dedication to the welfare of our farmers, the growth of our agricultural industry, and the food security of our country, rather than just a technical innovation.

## 1.3. PROBLEM STATEMENT

The shortage of easily accessible and reasonably priced resources for the precise diagnosis and efficient treatment of plant diseases that impact rice harvests are a major problem in Pakistan's agricultural regions, especially in rural areas. This is a complex subject that has a big impact on the livelihoods and financial security of the farming communities.

One significant obstacle is the lack of testing facilities in the area and the shortage of agricultural specialists. When it comes to diagnosing agricultural diseases, farmers frequently lack professional assistance, forcing them to make educated guesses. These choices—which are typically based on self-diagnosis—often lead to expensive and ineffective courses of action, which exacerbate the economic inequalities that farmers must contend with.

The use of anecdotal references, which are valuable but frequently lack scientific rigor and produce fewer effective results, exacerbates the issue. The problem is made worse by the financial burden of disease testing, which is more expensive than agricultural cultivation could ever bring in. Farmers are forced by this situation to make practical choices that might not be in line with scientific truth.

Another obstacle is the awareness of disease testing itself. The rural community often lacks the specialized knowledge and technical skills necessary for these procedures. Without such knowledge, farmers are still ill-prepared to perform these tests on their own.

## 1.4. AIM AND OBJECTIVES

### Aim

This project aims at developing a computer vision-based system to automate rice disease identification process and self-recommendation model for farmers and field assistants.

### Objectives

- ✓ To collect the dataset and analyze data of paddy leaves diseases and extract meaningful information (features) out of it.
- ✓ To select a machine learning model for accurately detecting and classifying different diseases in paddy crops based on input images.
- ✓ To Train the machine learning model on a large and diverse dataset of paddy crop images to improve its accuracy and efficiency.
- ✓ To develop a user-friendly interface for the web application, making it accessible and easy to use for farmers and other stakeholders in the agriculture industry.
- ✓ To integrate the machine learning model with a web application using Django to allow users to easily upload and classify images of diseased crops.
- ✓ To validate the accuracy and effectiveness of the model and the web application through extensive testing and evaluation.

## 1.5. SCOPE OF THE PROJECT

This project's scope includes the creation and deployment of "Doctor Paddy," a complex and multifunctional AI-powered system for managing and identifying rice crop diseases. The project aligns with the Sustainable Development Goals (SDGs), prioritizes addressing complexity (CEP) in agricultural disease management, and gives appropriate consideration to cultural, social, public, health, and safety concerns. This project also identifies strong risk mitigation techniques and acknowledges the possible health and public safety hazards connected to its solutions.

- **Cultural Sensitivity:** In order to ensure that the system respects and enhances current practices, the project takes into account the range of cultural practices found in Pakistan's farming communities.
- **Social Inclusivity:** The project's design is based on a social approach, which enables farmers with different levels of literacy and technology proficiency to use and access it.
- **Aspects Concerning the Public and Health:** The project is aware of the wider implications of its solutions for the public and health, especially with regard to guaranteeing food safety and averting negative outcomes associated with disease management.

**Mapping of Project with SDG (Sustainable Development Goals):**

The "Doctor Paddy" closely corresponds with a number of SDGs, including:

- **SDG”1: No Poverty:** Providing farmers with affordable options for increased agricultural earnings and decreased poverty is the first Sustainable Development Goal (SDG).
- **SDG 2: Zero Hunger:** Improving rice yields through efficient disease management in order to increase food security.
- **SDG 8: Decent Work and Economic Growth:** Increasing agricultural productivity will provide jobs and boost the economy in rural regions.
- **SDG 9: Industry, Innovation, and Infrastructure:** Fostering agricultural innovation and improving the infrastructure of technology.
- **SDG 10: Reduced Inequalities:** Closing the gap by ensuring that farming communities have equitable and accessible access to disease management.

## 1.6. THESIS ORGANIZATION

The rest of the thesis has been organized as follow.

Chapter 2 provides the literature review pf previous studies that had been conducted on rice diseases outbreaks in Pakistan, artificial Intelligence in agriculture and projects related to it. It also discusses state of knowledge, research gaps and theoretical foundation of our project. Chapter 3 gives insights about the research Methodology, data collection, ML model development and system design and implementation of the proposed model which has been further tested and evaluated in chapter 4 where results of the model training and testing have been attached, Chapter 5 discusses the key findings and contributions of our research, it also offers practical recommendations for further development of the system, At last, Chapter 6 includes citations of all the sources such as research papers, books and conference paper.

# Chapter 2

## LITERATURE REVIEW

As an essential staple meal, rice is extremely important for global subsistence. The development of this industry is essential to guaranteeing food security in Pakistan, where millions of hectares of arable land are used for rice production. However, there are several obstacles in the way of this endeavor, chief among them being natural disasters and the constant plague of illnesses that plague rice fields. Over the years, significant scientific efforts have been directed toward comprehending and resolving these issues. This study of the literature sets out to investigate the range of strategies used to prevent rice illnesses, increase crop yields, and adjust to a shifting environment. It makes its way across the complex terrain of research insights and discoveries, determining the adaptability of conventional farming methods and the changing approaches to managing diseases. We set the stage for the creation of our ground-breaking "Doctor Paddy: An AI-Powered Rice Crop Diseases Identification and Management System," which aims to change the direction of rice farming in Pakistan, by looking into previous research in this area.

### 2.1. PAKISTAN'S AGRICULTURE OF RICE.

The fact that rice is a key crop in Pakistan emphasizes its importance in the country's agricultural landscape. Rice is a major source of nutrition for the growing population and a vital lifeline for millions of farmers, with an estimated 2.5 million hectares planted to the crop each year and an annual production of about 7 million tons. Nevertheless, natural disasters such as weather anomalies, flooding, and the merciless destruction of plant diseases continue to pose a threat to the industry's health. It is necessary to untangle the historical efforts and research devoted to this undertaking in order to protect this pillar of nourishment from the threat of rice illnesses. [11]

### 2.2. PREVIOUS STUDIES ON RICE DISEASES.

In an effort to understand the complexities of rice diseases, scientists and researchers have painstakingly documented their results over the years. Many disease kinds, such as Brown Spot, Dead Heart, Downy Mildew, Hispa, Tungro, Bacterial Leaf Blight, Bacterial Leaf Streak, Bacterial Panicle Blight, and Blast, are covered by this large body of research. Every disease has a distinct set of signs and causes, necessitating careful approaches to both diagnosis and treatment. This earlier research has provided important insights into the diagnosis of various diseases, assisting in the identification of the signs, causes, and patterns connected to each ailment. Additionally, they have emphasized how critical it is to control diseases promptly in order to protect crop harvests. [12]

## 2.3. TECHNOLOGICAL PROGRESS.

In the current rapid age of technical advancement, sophisticated instruments and approaches have been developed to tackle rice-related diseases. Among these, convolution neural networks (CNNs), Artificial neural network (ANNs) or machine learning (ML) techniques, have emerged as potentially revolutionary methods for early disease identification. These artificial intelligence (AI) systems use image recognition technology to quickly and accurately diagnose rice plant illnesses from photos. [13].

## 2.4. CONVENTIONAL FARMING METHODS.

Previous even though contemporary technology is a powerful tool for managing illness, conventional farming methods that are firmly embedded in the region's agricultural history nevertheless play a critical role in preventing disease. Pakistani farmers have traditionally protected their crops from disease by rotating their harvests, controlling pests, and carefully choosing rice varieties that are resistant to various diseases. [14].

## 2.5. THE CHANGING FACE OF DISEASES.

The spread of rice-related diseases is dynamic. Disease outbreaks are influenced by regional variables, crop cycles, and climate. Because of its dynamic nature, it requires ongoing adaption. In order to fight diseases, farmers have modified their methods and introduced fresh approaches, such as timely planting, insect control, and the prudent application of fertilizers and pesticides. [15]

## 2.6. EFFECT OF CLIMATE CHANGES ON RICE DISEASES.

The introduction of novel disease complexes including Rice Blast, Bakanae, and Bacterial Leaf Blight exacerbates the issues posed by climate change. According to predictive research, rice yields are expected to drop dramatically by 2050—by as much as 17% from 2000 levels. This portends possible food insecurity in Asia for almost 1.6 billion people. In addition, it's predicted that by 2050, 14 million children in East Asia and the Pacific and 59 million children in South Asia would be malnourished. Furthermore, the study provides a thorough review of the effects of abiotic conditions on rice agriculture, including flooding, high temperatures, and drought. The study also looks at potential remedies, such as breeding resistant rice cultivars, creative management techniques, and making use of physiological and morphological features that are understood at the molecular level. [16]

## 2.7. FACTORS INFLUENCING FARMER'S RISK PERCEPTION.

The study from Dilshad Ahmed, Abdur Rauf, Muhammad Afzal made use of cross-sectional data from 450 rice farmers in six rice districts in Punjab, Pakistan, who were divided into three production categories: low, medium, and high. The Equally Likely Certainty Equivalent method was used in the study to determine farmers' attitudes regarding risk. Using a risk matrix, farmers' views were evaluated in relation to four types of catastrophic risks: drought, high input costs, rice illnesses, and extreme weather events including hail and heavy rain. The Probit model was used to estimate the variables impacting farmers' attitudes and risk perceptions. According to the data, farmers believe that the main dangers to rice farming are drought, rice diseases, excessive rainfall and hail, and high input costs. Furthermore, the findings demonstrated that the majority of farmers behave in a risk-averse manner. The study's estimates demonstrated how many factors—including education, gender, age, access to financing, size of the farm, religious beliefs, and ownership of livestock—significantly affect farmers' attitudes and perceptions of risk. [17]

## 2.8. DEEP LEARNING BASED RICE LEAF DISEASES DETECTION.

The research has been conducted by Muhammad Juman Jhatial and Noor Ahmed Shaikh, the model is intended to effectively distinguish between and identify a range of illnesses affecting rice leaves. The 400 photos of damaged rice leaves that make up the dataset for this study were taken from Kaggle. The study's training, validation, and testing phases for rice leaf disease identification are carried out on the Google Collab platform. Meticulous measures are implemented during the study process to guarantee accurate identification and a thorough description of the condition. Over 100 epochs, a crucial deep learning parameter, the model is refined. The deep learning model trained for 100 epochs performed quite well, as evidenced by the experimental findings, which are encouraging. Its precision, recall, and mean average precision (map) values were 1.00, 0.94, and 0.62, respectively. [18]

## 2.9. RICE CROP HEALTH THROUGH AI-BASED DETECTION.

The process starts with a residual network-based feature extractor and ends with a classifier called a Light Gradient Boosting Machine (LGBM). This approach is evaluated using a rice leaf dataset that is made available to the public, and the findings are impressive. The suggested method outperforms current state-of-the-art techniques in diagnosing infected rice plants with outstanding accuracy, sensitivity, and specificity. Its higher performance is further established by comparative evaluations using a variety of performance criteria. This method, which may be modified for application in different agricultural contexts, is based on computational intelligence and has potential for improving rice crop health management. This discovery has global significance for strengthening efforts to ensure food security and increasing crop output. [19]

## 2.10. ML ALGORITHM IN RICE DISEASES CLASSIFICATION.

Numerous classification algorithms are included in this study, such as fuzzy logic, principal component analysis, K-nearest neighbor (KNN), probabilistic neural networks (PNN), genetic algorithms, support vector machines (SVM), and artificial neural networks (ANN). Applications for the classifications of plant leaf diseases can be found in a variety of sectors, including biology and agriculture. For farmers, early knowledge of crop health and disease identification is critical to the development of successful control programs. [20]

## 2.11. IOT BASED FRAMEWORK FOR DETECTING RICE DISEASE.

The natural sensitivity of field plants to certain bacterial and fungal diseases has made the identification and detection of diseases in rice harvests more important. This research proposes an IoT-based architecture for rice disease predictions and detection and response. The framework is based on machine learning and deep learning techniques, which facilitate well-informed decision-making in smart farming systems. The suggested framework's accuracy and effectiveness in categorizing and predicting the different types of rice diseases is demonstrated by the experimental findings. The system generates remarkable results with up to 87.97% and 97.27% accuracy utilizing machine learning and deep learning models, respectively, when compared to top benchmark algorithms. In terms of evaluation criteria, such as accuracy, precision, recall, and F1-Score, the suggested framework performs better than current algorithms, offering an effective solution for rice disease diagnosis in the context of smart agriculture. [21]

## 2.12. CASE BASED METHOD TO DIAGNOSE RICE DISEASES.

The vulnerability of many rice plants to pests and diseases during their growth is a recurring problem in rice production. Rice plants are susceptible to various pests and diseases, including but not limited to leaf blight, grass, tungro, rice spout, and dwarf grass. Farmers frequently use pesticides or other treatment techniques that may not necessarily be the best fit for the type of disease or pest they are dealing with in order to combat these dangers. This less-than-ideal strategy occasionally results in fresh outbreaks of illnesses and pests.

The aim of this research is to enable farmers to detect early signs of pests and illnesses affecting rice plants by employing the case-based reasoning approach. By enabling farmers to focus their treatment efforts in the best possible way, this technique maximizes the efficacy of managing pests and diseases in rice farming. [22]

# Chapter 3

# METHODOLOGY

## 3.1. INTRODUCTION TO THE METHODOLOGY

This chapter outlines the research approach used to create rice crop diseases Identification-specific image recognition-based recommendation application. The following essential elements are included in the methodology:

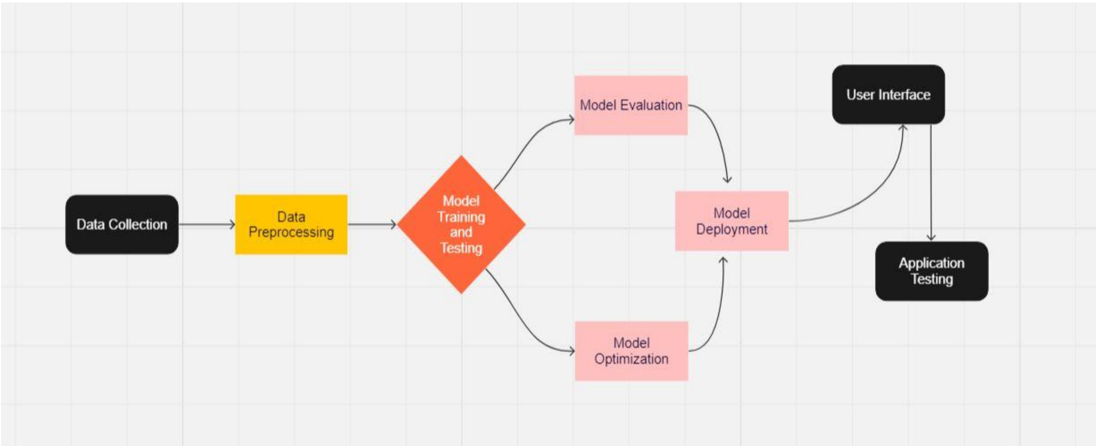


Figure 0.1: Flowchart

The project's methodology consists of multiple essential elements that guarantee the effective creation and assessment of the AI-driven rice crop disease detection and control system as shown in the figure 3.1.

### 3.1.1. DATA COLLECTION

The first step in gathering data is obtaining picture files pertaining to diseases that affect rice crops. These datasets come from a variety of sources, such as agricultural research institutes. Dataset for this project has been collected from Crop Production Department, SAU, Tandojam, High-resolution photos of rice crops in different phases of growth, both healthy and ill, are included in the data collection.

### 3.1.2. DATA PREPROCESSING

The obtained data is preprocessed before the model is trained. To standardize the dataset, this process entails resizing, normalizing, and augmenting images. The robustness and diversity of the dataset are increased by using techniques like data augmentation.

### 3.1.3. TRAINING AND TESTING

To train models for rice crop disease identification, the research uses ResNet50, a cutting-edge deep learning technique. Subsets of the dataset are used for testing and training. The model is fed labeled images during the training phase, and its accuracy and performance are assessed during the testing phase.

### 3.1.4. MODEL EVALUATION

A variety of evaluation metrics, including as accuracy, precision, recall, F1-score, and area under the Receiver Operating Characteristic (ROC-AUC), are used to thoroughly assess the performance of the trained CNN models. These metrics offer information on how well the algorithm detects and categorizes rice crop illnesses.

### 3.1.5. MODEL OPTIMIZATION

The goal of the optimization stage is to improve the accuracy and efficiency of the CNN models. To get better outcomes, you can use strategies like transfer learning and hyperparameter optimization. The models are improved to make sure they can identify diseases in the field in real time.

### 3.1.6. USER INTERFACE (WEB APPLICATION)

To give farmers an easy-to-use tool for interacting with the AI-powered system, a user-friendly web application has been built. By integrating the trained ResNet 50 model, the application enables users to upload photos of rice harvests and obtain real-time disease diagnosis. The user interface has been developed with accessibility and ease of use in mind, catering to a broad spectrum of users, including non-techies.

### 3.1.7. APPLICATION TESTING AND FEEDBACK

In this last stage, the web application is thoroughly tested in actual agricultural environments. Target users engage with the system and offer input; these users are mostly farmers and agricultural specialists. The user-friendliness of the program is evaluated through usability testing, and input is gathered for incremental changes. The effectiveness of the system in identifying diseases and its influence on crop management are assessed.

This thorough approach guarantees that every step of the research and development process for the AI-powered rice crop disease identification and management system is done in a methodical manner, from gathering data and training models to creating user interfaces and testing the system in real-world settings. The input and outcomes gathered at this stage will direct the system's improvement and possible incorporation into farming methods.

## 3.2. DATA COLLECTION AND PREPROCESSING

The Dataset Description and Images:

- The dataset has been collected from Crop Production Department SAU, Tandojam and Rice research center Tandojam.
- Training dataset of 10.407 (75%) labeled paddy leave images across 10 Classes (9 Diseases and normal leaf).
- We also Provide metadata for each image, such as paddy variety and age.
- Testing dataset of 3,469 (25%) of the 9 diseases and normal leaf.

**Figure 3.2 Normal Paddy leaf**

**Figure 3.3 Bacterial Leaf Blight**

**Figure 3.4 Bacterial Leaf Streak**

Figure 3.5 Hispa

Figure 3.6 Blast

Figure 3.7 Bacterial Panicle Blight

Figure 3.8 Tungro

Figure 3.9 Downy Mildew

Figure 3.10 Dead Hart

Figure 3.11 Brown Spot

## 3.3. CODE SNIPPETS FOR PREPROCESSING


Figure 0.12: Preprocessing 1

In the figure 3.12 it is shown that the images dataset of around 10317 images has been set to batch_size = 32, img_height = 225, img_width = 225.


Figure 0.13: Preprocessing-II

Figure 3.13 shows the results after preprocessing which found 8537 files belonging to 6 classes, using 6830 files for training, found 8537 files belonging to 6 classes. using 1707 files for validation. found 54 files belonging to 7 classes.

## 3.4. MODELS USED FOR TRAINING AND TESTING OF IMAGE DATA

**Convolutional Neural Network (CNN)**

The central architecture of this study is the Convolutional Neural Network (CNN). A type of deep learning models called CNNs was created especially for tasks involving picture recognition and classification. In this case, pictures are analyzed and CNNs are used to diagnose diseases in the rice crop. These models are ideal for complex picture processing because they are composed of many convolutional layers that apply different filters to detect features at different levels of abstraction.

**VGG16**

A well-known and well-liked Convolutional Neural Network architecture is the VGG16 model. Its deep architecture, with 16 weight layers—13 convolutional layers and 3 fully connected layers—is what sets it apart. Because of its exceptional performance in image classification tasks, VGG16 is used to improve the precision and accuracy of rice crop disease identification. Because of its well-known simplicity in architecture, its image analysis capabilities make it an invaluable addition to the field of study.

**ResNet-50**

Residual Network-50, also referred to as ResNet-50, is a ResNet architecture variation renowned for its remarkable depth and performance. ResNet-50 is a deep neural network model because it has 50 layers. In order to mitigate vanishing gradient issues and enable the training of deeper networks, ResNet models add residual blocks or skip connections. This model plays a key role in obtaining cutting edge outcomes in image identification, particularly in reliably and accurately identifying illnesses of rice crops.

**ResNet-25**

A variant of the ResNet architecture, ResNet-25 has 25 layers and a modest depth. Performance and computational complexity are balanced in this model. ResNet-25 preserves the benefits of skip connections and residual blocks, even though it is not as deep as ResNet-50, making it possible to accurately classify diseases affecting rice crops. Because of its effectiveness, it's a good option for agricultural settings looking to identify diseases in real time.

## 3.5. FRAMEWORK USED FOR MODEL TRAINING AND TESTING

### 3.5.1. TENSORFLOW

Google created the open-source machine learning framework TensorFlow. It is well known for being adaptable and strong when creating and refining machine learning models, especially deep neural networks. TensorFlow provides both a lower-level API for sophisticated model customization and fine-tuning and a high-level API for rapid model building. This framework is a good option for training Convolutional Neural Networks (CNNs) to detect and control rice crop illnesses because it is widely used for image analysis and classification tasks. Tools for data preprocessing, model validation, and deployment are all part of its extensive ecosystem, which guarantees a smooth end-to-end solution.

### 3.5.2. FASTAI2

Based on PyTorch, FastAI2 is an advanced and intuitive machine learning framework. It is renowned for being simple to use and for producing deep learning models quickly, which makes it the perfect option for this research endeavor. FastAI2 streamlines the machine learning workflow by offering streamlined APIs for preprocessing, importing data, and training models. Additionally, a variety of pre-trained models are included, facilitating rapid model selection and experimentation. The framework is useful for developing and refining CNNs for rice crop disease detection due to its ease of use and applicability.

### 3.5.3. PYTORCH

PyTorch is an open-source machine learning framework that has become well-known due to its user-friendly and flexible dynamic computation graph. Deep learning tasks such as image analysis and classification make extensive use of it. Convolutional neural networks (CNNs) and other sophisticated models can be easily developed and customized by academics because to PyTorch's dynamic nature and user-friendly interface. Because it provides a high degree of control over the model architecture and training process, it is especially useful for the development and fine-tuning of the models in this research effort.

## 3.6. LIBRARIES USED FOR ML ALGORITHM

### 3.6.1. NUMPY

NumPy, which stands for "Numerical Python," is a core Python module for carrying out matrix and numerical operations. In addition to several mathematical functions for carrying out tasks like statistical analysis, linear algebra, and more, it supports multi-dimensional arrays. NumPy is a vital tool in machine learning because it greatly expedites numerical calculations, making it ideal for data handling and matrix computations.

### 3.6.2. SCIKT-LEARN (SKLEARN)

A popular Python machine learning package, Scikit-learn is also known as sklearn. For jobs like data preprocessing, model selection, training, assessment, and hyperparameter adjustment, it provides a large range of tools. Scikit-learn is an indispensable library for machine learning research and applications since it is easy to use and has many applications, including classification, regression, clustering, and more.

### 3.6.3. PANDAS

Working with structured data is made easier with the help of this data manipulation library. It offers data structures that facilitate data transformation, cleansing, and storage, such as Data Frames and Series. Pandas is widely used in machine learning to import and preprocess datasets, simplifying the process of preparing data for model training and assessment.

### 3.6.4. MATPLOTLIB

Users may generate a vast array of static, animated, and interactive plots and charts. Matplotlib is a flexible data visualization library. In machine learning projects, it is frequently used to visualize data, model performance, and other outcomes. Researchers may successfully share their findings with others and acquire insights from data thanks to Matplotlib.

### 3.6.5. SEABORN

Seaborn is a Python data visualization library. It offers a higher-level interface and an extra layer of abstraction to produce visually appealing and educational statistical visuals. In order to extract insights from the data, Seaborn is especially helpful for producing aesthetically pleasing data visualizations like heatmaps and pair plots.

## 3.7. MODEL DEPLOYMENT

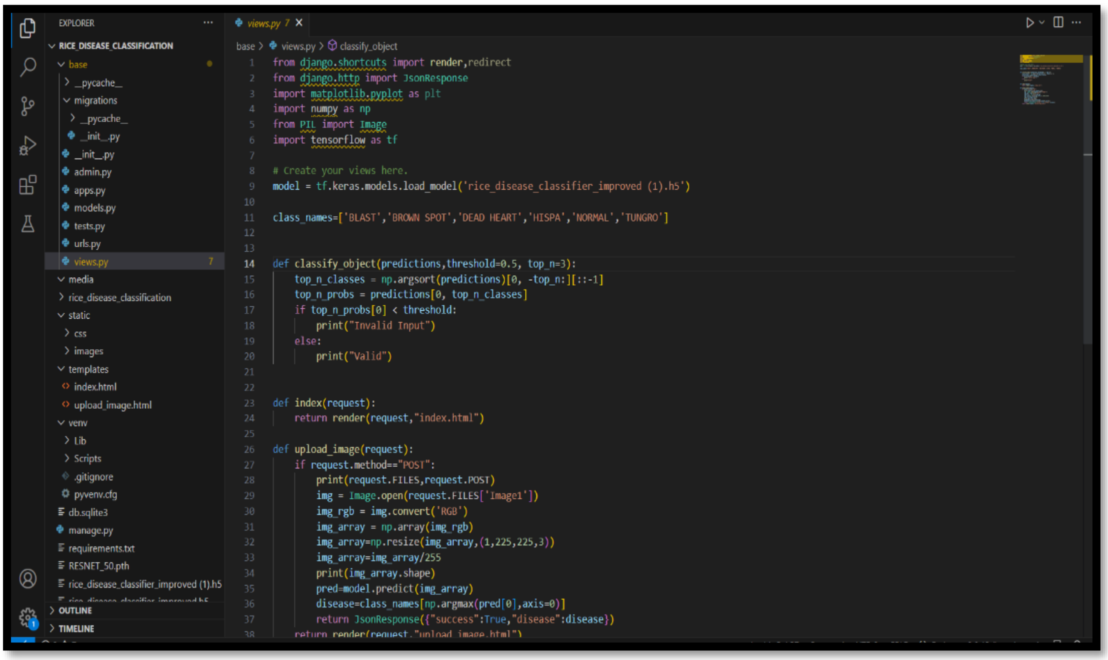


Figure 0.14: Model Deployment

In the figure 3.14 it is shown that the standard libraries of python such as NumPy, Matplotlib along with libraries of tensor flow and Django Framework have been imported, Further the dataset of paddy leaves has been loaded and then classes of paddy diseases are defined, the entire code snippet shows how our ResNet-50 is integrated with the web Interface that is developed using Django.

## 3.8. WEB INTERFACE

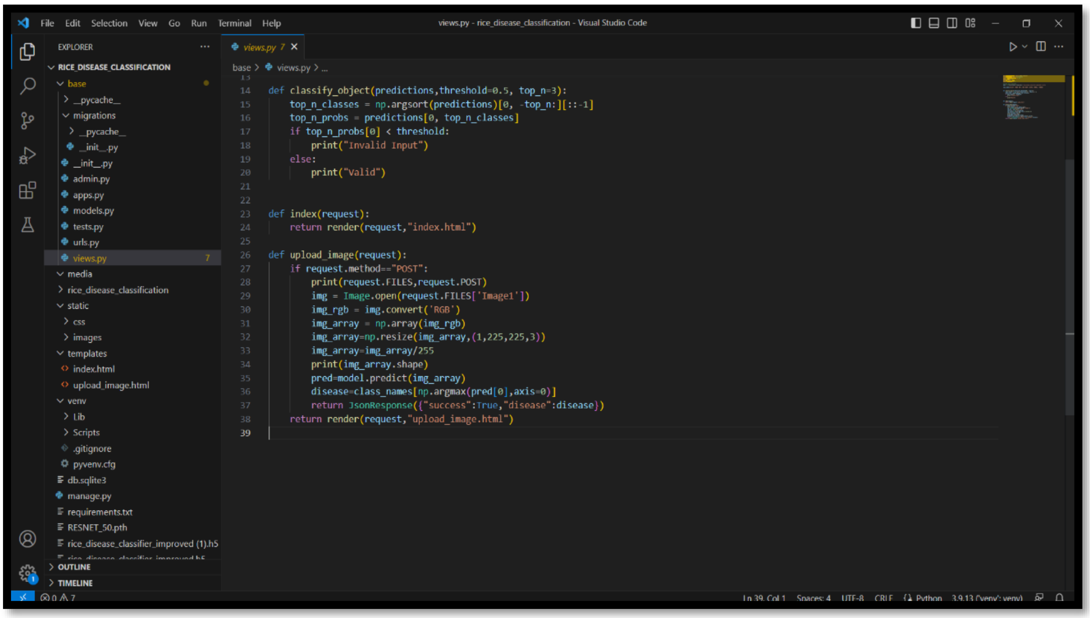


Figure 0.15: Web Interface

Figure 3.15 shows the code of developing the user interface where the advice will be visible to farmers on our user-friendly website, it is constructed with the aid of the following technologies:

- HTML
- CSS,
- JavaScript

### 3.8.1. HTML.INDEX

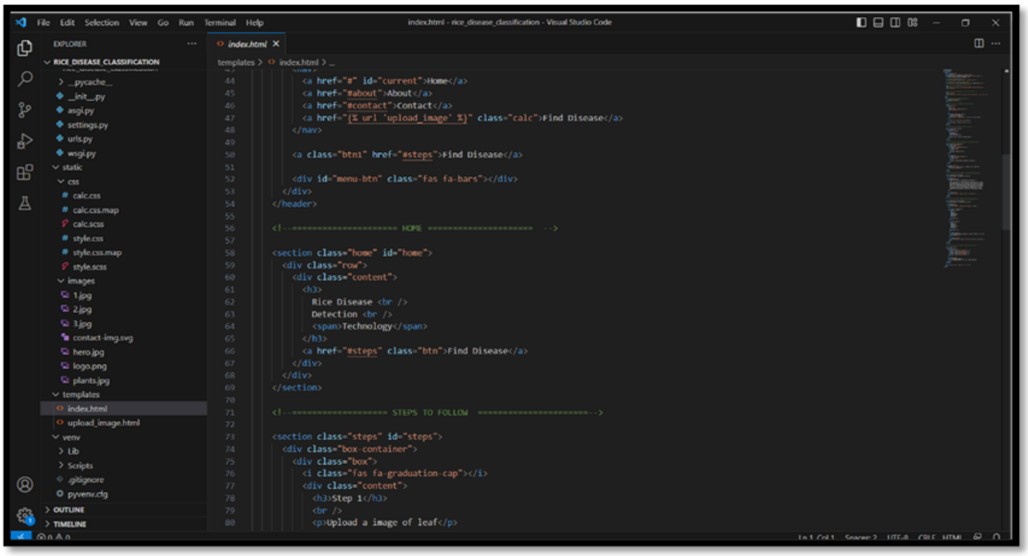


Figure 0.16 HTML INDEX page 1

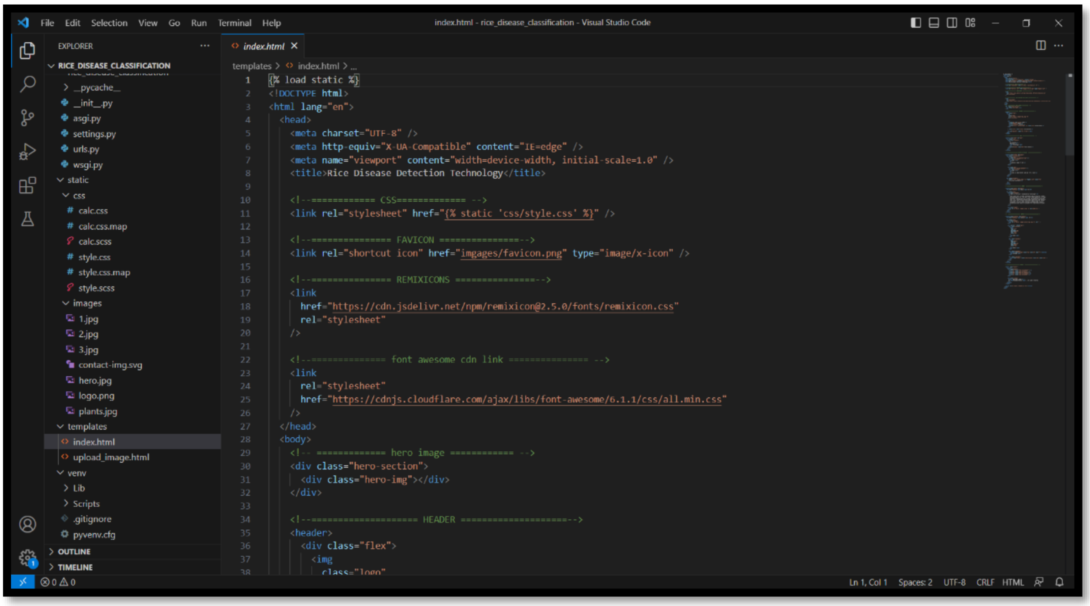


Figure 0.17 HTML.INDEX page 2

Figure 3.16 and 3.17 show HTML. Index pages in which code for front-end such as web layout, features placement, positioning, texts and links has been written.

### 3.8.2. STYLE.CSS

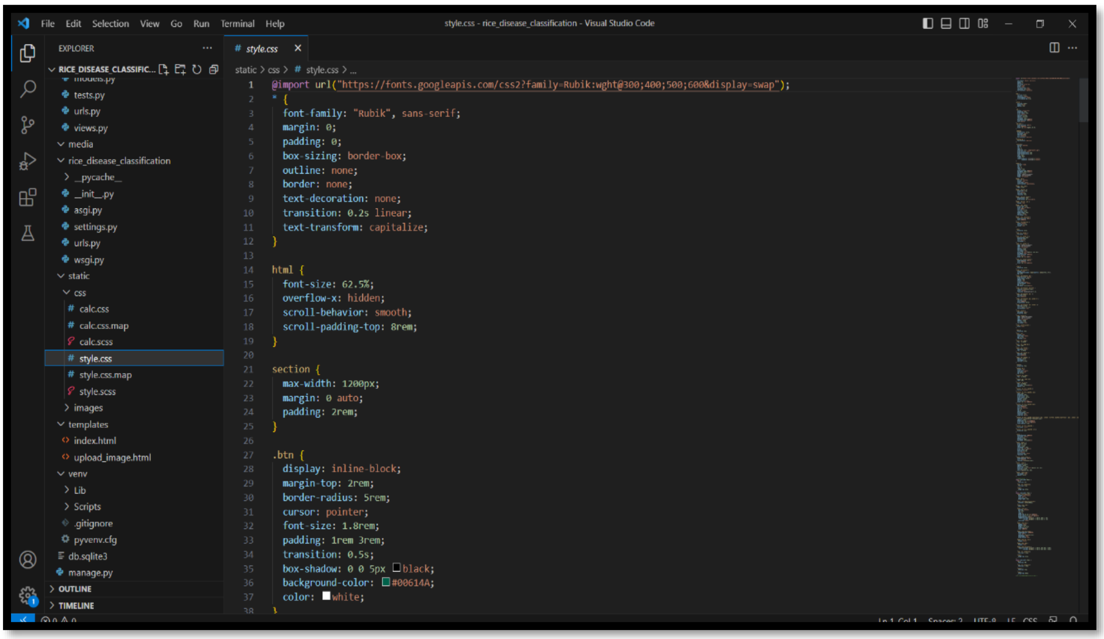


Figure 0.18 STYLE.CSS

Figure 3.18 shows Style. CSS page in which code for text fonts, padding, alignment, bg_color, transition and decorations has been written.

## 3.9. INTERFACE SNIPPETS

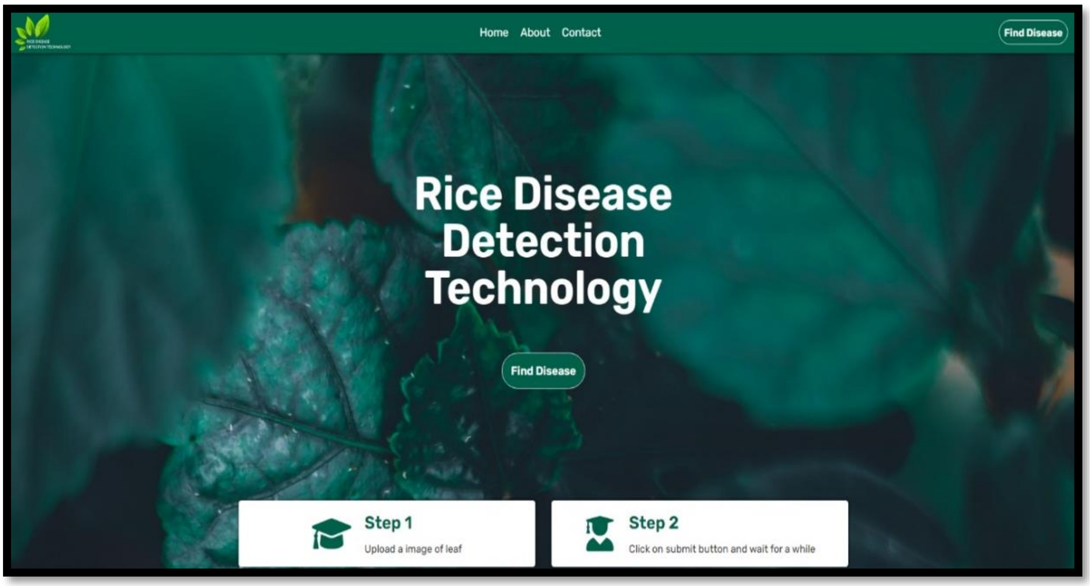


Figure 0.19: Web Interface 1

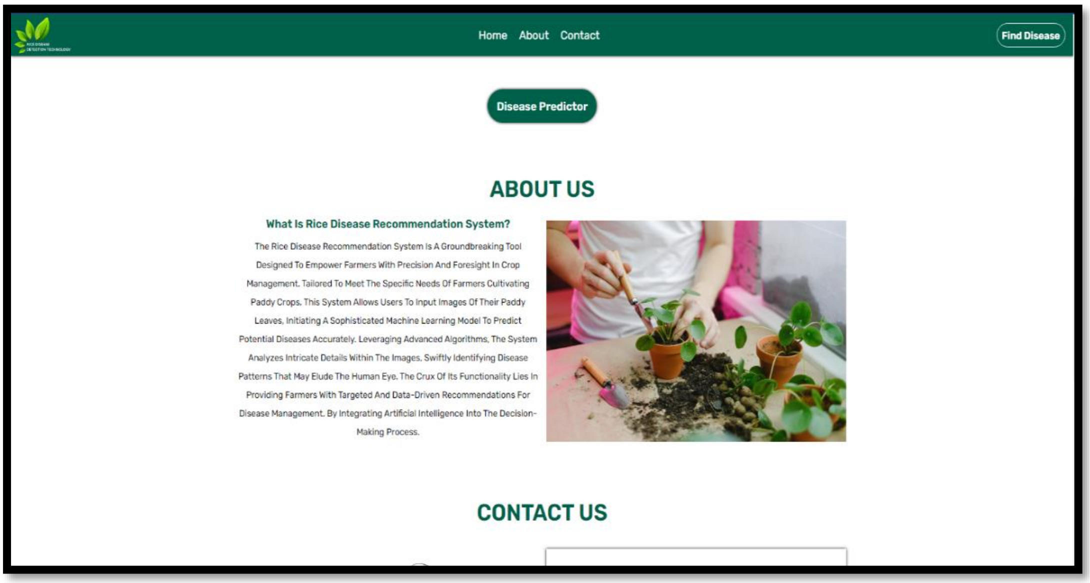


Figure 0.20: Web Interface 2

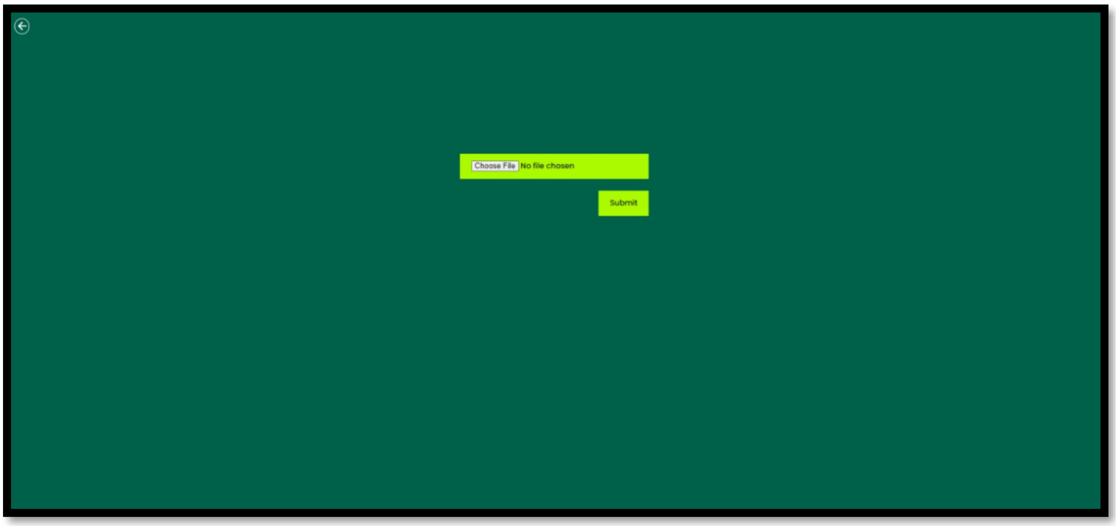


Figure 0.21: Web Interface 3

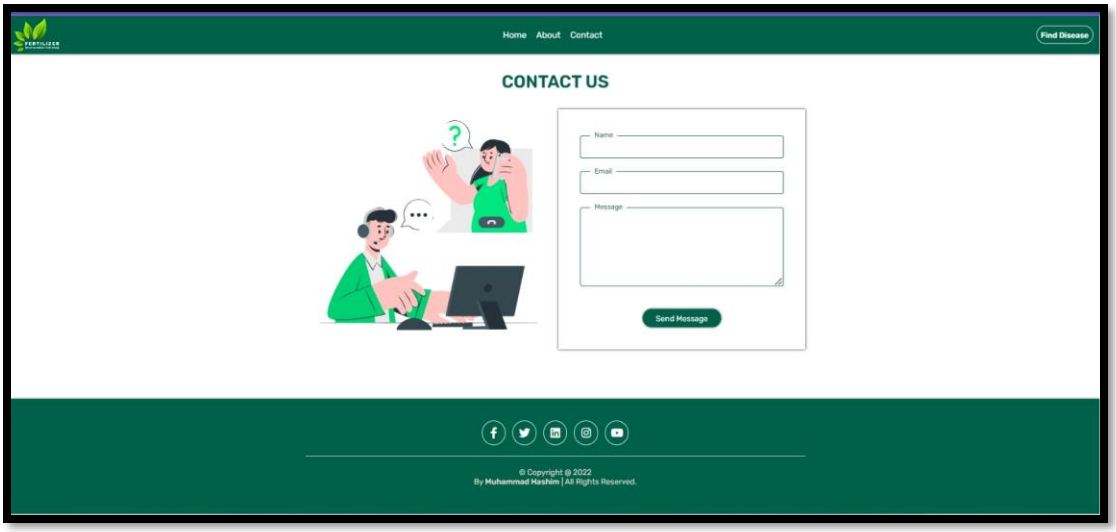


Figure 0.22: Web Interface 4

In the figures 3.19, 3.20, 3.21 and 3.22 the final product of our web interface is shown after complete development, it comprises of 4 pages, Farmers can easily click 'Find disease' button on first page which will direct them to second page where they will find another button 'Disease Predictor' clicking on it will direct them to an interface where they can choose an image from their system and upload to get the desired results on their screens, through last page they can contact us, leave any query or feedback.

## 3.10. TOOLS AND TECHNOLOGIES

### 3.10.1. JUPYTER NOTEBOOK

Jupyter Notebook is an open-source online tool that lets you make and distribute documents with narrative text, equations, live code, and visualizations. Its interactive and collaborative coding environment makes it especially well-liked in the fields of data science and machine learning. Python is only one of the many programming languages that Jupyter Notebook supports. It is a great tool for creating, organizing, and presenting machine learning and data analysis projects.

### 3.10.2. VISUAL STUDIO CODE (VS CODE):

Microsoft created Visual Studio Code as a free, open-source code editor. Developers use it extensively for a wide range of programming languages because of its rich feature set, which includes debugging, code completion, syntax highlighting, and extensions. Because of its reputation for speed and effectiveness, Visual Studio Code is a great option for creating, debugging, and maintaining software projects, including Django-built web apps.

### 3.10.3. DJANGO

Developed for quick creation of online applications, Django is a high-level web framework built in Python. It has built-in capabilities for user authentication, database administration, and other features, and it adheres to the Model-View-Controller (MVC) architectural pattern. The online interface of your AI-powered rice crop disease identification and management system can be developed with ease because to its ability to streamline the process of creating reliable and secure web apps.

A custom residual module function was defined. This function includes two 3x3 convolutional layers with ReLU activation and batch normalization. It also implements a residual connection by adding the output of the second convolutional layer to the initial input.

### 3.10.4. FIGMA

Figma is a cloud-based design tool that makes interface and user experience (UI/UX) design more collaborative. Multiple designers and stakeholders can collaborate in real-time on the design of user interfaces for online and mobile applications using this platform. Figma is a well-liked option for developing intuitive and aesthetically pleasing online interfaces because of its adaptability, collaborative tools, and cloud-based architecture.

### 3.10.5. ADOBE XD

Another effective tool for creating and testing user interfaces and experiences is Adobe XD. Designers use it extensively to produce interactive wireframes, mockups, and prototypes for online and mobile apps. Features including vector-based design, artboard generation, and several design-enhancing plugins are available in Adobe XD. It is useful for testing and visualizing your project's user interface.

# Chapter 4

## RESULTS AND DISCUSSION

Here, we provide the findings and a comprehensive analysis of 'Doctor Paddy: An AI-Powered Rice Crop Diseases Identification and Management System.' The project's path from start to finish has produced a plethora of information, insights, and potential answers to the enduring problems Pakistani rice farmers face. Following the main goals of the project, we have concentrated on providing farmers with a state-of-the-art artificial intelligence tool for rice disease diagnosis and management. We will examine the effectiveness of our AI models, their implications for managing the health of rice crops, and their potential to improve farmers' lives as we work through the findings and the debates that follow. Here, we examine the concrete results and their importance as we embark on our mission to change Pakistan's rice farming landscape.

### 4.1. PROJECT FLOW

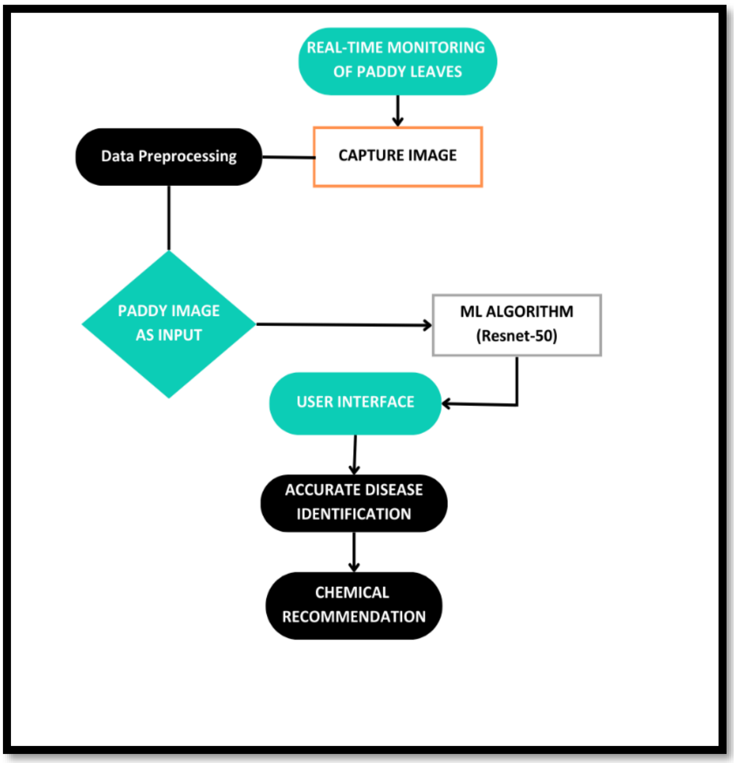


Figure 0.1: Project Flow

Figure 4.1 shows the flow of our project which starts by monitoring the paddy crops and identifying the infected leaves, farmers or field assistant can then click multiple clear pictures of those leaves, before sending those images as an input to the proposed ML model, images will be preprocessed which means their size adjustments, noise removal and normalization. Images then will be fed to the model which will test the images and accurately classify the diseases in their respective classes, Results will be visible on the web interface with the disease name and chemical recommendation.

## 4.2. MODEL LEARNING RATE

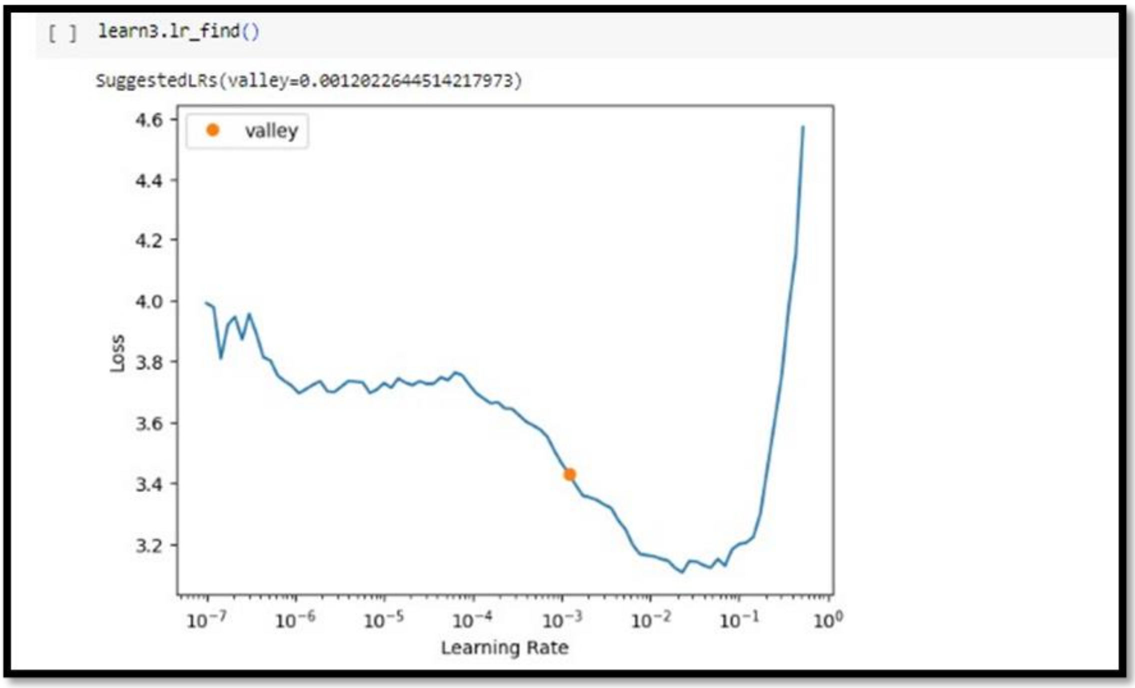


Figure 0.2: Model Learning Rate

It is shown in the figure 4.2 that how our algorithm learns or updates the value of a parameter estimates, it shows that the training of the dataset is reliable with the suggested value=0.00012022. The learning curve graphically depicts how a process is improved over time due to learning and increased proficiency.

## 4.3. MODEL LEARNING RATE

```
losses,idxs = interp.top_losses()

interp.print_classification_report()

                         precision    recall  f1-score   support

   bacterial_leaf_blight       0.98      0.99      0.99       100
   bacterial_leaf_streak       0.99      1.00      0.99        80
 bacterial_panicle_blight      1.00      0.97      0.99        80
                   blast       0.98      0.97      0.97       120
              brown_spot       0.96      0.99      0.98       104
              dead_heart       0.98      1.00      0.99       104
            downy_mildew       0.96      0.99      0.98       100
                   hispa       1.00      0.95      0.97       100
                  normal       0.98      0.99      0.99       104
                  tungro       0.98      0.96      0.97       104

                accuracy                           0.98       996
               macro avg       0.98      0.98      0.98       996
            weighted avg       0.98      0.98      0.98       996
```

Figure 0.3: Classification Report

Figure 4.3 shows the performance evaluation metrics for our algorithm, the mentioned parameters are precision, recall, F1-score and support, the classification report which is generated give insights about each of the diseases separately to know how our model is performing and identifying accurately to what class.

## 4.4. CONFUSION MATRIX

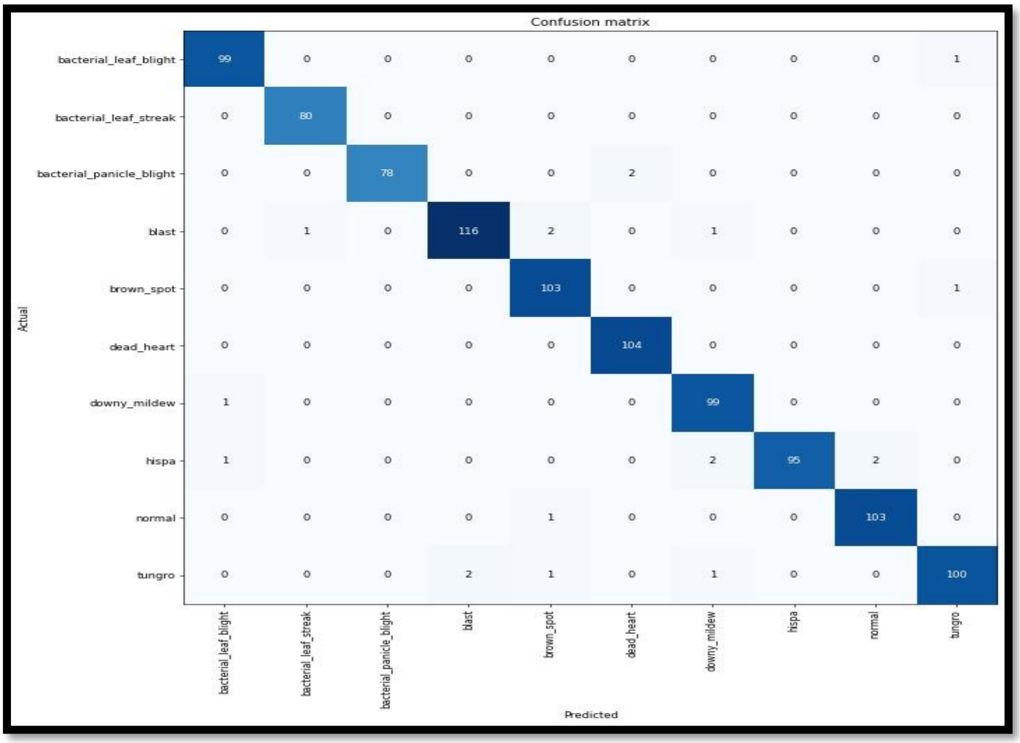


Figure 0.4: Confusion Matrix 1

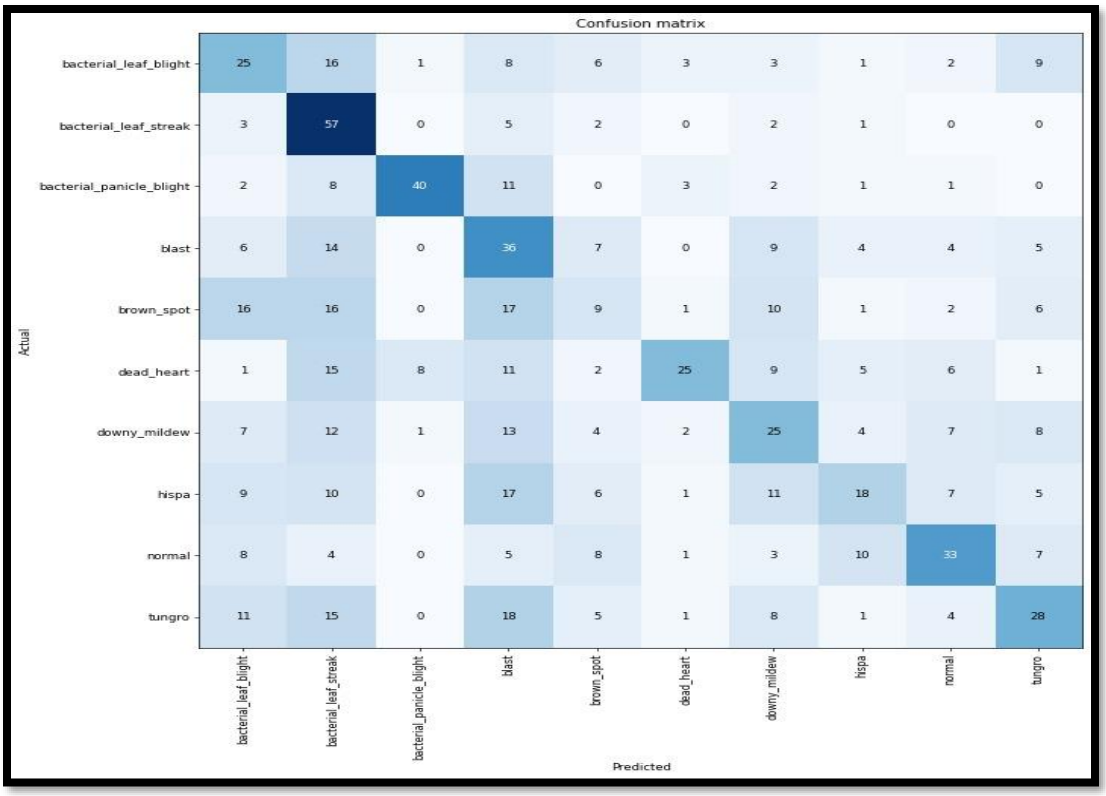


Figure 0.5: Confusion Matrix 2

In the Figure 4.4 and 4.5 it is shown the confusion matrix of 9 diseases starting from bacterial leaf blight to tungro, confusion matrix is used to show the relationship between the actual and predicted values by the model, in the main diagonal it can be seen blue color varying from light blue to dark blue, dark blue shows the maximum number of class images that the model find hard to train and is confused, Total number of images shown in this matrix is around 400 and it is a 10*10 matrix showing actual and predicted values by ResNet-50 model of each disease separately which clearly give us the idea about the images that the model is predicting and matching to the actual class defined.

## 4.5. MODEL SUMMARY (RESNET50)

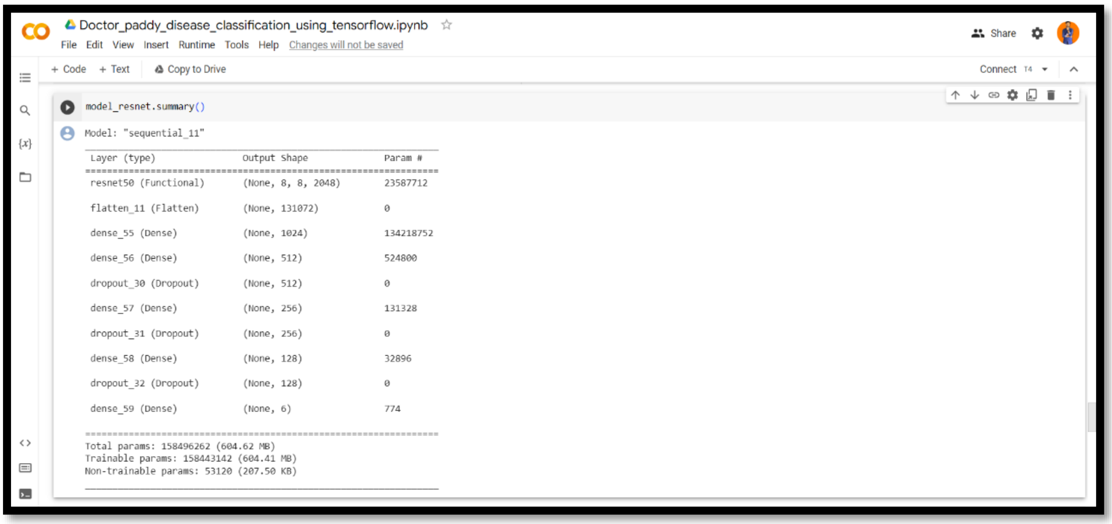


Figure 0.6: Model Summary

Figure 4.6 shows the summary of our proposed model which is ResNet-50, the table report reflects the strength of relationship between the model and dependent variable, it shows that there is total 158496262 parameters (604.62 MB), which are further sectioned into trainable params: 158443142 (604.41 MB) and non-trainable params: 53120 (207.50 KB).

## 4.6. MODEL ACCURACY SCORE (VGG-16)


Figure 0.7: Accuracy Score 1

Figure 4.7 shows the accuracy of the first model used for the training of the Paddy leaves dataset and that is VGG-16, After 12 epochs of training model is showing training loss of 35% and accuracy up to 75%.

## 4.7. MODEL ACCURACY SCORE (RESNET-25)

```
[ ] learn3.fine_tune(10,1e-3,freeze_epochs=4)
```

| epoch | train_loss | valid_loss | accuracy | time |
|---|---|---|---|---|
| 0 | 2.932814 | 1.687915 | 0.438994 | 00:51 |
| 1 | 2.049577 | 1.229880 | 0.597484 | 00:52 |
| 2 | 1.591374 | 1.040766 | 0.676730 | 00:51 |
| 3 | 1.252001 | 0.922402 | 0.696855 | 00:53 |

| epoch | train_loss | valid_loss | accuracy | time |
|---|---|---|---|---|
| 0 | 0.886974 | 0.721658 | 0.769811 | 01:00 |
| 1 | 0.736160 | 0.604612 | 0.808805 | 01:00 |
| 2 | 0.642757 | 0.564034 | 0.812579 | 01:00 |
| 3 | 0.478044 | 0.426578 | 0.844025 | 01:00 |
| 4 | 0.381861 | 0.404958 | 0.869182 | 01:00 |
| 5 | 0.302287 | 0.332336 | 0.898113 | 00:59 |
| 6 | 0.220844 | 0.293854 | 0.910692 | 01:00 |
| 7 | 0.179617 | 0.285198 | 0.919497 | 00:59 |
| 8 | 0.140979 | 0.269562 | 0.924528 | 00:59 |
| 9 | 0.135651 | 0.268976 | 0.920755 | 00:59 |

Figure 0.8: Accuracy Score 2

Figure 4.8 shows the accuracy report of the second model used for training that is ResNet-25, after 9 training epochs it is showing accuracy rising from 43% percent to 80% percent.

## 4.8. MODEL ACCURACY SCORE (RESNET-50)

```
[ ] learn3.fine_tune(10,1e-3,freeze_epochs=4)
```

| epoch | train_loss | valid_loss | accuracy | time |
|---|---|---|---|---|
| 0 | 2.932814 | 1.687915 | 0.438994 | 00:51 |
| 1 | 2.049577 | 1.229880 | 0.597484 | 00:52 |
| 2 | 1.591374 | 1.040766 | 0.676730 | 00:51 |
| 3 | 1.252001 | 0.922402 | 0.696855 | 00:53 |

| epoch | train_loss | valid_loss | accuracy | time |
|---|---|---|---|---|
| 0 | 0.886974 | 0.721658 | 0.769811 | 01:00 |
| 1 | 0.736160 | 0.604612 | 0.808805 | 01:00 |
| 2 | 0.642757 | 0.564034 | 0.812579 | 01:00 |
| 3 | 0.478044 | 0.426578 | 0.844025 | 01:00 |
| 4 | 0.381861 | 0.404958 | 0.869182 | 01:00 |
| 5 | 0.302287 | 0.332336 | 0.898113 | 00:59 |
| 6 | 0.220844 | 0.293854 | 0.910692 | 01:00 |
| 7 | 0.179617 | 0.285198 | 0.919497 | 00:59 |
| 8 | 0.140979 | 0.269562 | 0.924528 | 00:59 |
| 9 | 0.135651 | 0.268976 | 0.920755 | 00:59 |

Figure 0.9: Accuracy Score 3

Figure 4.9 shows the accuracy report of final model used for the training of paddy leaves dataset and it is ResNet-50, The model achieved highest accuracy of all other model used earlier, it shows 85% accuracy after 9 Epochs, Therefore, ResNet-50 has been used for integration with web interface.

## 4.9. RESULTS ON INTERFACE

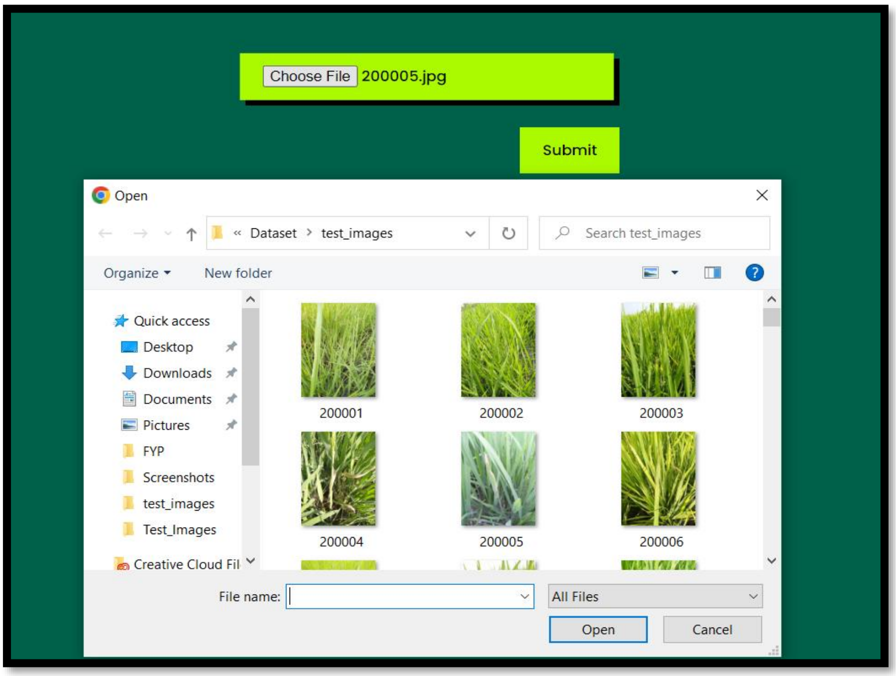


Figure 0.10 File selection

Figure 4.10 shows how to choose a file from the system, user will simply click on the 'choose file' button and it will enable them to select any file from their system and upload on the interface, soon after clicking on 'submit button' in few seconds the results will be generated on their screens.

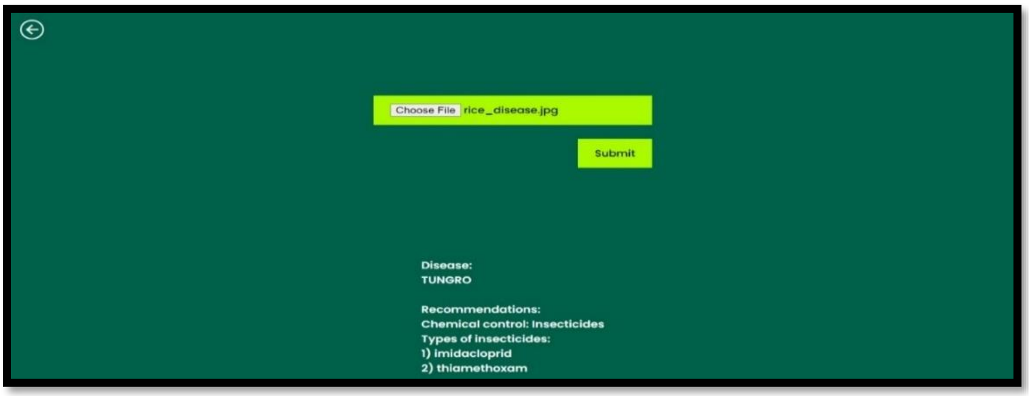


Figure 0.11: Result page 1

In the figure 4.11 it is shown that the result has been generated after a user has uploaded an infected paddy leaf image as an input, the model accurately identifies the disease as ‘Tungro’ and provides suitable recommendations that farmers should use to prevent the disease from spreading.

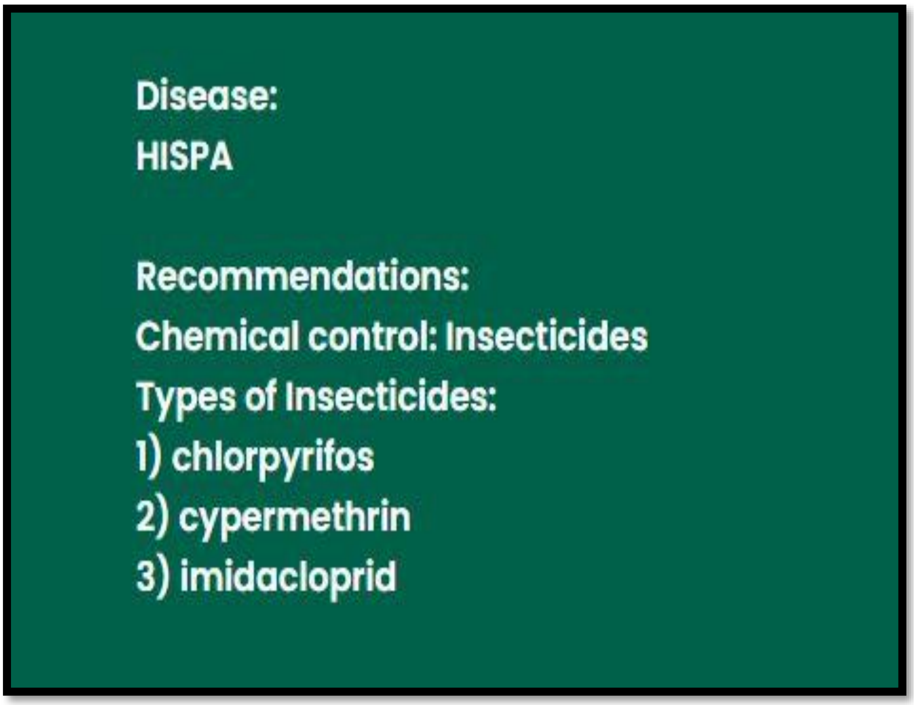


Figure 0.12: Result page 2

Figure 4.12 shows another result being generated after a user has provide a new input, the model accurately identifies the disease as ‘Hispa’ and provides suitable chemical recommendations on screen.

# Chapter 5

## CONCLUSION AND FUTURE RECOMMENDATIONS

In Pakistan's modern agricultural environment, rice production is an essential economic pillar and a source of livelihood for millions of farmers. But as this study trip has shown, the rice crop faces several difficulties, with infections being a major danger to crop yield and health. We started a revolutionary project in response to these difficulties, which resulted in the development of "Doctor Paddy: An AI-Powered Rice Crop Diseases Identification and Management System.", this innovative method gives farmers an effective tool for locating, tending to, and protecting their rice harvests. It is a ground-breaking move toward equipping farmers with technology that can transform their agricultural methods. Our approach has the potential to greatly improve the lives of Pakistani rice farmers by providing them with personalized management recommendations, real-time diseases identification, and superior image recognition. Through the integration of technology and conventional agricultural methods, we see a time when farmers will be able to effectively combat disease threats, minimize crop losses, and boost yields.

Our research's findings show how useful artificial intelligence is for diagnosing diseases. The models incorporated into "Doctor Paddy" demonstrate impressive precision in diagnosing a variety of rice infections, from blast to brown spot. With the use of this technology, diseases can be diagnosed quickly and accurately, negating the ambiguity and mistakes that come with manual identification. It gives farmers the information they need to take quick action, administer focused treatments, and lessen crop loss. One of our system's most important functions is helping to close the information gap that many Pakistani farmers are currently facing. Farmers have access to a multitude of knowledge regarding rice diseases and how to treat them when they include "Doctor Paddy" into their farming techniques. This information helps to prevent diseases and plan crops more effectively, which in turn increases the sustainability of rice production. It also helps with acute disease control. Our experience emphasizes how crucial teamwork is in the agriculture industry. In order to achieve the maximum potential of "Doctor Paddy," collaboration between government agencies, agricultural extension services, and farmers is essential.

Even if our initiative has reached important milestones, the field of AI-powered disease management for rice crops still has potential for improvement. The mentioned suggestions outline the prospective domains for forthcoming development and enhancements:

1) **Constant Refinement and Improvement of AI Models:**

"Doctor Paddy's AI models ought to be continuously enhanced and improved. In order to improve the precision and speed of disease diagnosis, future research can concentrate on growing the dataset, optimizing algorithms, and investigating deep learning approaches.

2) **Integration of IoT and Weather Data:**

Adding Internet of Things (IoT) devices for real-time data collecting and weather data may strengthen the system even further. This will improve precision by enabling the inclusion of climate and environmental elements in disease management recommendations.

3) **Training and Accessibility:**

Efforts ought to be undertaken to guarantee that "Doctor Paddy" reaches even Pakistan's most isolated farming villages. This entails training farmers to optimize the system's usefulness and facilitating access to it for those with little experience with technology.

4) **Policy Integration and Government assistance:**

It is critical that agricultural authorities and the government acknowledge the promise of AI-powered disease management and offer policy assistance. Advocating for the inclusion of such systems in government-led agricultural projects should be the focus of future work.

5) **Knowledge exchange and Collaboration:**

It's critical to encourage cooperation between various agriculture sector players as well as knowledge exchange among farmers. Subsequent endeavors may concentrate on developing forums where farmers may exchange their encounters with "Doctor Paddy" and collaboratively enhance its functionality.

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