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Programme:	

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We confirm that we have read and understood the Plymouth University regulations relating to Assessment Offences and that we are aware of the possible penalties for any breach of these regulations. We confirm that this is the independent work of the group.

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Common Rice Diseases Detector

By

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A Project Report

University of Plymouth

April 2024

Acknowledgements

We would like to extend our appreciation to everyone that worked with us and made this project a success. We would like to express our heartfelt gratitude to everyone who helped us finish our project successfully.

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Abstract

The "Common Rice Disease Detector" effort aims to tackle the vital problem of rice crop health, which has a substantial effect on the security of food worldwide. By providing farmers and agricultural specialists with a tool for quickly and accurately identifying common rice illnesses, this research hopes to reduce losses in rice quality and output. Among our goals is the creation of a user-friendly application for data analysis and image recognition using deep learning methods, including Convolutional Neural Networks (CNNs). By taking a picture of a leaf, users can quickly and accurately diagnose rice illnesses thanks to the usage of a smartphone application. We were able to precisely classify both healthy leaves and illnesses such as Hispa, Brownspot, and leaf blast by utilizing CNNs.

As part of the research approach, photos of healthy and sick rice leaves were collected from Kaggle. React was used in the development of the mobile app prototype, which integrated the CNN illness detection algorithm. Although the three diseases stated above are the main emphasis of this version, future updates will try to add more rice diseases to the app's capabilities. Through the provision of current and useful information to stakeholders, this effort helps to improve food security through crop management methods.

Keywords: Common Rice Disease Detector, deep learning, Convolutional Neural Networks, mobile application, image recognition, food security.

Figures

Tables

Contents

Chapter 1

Introduction

Rice is a staple crop that feeds more than half of the world's population and is essential to food security in the field of global agriculture. Yet, illnesses remain a serious threat to rice farming despite its importance. These illnesses provide a complex challenge to global efforts to ensure food security since they not only jeopardize crop output but also compromise the sustainability and quality of rice cultivation.

Farmers must take prompt, accurate action in the complex tango between managing diseases and cultivating rice. Timely detection and management of rice infections is critical to reducing crop losses, protecting yields, and guaranteeing the ongoing availability of this vital grain. Unfortunately, timely identification and effective management measures are frequently hampered by the complexity and diversity of rice diseases, which exacerbates the situation for farmers.

Let me introduce you to the "Common Rice Disease Detector" initiative, an innovative and hopeful response to agricultural hardship. With the use of technology, this ground-breaking project aims to transform rice farming's capacity for disease detection and diagnosis. Through the utilization of state-of-the-art developments in machine learning, image recognition, and data analysis, our research aims to provide farmers and agricultural experts with an intuitive application that can quickly diagnose and categorize common rice illnesses.

This project's fundamental value is found in its dedication to offering practical, approachable answers to the problems facing rice farming. Our program attempts to bridge the gap between traditional disease control approaches and contemporary technology developments by enabling users to simply take an image of a rice leaf. By promptly identifying and categorizing rice illnesses, farmers would get the essential knowledge to execute focused management strategies, reduce crop losses, and ensure food security.

We explore the specifics of our project in more detail in the parts that follow, explaining its goals, processes, and expected results. We examine the present status of research on rice illnesses and place our findings in the perspective of the broader discussion on food security and agricultural sustainability. We also describe the precise research problems that motivate this effort and the objectives that this technology-driven solution is intended to accomplish.

As a team, let's set out on an innovative and cooperative path to empower farmers, increase agricultural production, and ensure the continued success of rice growing globally.

Purpose

1. Enhancing Food Security: The project helps to protect crop productivity and quality, which in turn ensures food security for people that depend on rice as a staple diet by facilitating early detection and quick management of rice illnesses.

2. Empowering Farmers: By giving farmers an easy-to-use tool for identifying diseases, the program enables them to take prompt action, such as putting in place the proper management measures and, if needed, requesting assistance.

3. Encouraging Agricultural Extension: To provide farmers with information and best practices, agricultural extension personnel are essential. They now have a useful tool thanks to the project to help farmers with crop protection and disease control.

4. Supporting Research and Education: The disease detection system can be used by researchers, agronomists, agricultural specialists, and educational institutions to support their research as well as to give students hands-on experience in plant pathology and agriculture.

5. Improving Agricultural Management Efficiency: Government agricultural agencies, commercial rice farmers, and agricultural consultants can all use technology to efficiently monitor and control disease outbreaks, which will improve resource allocation and agricultural practices.

6. Minimization of Financial Losses: Because rice infections can result in lower yields and lower-quality food, farmers may suffer large financial losses. Through the implementation of focused management measures and early diagnosis, the initiative seeks to reduce these losses and enhance the financial sustainability of rice farming operations.

7. Sustainable Agriculture Practices: One of the most important aspects of sustainable agriculture is the prompt detection and treatment of rice illnesses. The initiative supports integrated pest control techniques and lessens the need for chemical interventions, which helps to maintain soil health and biodiversity while ensuring the long-term sustainability of rice farming systems.

8. Resilience to Climate Change: A growing number and severity of crop diseases are among the new difficulties that climate change brings to agriculture. The disease detection system gives farmers a tool to better anticipate and reduce disease risks, enabling them to adjust to changing environmental conditions.

9. Access to Remote Areas: Agricultural knowledge and resources are not widely available in many places, particularly in developing nations. This is especially true in isolated rural areas. By giving farmers access to disease identification tools even in places with limited extension services or internet availability, the project's mobile application can close this gap.

10. Data-driven Insights: By gathering and analyzing data, the initiative can provide important new information about the frequency, geographic distribution, and long-term trends of rice diseases. Research, policy-making, and focused initiatives can all benefit from this data to enhance disease management tactics on a regional, national, and international scale.

11. Capacity Building and Knowledge Sharing: The project promotes capacity building and knowledge sharing within farming communities by providing farmers, extension agents, and agricultural stakeholders with an easy-to-use disease detection tool. This increases the ability of communities to respond to agricultural difficulties cooperatively, in addition to strengthening the resilience of individual farmers.

Justification

Business Justification

1. Market Demand: New agricultural technologies with the potential to increase crop output and quality are becoming more and more in demand. Since rice is a staple crop for more than half of the world's population, there is a sizable market for products that address the difficulties that rice farmers encounter, especially when it comes to managing diseases.

2. Competitive Advantage: Agricultural technology companies can get a competitive advantage by creating an application that is both accurate and user-friendly for detecting rice disease. In the agriculture industry, gaining market share and building a reputation for oneself can be achieved by being one of the first to provide such a solution.

3. Revenue Generation: There are several ways that the project may make funds, including licensing the technology to government organizations, farmers, educational institutions, and agricultural extension services.

4. Partnership Opportunities: You can find opportunities for partnerships by working with governmental agencies, research institutes, and agricultural organizations. These kinds of partnerships can expand the project's market reach, credibility, and resource availability.

Social Justification

1. Food Security: In areas where rice is a staple grain, ensuring food security is an essential social demand. Through the project's assistance in the early diagnosis and treatment of rice illnesses, food production and availability are protected, improving global food security.

2. Empowering Farmers: Having access to technologically advanced solutions, such as the rice disease detector, can be extremely beneficial for smallholder farmers. The project improves farmers' livelihoods, resilience, and economic empowerment by providing them with the tools they need to recognize and successfully manage infections.

3. Sustainable Agriculture: Sustainable agricultural methods depend on efficient disease control. Through targeted disease management, the project helps farmers minimize their dependency on chemical pesticides, promoting ecologically friendly farming practices and supporting agricultural sustainability.

4. knowledge Distribution: The project makes it easier for farmers, agricultural extension agents, and students to learn about best practices and agricultural information. This boosts creativity, encourages ongoing education and skill development, and helps the agriculture industry increase its capacity.

5. Public Health: Several rice diseases may have direct or indirect effects on public health. The project indirectly improves public health by guaranteeing the availability of wholesome food supplies by assisting in the mitigation of disease outbreaks in rice fields.

Scope and Objectives

Scope

- Image Analysis: The goal of the project is to create algorithms that can identify common disease symptoms by evaluating photographs of rice leaves.
- Segmentation: Methods to focus on the afflicted area for more precise disease detection will be used by separating the rice leaf from the backdrop.
- Disease Identification: Using the symptoms shown in the photos as a guide, the system will be built to reliably identify and categorize prevalent illnesses that impact rice plants.
- User Interface Development: To make it simple for farmers and agricultural experts to take and submit pictures of rice leaves for examination, a user-friendly mobile application interface will be created.
- Integration with Backend Services: To process data, identify diseases, and display results, the application will be integrated with backend services.
- Data management: To train and test the machine learning models, the project will gather and annotate a broad dataset of rice leaf images with related disease classifications.
- Deployment and Testing: To guarantee accuracy, dependability, and performance under varied circumstances, the finished application will be put into use on cloud services and put through a rigorous testing process.
- Documentation: A wealth of information will be supplied, such as user guides, technical specs, and instructions for updating and maintaining the system.

Objectives

1. Image Analysis Module: Create algorithms to examine photos of rice leaves and identify disease symptoms.
2. Segmentation Module: Use techniques in the Segmentation Module to isolate rice leaves from image backgrounds.
3. Disease Identification Module: Develop machine learning models that can precisely identify and categorize common diseases affecting rice.
4. Mobile Application: Create a user-friendly smartphone application that enables users to take and submit pictures to diagnose diseases.
5. Backend Services: Configure backend services for presenting results, identifying diseases, and processing data.
6. Dataset: For training and validation, gather and label a dataset of photos of rice leaves with illness information.
7. Cloud Deployment: For scalability and accessibility, deploy the application on cloud services like Microsoft Azure, Google Cloud, or Amazon Web Services.
8. Testing and Validation: To guarantee the precision, dependability, and functionality of the system, carry out a thorough testing and validation process.
9. Documentation: Write thorough documentation that includes technical specifications, user manuals, and maintenance instructions.
10. Training and Support: Give users access to tutorials and troubleshooting manuals, among other training and support resources.

Boundaries

The initiative may not cover all potential diseases rather, it will concentrate especially on prevalent diseases that harm rice plants.A number of variables, including dataset diversity, lighting, and image quality, may have an impact on how accurately diseases are identified. The application will offer suggestions for managing diseases however, it will not offer detailed treatment regimens or guidance on agriculture.The project will use the cameras on smartphones to take pictures it will not involve developing hardware for specialized imaging equipment.The initiative does not address data privacy, agricultural practice compliance regulations, or legal obligations related to those practices.The system may not be suitable for expert users or agricultural science specialists, as it is intended primarily for people with rudimentary technological skills.In order to handle newly discovered diseases and enhance the precision of disease detection algorithms beyond the original project scope, ongoing upgrades and enhancements might be required.

Chapter 2

Literature review

The research process for creating a Common Rice Diseases Detector requires a thorough analysis of the body of knowledge on rice disease detection. A wide range of research projects covering different techniques and technical approaches are presented in the body of literature. Researchers have looked at a variety of approaches to efficiently diagnose and manage common rice illnesses, ranging from conventional diagnostic procedures to the application of cutting-edge technology like machine learning and remote sensing.

Extensive study has been conducted to detect common rice diseases, such as blast, sheath blight, bacterial leaf blight, and brown spot, according to a thorough review of the literature. Molecular biology tests, spectrum analysis, picture processing, and other detection methods have all been investigated in these investigations. Principal findings from relevant studies highlight how cutting-edge technology may increase disease detection's precision and efficacy, allowing for prompt intervention and better crop management techniques.

Previous research had certain benefits and drawbacks, even with the progress gained in the subject. Investigating cutting-edge techniques and technology is one significant benefit; these have shown promise in enhancing the accuracy and speed of illness diagnosis. These studies, however, frequently include flaws like inconsistent methodology that make it difficult to compare the findings between research and provide inconsistent outcomes. The broad use of these technologies in actual agricultural contexts is further complicated by the limitations placed on many research endeavors by variables including price, scalability, and accessibility.

Additionally, a critical review of the literature reveals several flaws and holes that need to be investigated further. One notable exception is the scant attention paid to creating workable, user-friendly solutions that are specific to the requirements of smallholder farmers. Furthermore, integrated methods for crop health monitoring and disease management—both critical to sustainable agriculture are not given enough attention. These inadequacies offer a chance for new research to fill in the gaps and increase our understanding of rice disease detection and control.

Aiming to address these shortcomings, the proposed study would create a Common Rice Diseases Detector that combines state-of-the-art technology with useful, intuitive user interfaces. The goal of this research is to improve and broaden previous knowledge in the subject by utilizing innovative approaches and incorporating new data. This research aims to further the current conversation on rice disease detection and management by encouraging debate and investigation of theoretical frameworks and workable solutions, ultimately aiding in the creation of sustainable farming methods.

Several instruments and devices, some specifically designed for rice, are currently on the market for diagnosing plant diseases. These systems range in sophistication, accuracy, and usefulness. The following are some problems on current solutions,

- Accuracy: A disease detection system's accuracy can be influenced by a number of factors, such as the level of training data quality and the intricacy of the machine learning algorithms used.
- Dependency on Technology: Mobile apps and cloud-based solutions require internet connectivity and telephones, which are not available in all agricultural locations.
- Cost: Certain complicated solutions may be too costly for small-scale farmers to purchase as membership dues, software, or hardware.
- Accuracy: The intricacy of the machine learning algorithms used and the quality of the training data are two factors that might impact a disease diagnosis system's accuracy.

Possible Solution for the problems

1. Improved Data Quality: Make sure the dataset is representative, diversified, and well labeled before using it to train the detection model. Obtaining data under diverse climatic conditions and from different places might improve the accuracy of the model.
2. Advanced Algorithms: Use cutting-edge deep learning or machine learning techniques designed specifically for image identification applications. Methods such as convolutional neural networks (CNNs) have demonstrated exceptional precision in identifying crop diseases.
3. Simplicity in Deployment: Create a detector that is simple to use and deploy, especially in areas with poor access to technology. Creating a web-based tool or a mobile application that farmers can use with little training may be necessary to achieve this.
4. Compatibility with Low-Tech Solutions: To increase the detector's range, think of combining it with low-tech devices like basic handhelds or feature phones.
5. Open-source Solutions: To reduce the requirement for pricey proprietary software, design the detection model using open-source frameworks and libraries.
6. Cloud Services: Use cloud computing resources for inference and training; these can provide flexible and affordable scalability.
7. Partnerships and Grants: Seek collaborations with academic institutions, governmental bodies, or non-profit organizations that can offer financial assistance or other resources to aid in the creation and implementation of the detector.

Present the theoretical framework

Agricultural science, machine learning, and image processing provide the theoretical foundation for the Common Rice Diseases Detector app. The app is primarily based on the concepts of illness detection, categorization, and management. It emphasizes the use of technological breakthroughs to enable prompt and precise diagnosis of common rice diseases.

Important words and ideas that are essential to the theoretical framework are as follows,

1. Image processing and machine learning:

Many studies have examined the use of machine learning techniques, such as convolutional neural networks (CNNs), to analyze plant leaf photos and detect diseases. These studies usually make use of big datasets of images that have had disease labels added for training and validation.

2. Mobile Applications

Some research has been done on creating mobile apps for diagnosing plant diseases. These apps usually collect images of plant leaves using smartphones' cameras, which are then analyzed using machine learning models to identify ailments.

3. Data Annotation and Collection

Research also includes techniques for compiling and annotating large collections of plant photographs that contain disease information. This step is crucial for machine learning models to be correctly trained for disease detection.

4. Cloud-Based Solutions

A few studies have looked into the use of cloud-based diagnosis systems for agricultural diseases. These systems execute complex machine learning algorithms and evaluate vast volumes of visual data by utilizing cloud computing capabilities.

5. Integrating Disease Diagnosis Systems with Agricultural Extension Services

Some research has focused on combining these systems to provide farmers with current information and guidance on controlling diseases.

6. Disease Recognition

The capacity of the app to recognize visual cues, such as leaf discoloration, lesion formation, and irregular growth patterns, linked to major rice illnesses is being discussed here. Image processing methods are used to automatically detect diseases by extracting pertinent information from photos taken using mobile devices or by drones.

7. Classification Algorithms

To classify paddy diseases using characteristics collected from images, machine learning methods are essential. High accuracy disease type distinction is achieved by the training of supervised learning models, including convolutional neural networks (CNNs), on labeled datasets. These models are trained to distinguish between weak and healthy paddy plants by identifying minute differences in symptom manifestation.

8. Disease Management Strategies

The app recommends suitable management options for managing rice conditions by integrating data on crop phenology, agronomic practices, and disease epidemiology. Advice on crop rotation, when to use fungicides, and cultural measures that lessen disease pressure and minimize yield losses are all included in this.

Models that quantify the degree of disease damage to rice plants based on visual evaluations of symptom severity, such as the Disease Severity Index (DSI), provide support for the theoretical framework. A Decision Support System (DSS) is also integrated into the app, combining historical disease incidence data with real-time weather, crop development stage, and crop circumstances to deliver customized disease management recommendations for each farm setting.

The Common Rice Diseases Detector app provides farmers with the information and resources necessary to properly protect their crops against common rice diseases by fusing theoretical concepts from several academic fields. This approach to disease detection and treatment is holistic. The software is always looking for ways to improve its accuracy, usefulness, and influence on food security and agricultural output.

Chapter 3

Methodology

The Common Rice Diseases Detector uses a multifaceted methodology that combines machine learning and image processing approaches. In order to guarantee the validity of the results, this section describes the procedures and methods used for data collection and analysis.

Overall Approach

The method uses a combination of machine learning and image processing approaches to identify and categorize common rice diseases based on outward signs. The main implements and supplies used are,

1. Image Processing Software: used image preprocessing, segmentation, and feature extraction techniques from photos of rice plants using software tools like OpenCV and scikit-image.

2. Machine Learning Frameworks: developed and trained machine learning models for tasks involving the categorization of diseases using Python libraries such as scikit-learn and TensorFlow.

3. Dataset Collection: compiled a varied collection of tagged photos of paddy plants with the frequent illnesses brown spot, blast, sheath blight, and bacterial leaf blight as well as photographs of healthy paddy plants.

4. Model Training and Evaluation: Utilizing the dataset, convolutional neural network (CNN) architectures, were trained to discover distinguishing characteristics linked to various rice illnesses. used measures including accuracy to assess the performance of the model.

Evaluation of Methods

Challenges Encountered

1. Limited Dataset: Accurately labelling photos depicting different illness stages and environmental circumstances was necessary but obtaining a sufficiently big and diverse dataset proved to be difficult.
2. Class Imbalance: The dataset's unequal class distributions presented difficulties for the model to train on, necessitating the use of methods like class weighting and data augmentation to reduce bias.
3. Model Generalization: It was difficult to ensure that trained models would generalize across various rice cultivars, development phases, and environmental circumstances; this called for effective transfer learning and validation methodologies.

Justification for Technique Selection

The precise rice diseases being targeted, and the required degree of precision determine whether image processing and machine learning approaches should be used.

Image Segmentation: In cases of straightforward disorders with clear color differences, thresholding may be adequate. For improved accuracy, deep learning-based segmentation models may be required for complicated illnesses with complex patterns.

Feature Extraction: The traits of the diseases being targeted determine which attributes are selected. Some people may only need color characteristics, while others may require texture analysis or form descriptors.

Classification: However, because Convolutional Neural Networks (CNNs) can automatically learn significant elements from the data, they have been shown to be very beneficial for a wider range of illnesses with complicated patterns.

Work breakdown

Project Phases and Deliverables

01.Planning

- Project Planning
- Project Proposal Document
- Feasibility Analysis
- Technical & Functional Specification Document

02.Design

- Database Design
- Software Design
- Interface Design

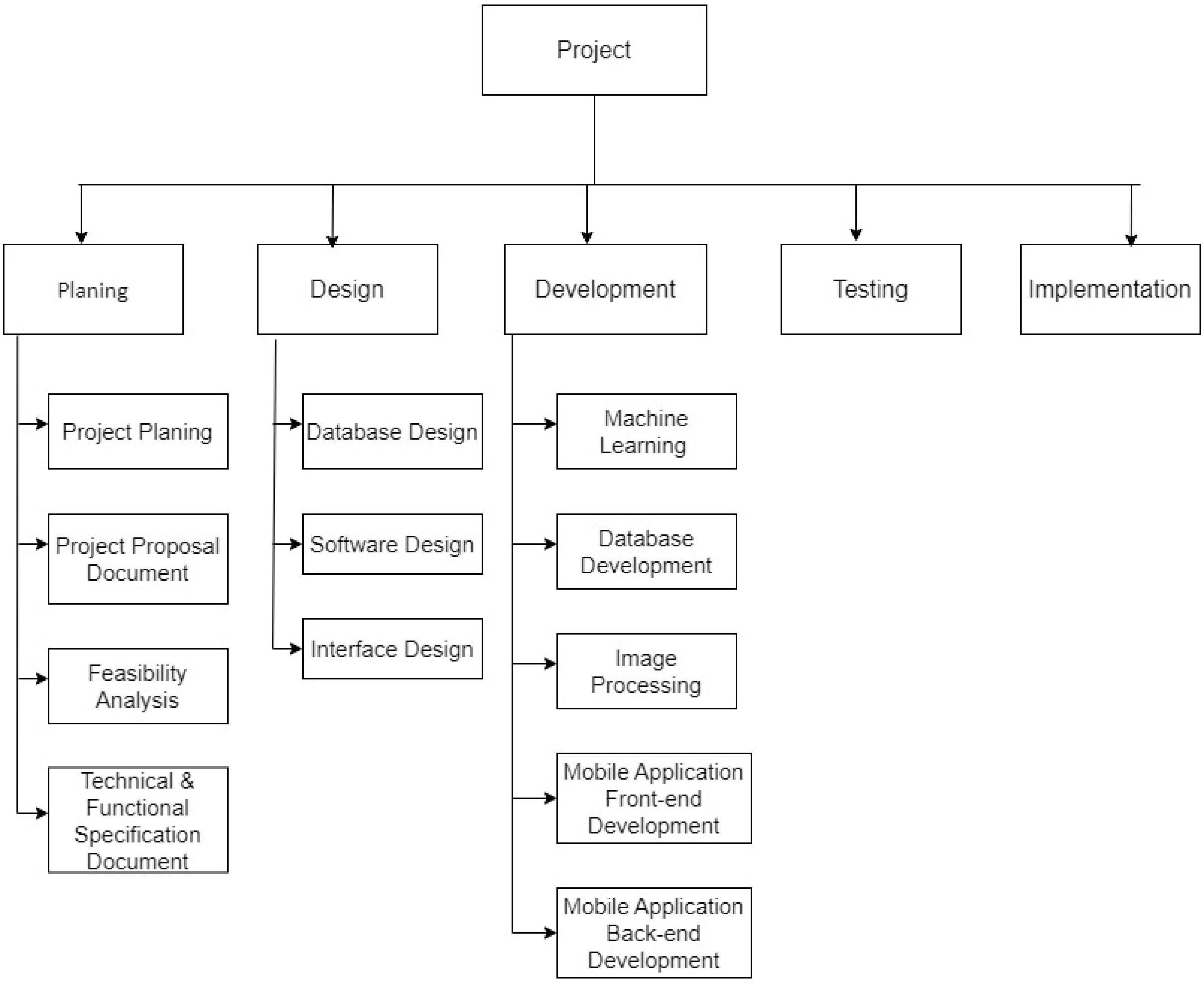
03.Development

- Machine Learning
- Database Development
- Image Processing
- Mobile Application Front-end Development
- Mobile Application Back-end Development

04.Testing

05.Implementation

Tasks breakdown



1 Tasks breakdown

Project Timeline and Task Duration

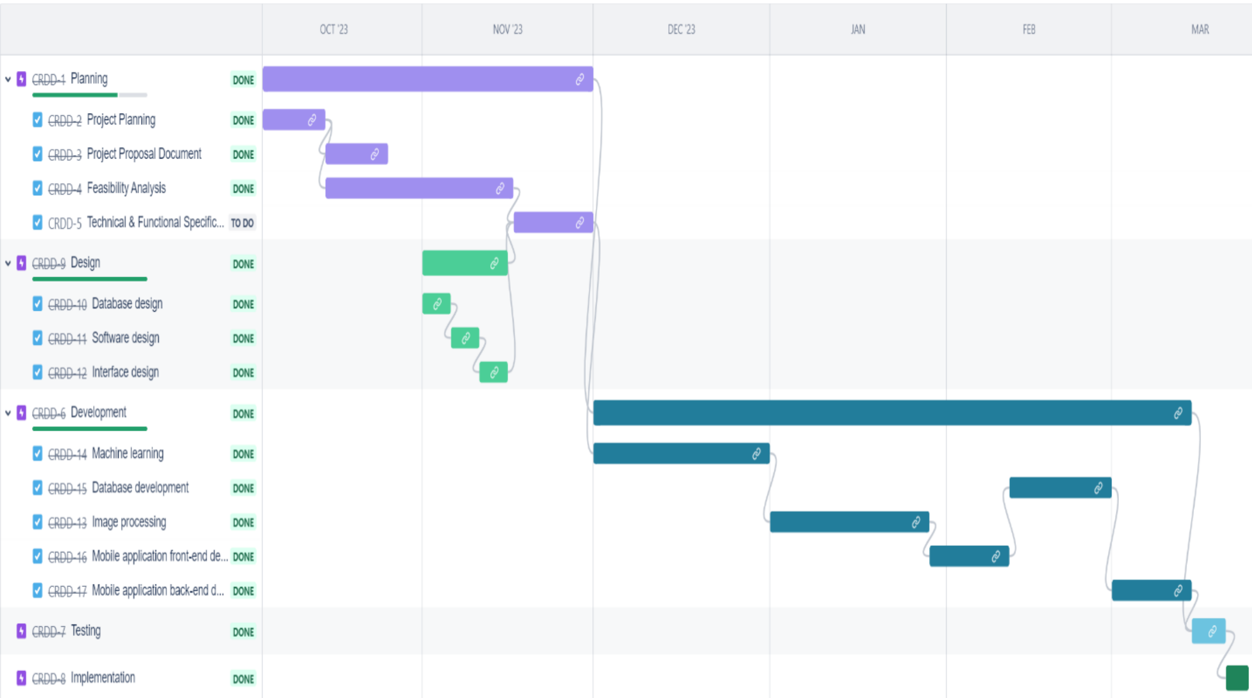
Task Name	Task Started	Task Finished	Duration	Percentage of Task Done
Planning	04/10/2023	30/11/2023	58 days	100%
Project Planning	04/10/2023	14/10/2023	11 days	100%
Project Proposal Document	15/10/2023	25/10/2023	11 days	100%
Feasibility Analysis	15/10/2023	16/11/2023	12 days	100%
Technical & Functional Specification Document	17/11/2023	30/11/2023	14 days	
Design	01/11/2023	15/11/2023	16 days	100%
Database Design	01/11/2023	05/11/2023	6 days	100%
Software Design	06/11/2023	10/11/2023	5 days	100%
Interface Design	11/11/2023	15/11/2023	5 days	100%
Development	01/12/2023	14/03/2024	105 days	100%
Machine Learning	01/12/2023	31/12/2023	31 days	100%
Database Development	12/02/2024	29/02/2024	17 days	100%
Image Processing	01/01/2024	28/01/2024	28 days	100%
Mobile Application Front-end Development	29/01/2024	11/02/2024	13 days	100%
Mobile Application Back-end Development	01/03/2024	14/03/2024	13 days	100%
Testing	15/03/2024	20/03/2024	5 days	100%
Implementation	21/03/2024	24/03/2024	3 days	100%

1 *Project Timeline and Duration*

Dependencies

This project is mainly divided into 5 phases as Planning, Design, Development, Testing and Implementation. In this project, the design phase is the second phase of this project. It is divided into main 3 deliverables as Database Design, Software Design and Interface Design. All 3 parts were completed before the completion of Feasibility Analysis in planning phase and before the start of Technical & Functional Specification Document also in planning phase. This is the only dependency in this project.

Gantt Chart



2 Gantt chart

Critical Path & total time duration

The longest series of activities that define the project's overall time is referred to as the critical path. In this project, has two main critical paths. They are the planning phase and development phase. It took nearly 2 months to complete the deliverables in each phase separately. Also, the testing phase took one month to complete its deliverables.

Total time duration = 186 Days (6 Months)

Milestones

- Project Proposal Document
- Feasibility Analysis
- Development
- Testing

User requirement

Users (Stakeholders)

- Farmers
- Agricultural Extension Officers
- Researchers
- Government Agencies
- Crop Consultants
- Non-Governmental Organizations (NGOs)

User Interviews/observations and Surveys (fact gathering)

- Interview farmers to learn about their requirements, inclinations, and difficulties in detecting rice diseases.
- Speak with government organizations to learn about their requirements for reporting and data management related to disease surveillance.
- Use online research forms.
- Speak with agricultural advisors to learn more about what is needed for decision support systems and precise disease detection.
- Speak with NGOs engaged in the agricultural sector to learn more about the needs for training and community outreach initiatives.

Ways of Facts gathering

To do that we get some interviews from Farmers, Agricultural extension officers and Researchers. Here are the questions we asked them and the answers they replied.

We took details by dividing questions into main 5 parts.

General Paddy Diseases

Questions

1. What are the most common paddy diseases you meet in your fields?
2. Could you explain these diseases' initial warning signs and symptoms?
3. How do these diseases usually develop over time?
4. What difficulties do you have the most while identifying paddy diseases?

Common answers

1. Most Common Diseases: Blast disease, Brown spot disease, Sheath blight, Tungro virus disease
2. Early Signs: Discoloration, wilting, stunted growth, unusual spots or markings. Descriptions will be specific to each disease.
3. Progression: With time symptoms frequently get worse, affecting the whole plant and perhaps spreading to others.
4. Difficulties: Lack of easily accessible diagnostic tools, difficulty differentiating early indications from other problems.

Data Collection

Questions

1. Would you feel okay with us taking photos of your paddy plants at various growth stages? (healthy and diseased)
2. Are there certain seasons of the year or stages of development when diseases are easiest to spot visually?
3. Would you be prepared to provide any current images you may have of your paddy fields that show either healthy plants or plants with a particular disease?

Common answers

1. Comfort Level: Given the right justification and permission, the majority of farmers probably wouldn't mind being photographed.
2. Timing: Responses will differ based on the illness. While some may exhibit more pronounced symptoms later on, others may be easiest to identify in their early stages. Here farmers can provide particular perspectives.
3. Existing Photos: Depending on their methods and prior experiences, some farmers may have photographs.

Impact of Paddy Diseases

Questions

1. What is the usual impact of these diseases on your paddy crop yield?
2. Do you employ any particular therapies to manage these illnesses?
3. What is your experience with the effectiveness of these treatments?
4. How much do paddy diseases cost your farm financially?

Common answers

1. Impact on Yield: Decreased grain yield and lower-quality harvest. Based on their experience, farmers are able to provide precise numbers.
2. Treatments: Depending on the illness, fungicides and insecticides. Certain goods that farmers use may be mentioned.
3. Treatment Effectiveness: Depending on the weather, the severity of the condition, and the timing of the administration, the effectiveness may vary. Farmers can communicate their rates of success.
4. Economic Impact: Reduced income as a result of a lower yield and higher treatment expenses.

Preferences for Disease Detection Tool

Questions

1. How would a paddy disease detection tool be most helpful to you? (mobile app, field device)
2. Which features of such a tool would you find most helpful? (disease identification, treatment recommendations)
3. For a tool like this, how crucial is simplicity of use?
4. Which language would you want to see the tool accessible in?

Common answers

1. Mobile application: Practical and easy to use for farmers working in the field.
2. Features: Potential therapy options, clear visuals or descriptions of diseases for easy identification.
3. Usability: Critically crucial. Farmer preferences could go toward less steps and simpler interfaces.
4. Language: It would be best to use the native tongue, Sinhala.

Additional Information

Questions

1. Which particular varieties of paddy do you grow as your main crop?
2. What are the normal growth conditions in this area for paddy?
3. Apart from disease, are there any other variables that might impact the well-being of your paddy plants?

Common answers

1. Paddy Types: Farmers shared the specific varieties their cultivated with so many details.
2. Growing Conditions: They cover things like normal weather patterns, soil fertility, and irrigation methods.
3. Other Factors: Nutrient deficits and pests like stem borers might be highlighted.

We may learn a great deal from farmers about the particular difficulties they have with paddy diseases by posing these kinds of inquiries. This data is essential for customizing our paddy disease detector project to meet their requirements and guarantee that it offers a workable answer for their farms.

Online research forms

1. This useful PDF file can assist you in diagnosing rice plant diseases such as brown spots, leaf smut, and bacterial leaf blight! This dissertation, which G. R. I. L. Jayasooriya submitted to the University of Colombo School of Computing for credit toward a master's degree in computer science, offers insightful information about various plant diseases.

- https://dl.ucsc.cmb.ac.lk/jspui/handle/123456789/4630
- PDF - 2018 MCS 041

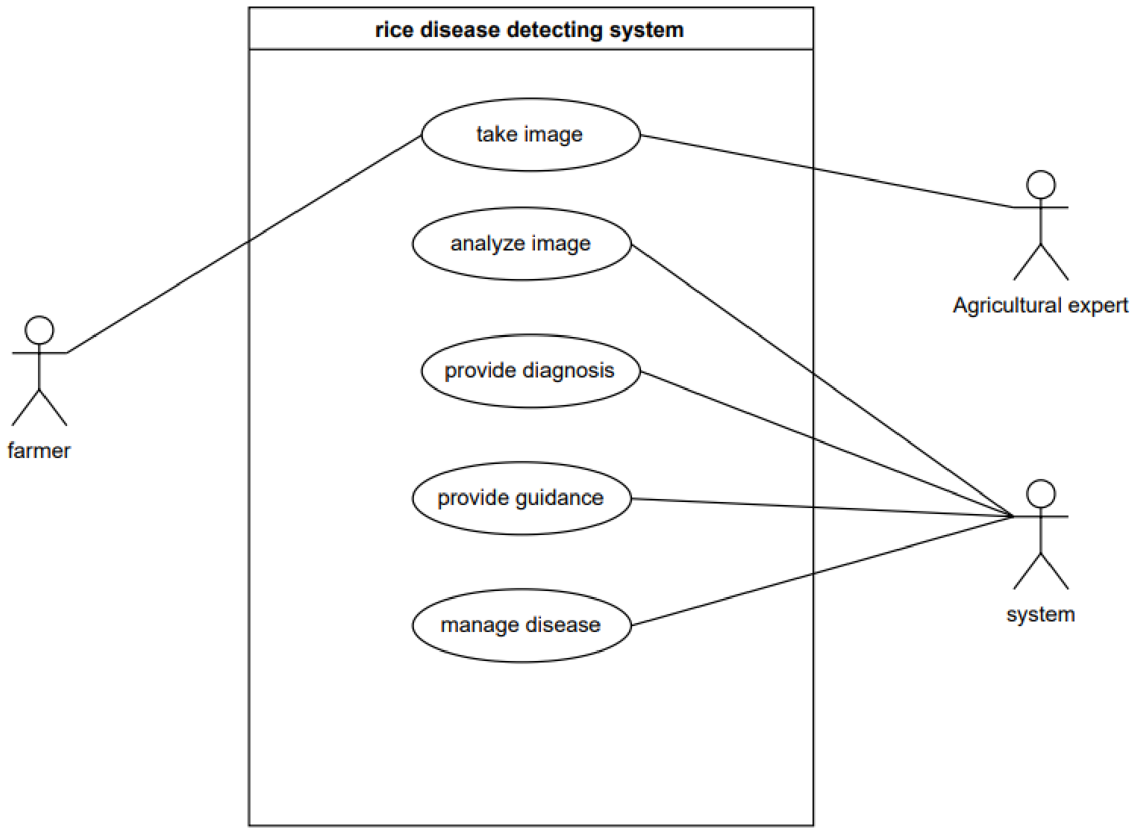
2. In Sri Lanka, the Batticaloa district has a significant rice output limitation from rice diseases including blast and sheath blight. A research was carried out to determine the incidence and prevalence of illnesses in paddy fields and to evaluate rice diseases in certain locations. According to the report, the most common diseases impacting 88% and 86.7% of fields, respectively, were blast and sheath blight. The rice types that were more prone to or resistant to certain illnesses were also determined by the study. In order to reduce disease outbreaks and boost output, farmers were counseled to plant resistant cultivars and implement appropriate field management techniques.

- PDF - Inaternational Symposium 2017 - SEUSL (67)

Use Case Analysis

Include use cases such illness detection in real time, historical data analysis, farmer decision assistance, research data access, and the provision of instructional resources. Examine each use case in detail to comprehend the players, their objectives, and the ways in which those objectives will be met. Provide hypothetical situations to show how various stakeholders will utilize the system in various situations. Rank use cases according to their viability and significance.

Use Case Diagram



3 *User Case Diagram*

Personal Development

Provide up-to-date knowledge on agricultural informatics and disease detection technologies to staff members working on system development. Assist team members in developing their abilities by offering mentoring programs, online courses, and seminars. To keep up with developments in the sector, encourage the team members to pursue professional growth and ongoing education.

Requirements Prioritization

- Set requirements in order of importance for the system's success and compatibility with the demands of stakeholders.
- Think about aspects like the influence on cost-effectiveness, scalability, usability, and illness detection accuracy.
- Include stakeholders in setting priorities so that their top priorities are met first.
- To prioritize needs according to their significance, use strategies like Moscow (must have, should have, could have, won't have) prioritization.

Functional/ Non-Functional Requirements

Functional Requirements

- Real-time disease detection using image processing algorithms.
- Database for keeping track of historical documents and diseases information.
- User-friendly interface for farmers to input data and receive results.

Tools for analytics and reporting that help stakeholders spot patterns and come to wise judgments.

Non-Functional Requirements

- Scalability to manage large volumes of data.
- High accuracy in disease detection.
- Protocols for security to safeguard private data.
- Usability across various devices and different internet access speeds.

Validation and Verification of the findings

- Test and evaluate the system against benchmark datasets and real-world scenarios to confirm that it functions as intended.
- Confirm whether the system satisfies the needs found in the use case analysis, user interviews, and surveys.
- To make sure the system satisfies stakeholders' requirements and expectations, involve them in user acceptability testing.
- To ensure that the system's outputs are accurate and dependable, conduct routine evaluations and audits.

Functional Specification

Functional Requirement 1

Requirement ID: FR1

Requirement Description: Real-time disease detection using image processing algorithms.

Dependencies: Needs access to image-capturing hardware (such as cameras or cellphones), image processing software, and a dependable internet connection in order to process photos in real time.

Acceptance Criteria: At least 95% accuracy in identifying disease in photos is required for the disease identification algorithm.

Real-time processing should occur within 5-20 seconds of image submission according to performance of the device.

Priority: High

Functional Requirement 2

Requirement ID: FR2

Requirement Description: Database for keeping track of historical documents and diseases information.

Dependencies: Needs a dependable server to host the database and a database management system (DBMS) to store and manage data.

Acceptance Criteria: For documents and diseases information, a database should provide CRUD (Create, Read, Update, Delete) activities.

Only authorized individuals should be able to access data, which should be securely kept.

Priority: High

Functional Requirement 3

Requirement ID: FR3

Requirement Description: User-friendly interface for farmers to input data and receive results.

Dependencies: Calls for connectivity with the backend system for data processing and a frontend application or web interface available from various platforms such as desktops, tablets, and smartphones.

Acceptance Criteria:

An interface should have clear directions for entering data and be simple to use.

A user-friendly format such as a text notice or graphical depiction should be available for farmers to obtain the findings of disease detection.

Priority: High

Functional Requirement 4

Requirement ID: FR4

Requirement Description: Tools for analytics and reporting that help stakeholders spot patterns and come to wise judgments.

Dependencies: Requires interaction with data analysis tools or algorithms and access to previous data kept in the database (FR2).

Acceptance Criteria: Trends in the incidence of diseases, regional patterns, and possible risk factors should all be available through analytics tools.

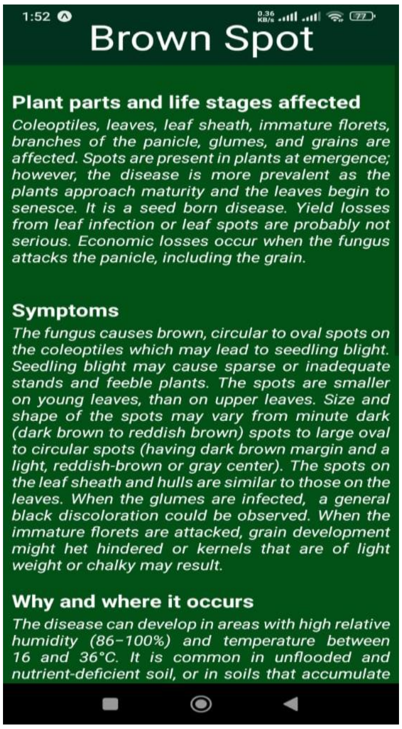
Reporting elements ought to enable stakeholders to produce customized reports according to predetermined standards.

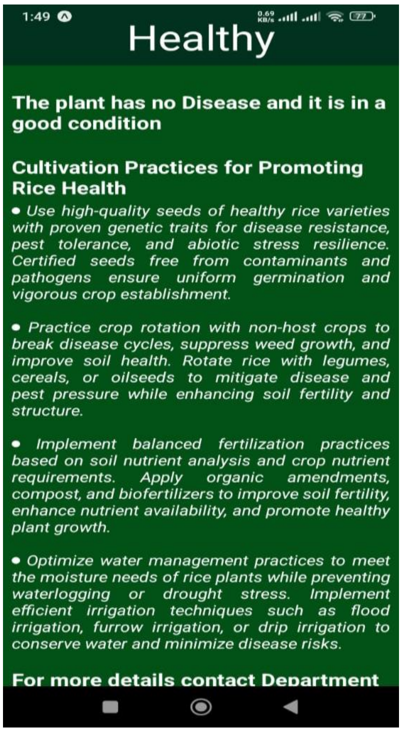
Priority: Medium

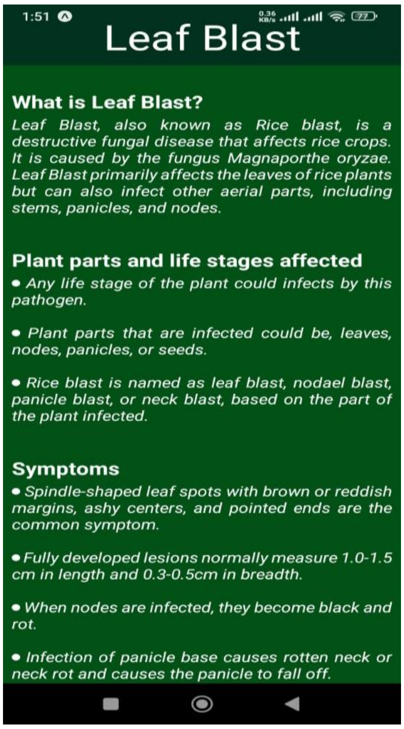
Technical Specification

User Interface Design – UI/UX

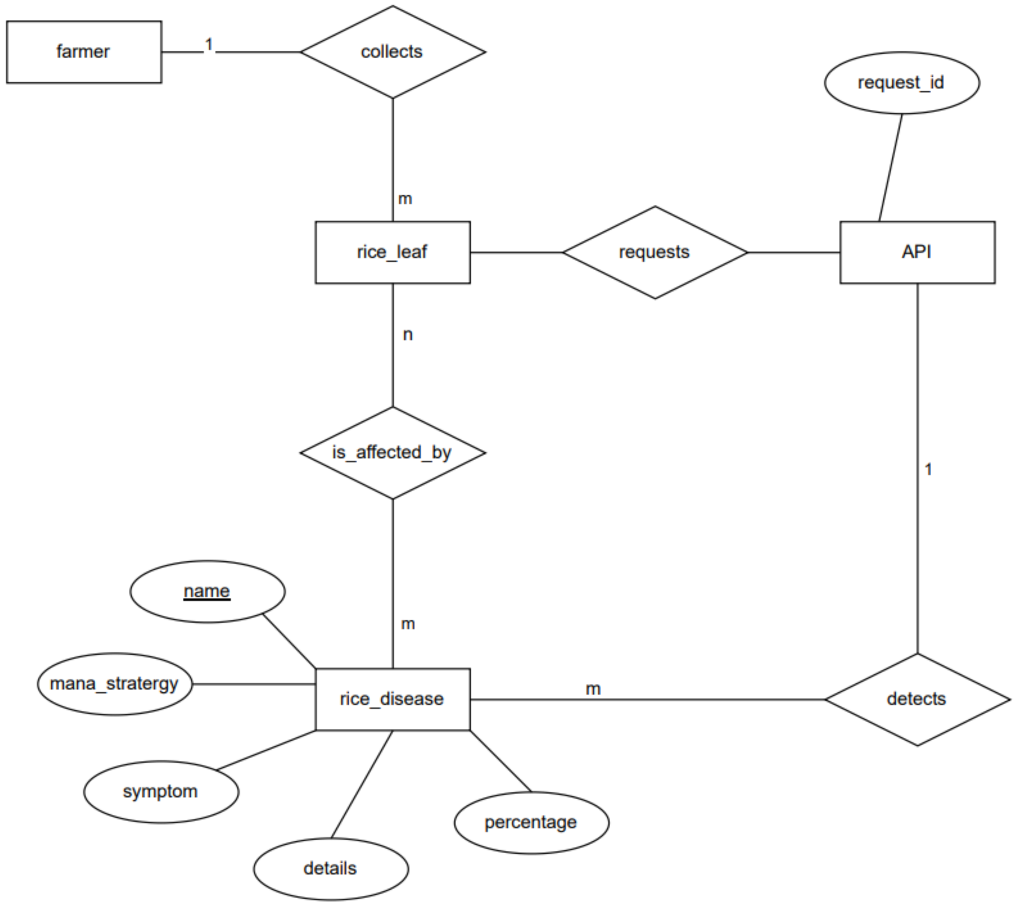
4 UI/UX


1:52
Brown Spot
Plant parts and life stages affected
Coleoptiles, leaves, leaf sheath, immature florets, branches of the panicle, glumes, and grains are affected. Spots are present in plants at emergence; however, the disease is more prevalent as the plants approach maturity and the leaves begin to senesce. It is a seed born disease. Yield losses from leaf infection or leaf spots are probably not serious. Economic losses occur when the fungus attacks the panicle, including the grain.
Symptoms
The fungus causes brown, circular to oval spots on the coleoptiles which may lead to seedling blight. Seedling blight may cause sparse or inadequate stands and feeble plants. The spots are smaller on young leaves, than on upper leaves. Size and shape of the spots may vary from minute dark (dark brown to reddish brown) spots to large oval to circular spots (having dark brown margin and a light, reddish-brown or gray center). The spots on the leaf sheath and hulls are similar to those on the leaves. When the glumes are infected, a general black discoloration could be observed. When the immature florets are attacked, grain development might het hindered or kernels that are of light weight or chalky may result.
Why and where it occurs
The disease can develop in areas with high relative humidity (86–100%) and temperature between 16 and 36°C. It is common in unflooded and nutrient-deficient soil, or in soils that accumulate


1:49
Healthy
The plant has no Disease and it is in a good condition
Cultivation Practices for Promoting Rice Health
• Use high-quality seeds of healthy rice varieties with proven genetic traits for disease resistance, pest tolerance, and abiotic stress resilience. Certified seeds free from contaminants and pathogens ensure uniform germination and vigorous crop establishment.
• Practice crop rotation with non-host crops to break disease cycles, suppress weed growth, and improve soil health. Rotate rice with legumes, cereals, or oilseeds to mitigate disease and pest pressure while enhancing soil fertility and structure.
• Implement balanced fertilization practices based on soil nutrient analysis and crop nutrient requirements. Apply organic amendments, compost, and biofertilizers to improve soil fertility, enhance nutrient availability, and promote healthy plant growth.
• Optimize water management practices to meet the moisture needs of rice plants while preventing waterlogging or drought stress. Implement efficient irrigation techniques such as flood irrigation, furrow irrigation, or drip irrigation to conserve water and minimize disease risks.
For more details contact Department

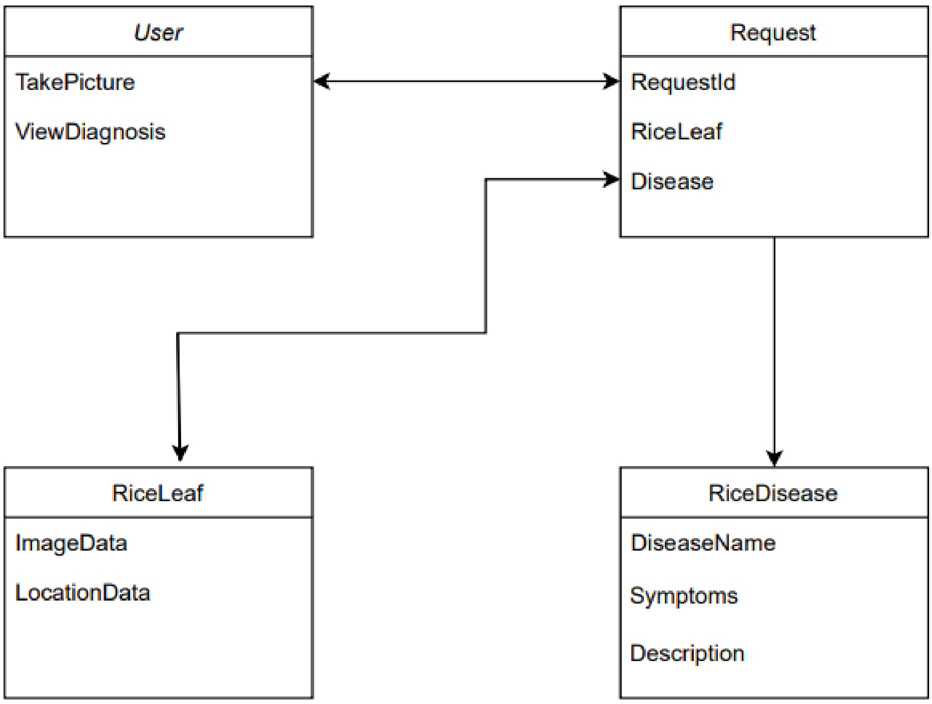

1:51
Leaf Blast
What is Leaf Blast?
Leaf Blast, also known as Rice blast, is a destructive fungal disease that affects rice crops. It is caused by the fungus Magnaporthe oryzae. Leaf Blast primarily affects the leaves of rice plants but can also infect other aerial parts, including stems, panicles, and nodes.
Plant parts and life stages affected
• Any life stage of the plant could infects by this pathogen.
• Plant parts that are infected could be, leaves, nodes, panicles, or seeds.
• Rice blast is named as leaf blast, nodael blast, panicle blast, or neck blast, based on the part of the plant infected.
Symptoms
• Spindle-shaped leaf spots with brown or reddish margins, ashy centers, and pointed ends are the common symptom.
• Fully developed lesions normally measure 1.0-1.5 cm in length and 0.3-0.5cm in breadth.
• When nodes are infected, they become black and rot.
• Infection of panicle base causes rotten neck or neck rot and causes the panicle to fall off.

ER Diagram



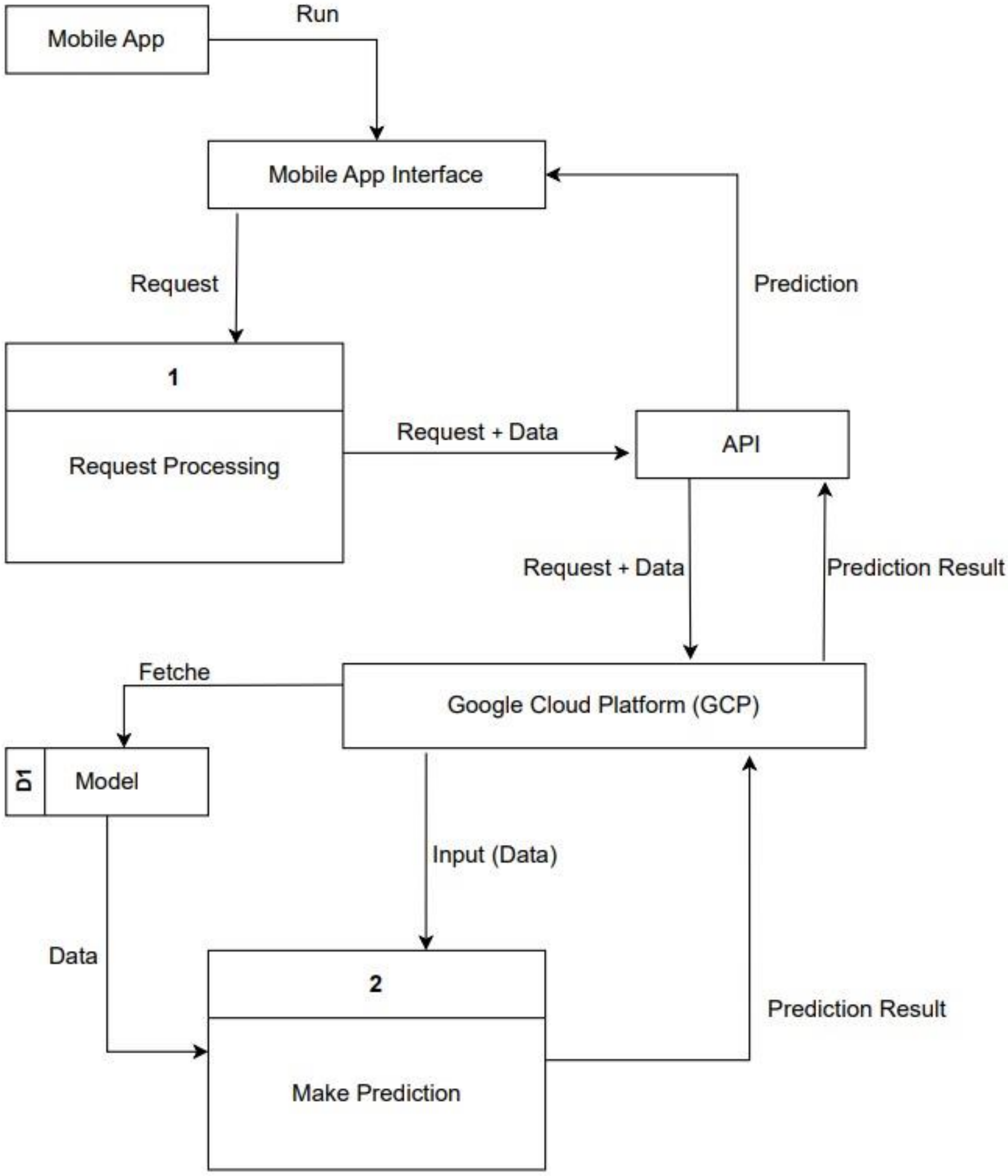
5 ER Diagram

Class Diagram



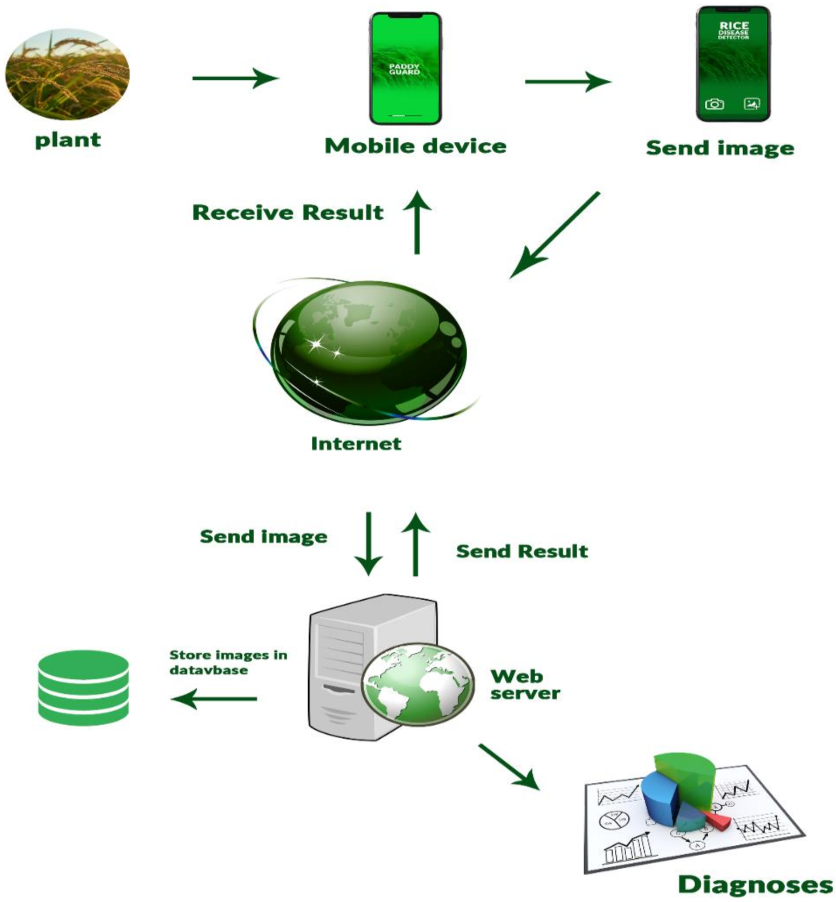
6 Class Diagram

Data Flow Diagram (DFD)



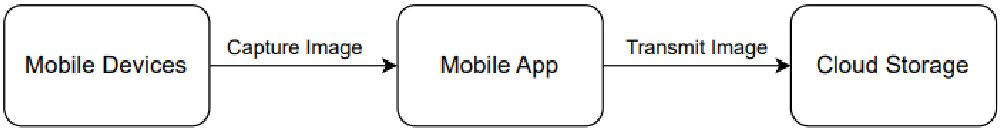
7 Data Flow Diagram (DFD)

System Architecture



8 System Architecture

Deployment and Infrastructure



9 Infrastructure

Testing Strategy

1.Unit Testing

- To make sure everything is working properly, test each component of the program separately (picture pre-processing, illness detection methods).

2.Integration Testing

- Make that the application's various components are seamlessly integrated and communicate with one another.

3.Functional Testing

- Test all of the application's features from the farmer's viewpoint, considering use scenarios such as information access, image capturing, and analysis.

4.Non-Functional Testing

- In here, we have done some testing like Usability Testing, Performance Testing and Compatibility Testing as additional testing for the system.

5.Data-Driven Testing

- Make use of this extensive collection of paddy photos that depict a range of diseases, hardy plants, and difficult situations.
- Make sure the program keeps its high level of accuracy.

6.Edge Case Testing

- Examine the behaviour of the program with uncommon or unexpected inputs.

Dependencies

1.Programming Language

You will require a programming language. Python is often used for computer vision and machine learning tasks because of its large library.

2.Operating System

Development may be done on the most popular operating systems, including Windows, macOS, and Linux.

3.Libraries and Frameworks

- Tensor-Flow or PyTorch: Neural network construction and training tools are provided by these deep learning frameworks.
- Open-CV: necessary for operations related to image processing, including feature extraction, preprocessing, and picture loading.
- Scikit-learn beneficial for applying machine learning algorithms to assessment and classification tasks.
- Pillow: for purposes involving picture processing.
- Matplotlib or Seaborn: In order to visualize data.

4.Pre-trained Models

You may utilize pre-trained models for transfer learning, depending on the detector's complexity.

5.Data

To train the detector, a dataset comprising photos of rice plants afflicted with various illnesses is essential.

6.APIs

- Google Cloud API
- Fast API
- TensorFlow Serving

7.Development Environment

- VS Code
- jupyter notebook

8.Version Control

- Git
- GitHub

Implementation of the Solution

Data Collection: Compile a large collection of photos representing several rice diseases, such as flax leaf spot, bacterial blight, and leaf blast, in order to properly train the machine learning model.

Model Development: For precise disease diagnosis, apply deep learning methods such as Convolutional Neural Networks (CNNs). Utilizing the gathered dataset, train the model to identify and categorize various rice diseases.

Training and Testing: Divide the dataset into testing and training sets so that the performance of the model can be assessed. To increase accuracy and decrease overfitting, use data improvement techniques like as picture preprocessing, random affine transformations, and data augmentation.

Cloud Integration: Use cloud resources to provide real-time disease diagnosis in the field and integrate cloud-based image processing capabilities to handle massive datasets quickly.

App Development: Create a mobile application that is easy to use and incorporates the trained model for disease detection in rice fields while on the road. Make sure the software is highly accurate, easy to use, and affordable for agriculture experts and farmers.

Deployment and Testing: Test the app's ability to reliably diagnose different rice diseases by deploying it in real-world situations. To enhance the functionality and performance of the app, get user feedback.

Chapter 4

Results & Discussion

In this section, outline the findings of your research in a concise and objective manner, refraining from interpreting their meaning. Subsequently, engage in a discussion to provide analysis, interpretation, and contextualization of the results.

Test Case	Test Description	Prerequisite	Test Procedure	Input Data	Expected Result	Actual Result	Status	Severity	Comments
C_01	Verify whether the app is running on mobile.	1. Mobile should be up and running. 2. Expo Go app must be downloaded. 3. Mobile device and the pc/laptop should be connected to the same network.	1. User should scan the QR provided by the expo cli in you laptop/pc using Expo Go app.	QR	The app should be installed and run on the mobile device.	same	Pass	High	
C_02	Verify whether the app is requesting permission to use the camera.	1. Mobile should be up and running. 2. Expo Go app must be downloaded. 3. Mobile device and the pc/laptop should be connected to the same network. 4. App should be installed on the mobile.	1. Run the app. 2. Click the camera icon on the app.		App should be requesting permission to use the camera.	same	Pass	High	
C_03	Verify whether the app is requesting permission to use the gallery.	1. Mobile should be up and running. 2. Expo Go app must be downloaded. 3. Mobile device and the pc/laptop should be connected to the same network. 4. App should be installed on the mobile.	1. Run the app. 2. Click the gallery icon on the app.		App should be requesting permission to use the gallery.	same	Pass	High	
C_04	Verify whether the app can access the camera and the gallery on mobile.	1. Mobile should be up and running. 2. Expo Go app must be downloaded. 3. Mobile device and the pc/laptop should be connected to the same network. 4. App should be installed on the mobile. 5. App should have the permission to use camera and gallery.	1. Run the app. 2. Click the gallery icon on the app. 3. Click the camera icon on the app.		Camera and gallery should open.	same	pass	High	

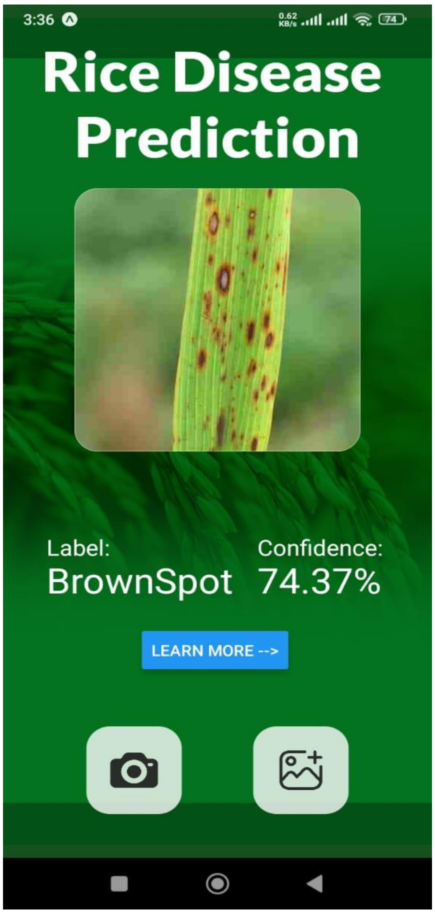
2 Test case

C_05	Verify whether the user can select an image and the prediction of the selected image will be displayed on the screen.	1. Mobile should be up and running. 2. Expo Go app must be downloaded. 3. Mobile device and the pc/laptop should be connected to the same network. 4. App should be installed on the mobile. 5. App should have the permission to use camera and gallery.	1. Run the app. 2. Click the gallery icon on the app. 3. Select an image of a rice leaf.	Image	The prediction of the selected image should be displayed on the screen with the image.	same	pass	High	
C_06	Verify whether the user can take a photo and the prediction of the photo will be displayed on the screen.	1. Mobile should be up and running. 2. Expo Go app must be downloaded. 3. Mobile device and the pc/laptop should be connected to the same network. 4. App should be installed on the mobile. 5. App should have the permission to use camera and gallery.	1. Run the app. 2. Click the camera icon on the app. 3. Take a photo of a rice leaf.	Photo	The prediction of the photo should be displayed on the screen with the photo.	same	pass	High	
C_07	Verify whether the user can go to "Learn More -->" page.	1. Mobile should be up and running. 2. Expo Go app must be downloaded. 3. Mobile device and the pc/laptop should be connected to the same network. 4. App should be installed on the mobile. 5. App should have the permission to use camera and gallery.	1. Run the app. 2. Click the camera/gallery icon on the app. 3. Take a photo/select an image of a rice leaf. 4. Click the **Learn More -->** button.		User should be successfully redirected to the Learn More --> page.	same	pass	High	

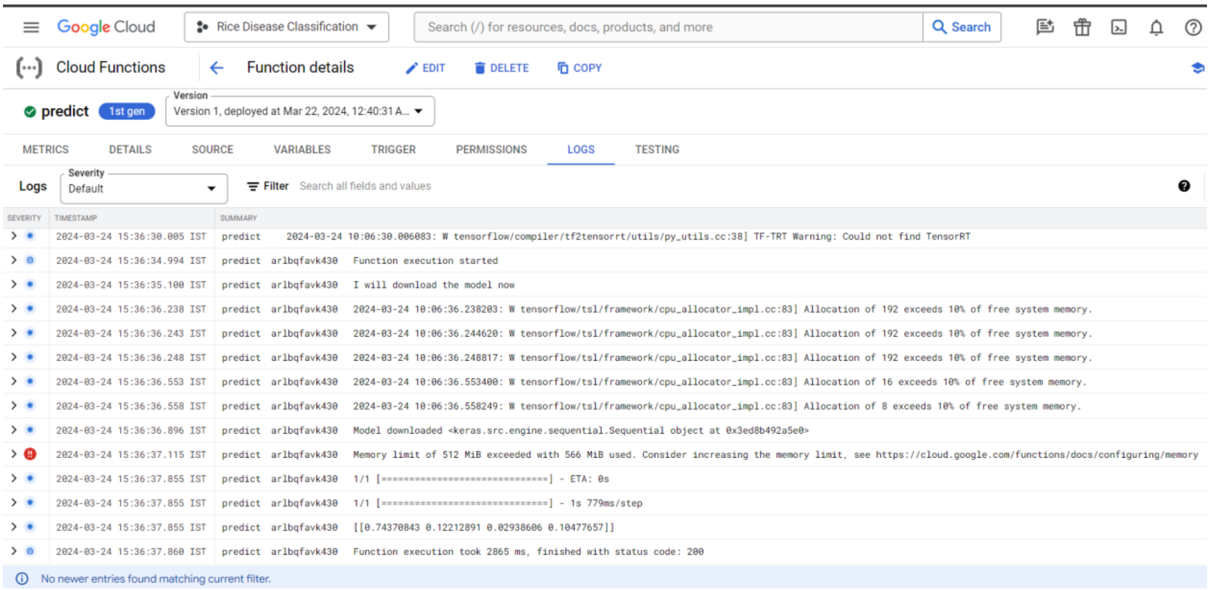
3 Test case

Discussion

The amount of confidence that an illness has is displayed when we check it with an image using our mobile application. Then the command that generates through app we can see in the



10 Mobile Interface



11 Google Cloud Logs.

Chapter 5

Conclusion and Future Works

In conclusion, our work on the Common Rice Diseases Detector app has provided important new understandings into how technology and agriculture interact. By creating and utilizing this cutting-edge technology, we have effectively illustrated how machine learning algorithms can reliably diagnose common rice diseases. Our software enables farmers to take proactive steps in controlling crop health, hence reducing yield losses and boosting sustainable farming practices, by giving them access to fast and accurate diagnostic information. Furthermore, the project's focus on accessibility and user-friendliness guarantees that farmers in rural areas may also profit from this technology, highlighting its potential to democratize agricultural innovation and improve global food security.

It is essential to acknowledge the constraints of our research, nevertheless. The Common Rice Diseases Detector app is promising when tested in controlled situations, but in real-world settings, factors including different disease strains, environmental factors, and technical infrastructure might affect how well it performs. Sustaining research and development activities will be necessary to tackle these obstacles, incorporating end-user feedback and continuously improving the detection model. Notwithstanding these obstacles, our study is a significant advancement in the use of technology to address urgent agricultural concerns and opens the door to future farming techniques that are more resilient and sustainable.

Future Works

The Common Rice Diseases Detector App’s Future Works provide fascinating chances for more investigation and improvement of the existing study. Here are a few possible areas to investigate and enhance in the future.

1. Increase the number of paddy diseases: Currently, we have designed this App to identify only a few special diseases of the paddy crop. If they are Hispa, Leaf Blast and Brown Spot. In the future, this app is expected to increase the number of diseases in the paddy crop. Also, it is hoped to create an App that detects all the diseases of the paddy crop.

2. Enhanced Disease Classification: Although the app's present version correctly identifies prevalent rice disorders, future work may concentrate on broadening the scope of diseases that are recognized. The app's diagnostic skills might be further enhanced by adding new disease kinds and variants, giving farmers a more thorough grasp of crop health concerns.

3. Recreate the app with Local Language: Currently this app interfaces are display with English language. As agricultural country our farmers also use this app. Therefore, we hope to create this app interfaces in Sinhala language for their convenience.

4. Machine Learning Optimization: Further investigation into machine learning methods and algorithms may help to improve the functionality of the app. Investigating techniques for ensemble modeling, federated learning, or transfer learning may improve the app's capacity to generalize across many geographical locations and environmental circumstances, hence enhancing its dependability in a variety of agricultural environments.

5. Community Engagement: Encourage a feeling of community among app users by giving them the chance to interact, exchange ideas, and share experience and best practices for managing and detecting rice disease.

Reference list

- Rice research and development institute, Bathalangoda. “RICE in SRI LANKA - RICE DISEASES.” Commonricediseases, Department of Agriculture Sri Lanka. https://doa.gov.lk

- Rice Leaf Diseases Detection Using Machine Learning
  Authors: Priyanka Kulkarni, Swaroopa Shastri
  https://www.researchgate.net/publication/377215046_Rice_Leaf_Diseases_Detection_U sing_Machine_Learning

- Augmented Rice Plant Disease Detection with Convolutional Neural Networks
  Authors: Hairani Hairani , Triyanna Widiyaningtyas
  https://www.researchgate.net/publication/377852812_Augmented_Rice_Plant_Disease_Detection_wit h_Convolutional_Neural_Networks

- Level up with the largest AI & ML community https://www.kaggle.com

- http://www.statistics.gov.lk/Agriculture/StaticalInformation/PaddyStatistics#gsc.tab=0

- Diagnosis of bacterial leaf blight, brown spots and leaf smut rice plant diseases.
  Author: G. R. I. L. Jayasooriya
  https://dl.ucsc.cmb.ac.lk/jspui/handle/123456789/4630
  PDF - 2018 MCS 041

- ASSESSMENT OF RICE (ORYZA SATIVA) DISEASES IN SELECTED G.N. DIVISIONS IN BATTICALO DISTRICT
  Authors: S.L.Rasmiya Begum and A.N.M.Mubarak Department of Biosystems Technology, Faculty of Technology, South Eastern University of Sri Lanka, Sri Lanka.
  PDF - Inaternational Symposium 2017 - SEUSL (67)

Appendix 1: [User Guide]

User Guide

Mobile App:

- Download the app: The App is available for download on Android devices. (By using QR code)
- Install the App: Tap on the download file install the app on your device. Once installed, tap on the app icon to open it.
- Launch the App: Open the app on your device.
- Access Camera: You must give permission to access your device's camera. Tap on "Allow" to enable the app to use your camera.
- Capture Image: Position your device's camera over the rice plant and tap on the shutter button.
- Enter Picture for Prediction: You can enter image from your phone gallery or capture image and enter it.
- Wait for Prediction: The app will analyse the submitted image using its disease detection algorithms.
- View Results: After the analysis is complete, the app will display the results.
- More Information: You also have access to additional information about the detected disease.

Appendix 2: [Resource Allocation]

Resource Allocation

Lanka Pathmakumara - 10899186

A key member of our paddy disease detector project team, Lanka has made noteworthy advances in the field of machine learning. His knowledge in this field was essential to our project's success.He concentrated mostly on creating and optimizing the machine learning model. He painstakingly created algorithms, used labeled datasets to train the model, and then enhanced its functionality. Lanka made sure that our system correctly recognized and categorized paddy crop illnesses from photos by utilizing his expertise in feature extraction, feature selection, and classification approaches. His commitment went beyond the technical details as well. He worked in tandem with other team members, exchanging ideas and overcoming obstacles. His meticulousness throughout the testing and validation phases demonstrated his dedication to the project's success. His individual input greatly improved our technique for detecting paddy diseases, allowing farmers to avert large losses and raise crop quality. His machine learning knowledge was invaluable to us in accomplishing the objectives of the project.

Senadheerage Dinethmin - 10899275

Dinethmin played a crucial role in our paddy disease project team and produced significant advancements in the field of mobile application development. His knowledge in this field really enhanced our project. Developing a reliable and user-friendly mobile application was Dinethmin's main duty. He gave careful consideration to the UI of the app, making sure that it is easy to use and navigate. When he added capabilities like picture capture, illness categorization, and real-time notifications, his coding expertise was evident.
Furthermore, He engaged in active collaboration with fellow team members, soliciting comments and implementing enhancements. His dedication went beyond programming; he tested everything thoroughly, fixed errors right away, and improved stability all around. His individual effort was crucial in enabling farmers to utilize our mobile app-based paddy disease detection system. His commitment and technical expertise greatly increased the effect of our effort.

Thuseya Rankelum - 10899423

As an important member of the project team for our paddy disease detector, Rankelum was instrumental in the development of our documentation and API. His efforts have improved the general usability and functionality of the project. He made sure that all team members had access to clear instructions and references by thoroughly documenting every part of our system. He included usage instructions, data flow, API endpoints, and system architecture in his well-organized documentation. Thuseya's meticulous attention to detail made it easier for team members to collaborate and expedited the development process.He was the driving force for our API design in addition to the documentation. He created and put into use endpoints for system status, model predictions, and data retrieval. His strong API made it simple for other apps to communicate with our paddy disease detection system. His commitment went beyond only doing technical work. He answered questions and offered ideas throughout his active participation in team meetings. His dedication to upholding a culture of open communication and encouraging teamwork was admirable.

Kenath Kapilarathna – 10899412

Kenath made significant contributions in the areas of mobile application development and API development. His knowledge really enhanced our project and made it more user-friendly and accessible. The main task assigned to Kenath was to develop a reliable and user-friendly mobile application. His careful interface design ensures easy navigation and the best possible user experience. When he added capabilities like picture capture, illness categorization, and real-time notifications, his coding expertise was evident.In addition, He actively participated in teamwork by asking for input and implementing changes. His dedication went beyond programming; he tested everything thoroughly, fixed errors right away, and improved stability all around. Concurrently, He was instrumental in creating the API that functioned as the foundation of our system. He created and put into use endpoints for system status, model predictions, and data retrieval. His strong API made it possible for outside programs to communicate with our paddy disease detection system without any problems.

Liyanage Perera - 10898869

As a vital person of our paddy disease detector project team, Liyanage made important contributions to the field of UI/UX Design. His knowledge in this field significantly improved our system's accessibility and user experience. The user interface (UI) for our paddy disease detection program was painstakingly designed by Liyanage. His goal was to create a design that would appeal to both farmers and agricultural specialists, while also being visually beautiful and intuitive. Liyanage made sure the app was simple to use and navigate by paying attention to user demands and behavior. He made contributions to improvements in user experience (UX) in addition to UI design. He iterated on design components, tested usability, and got input from prospective consumers. His attention to detail was evident in the font, iconography, and color schemes he used to create a unified and captivating user experience.

Thuduwa Silva - 10899212

An important contributor to our paddy disease detector project team, Silva was instrumental in the documentation process. His efforts have improved the general usability and functionality of the project. Every facet of our system was painstakingly documented by Silva, guaranteeing that team members had access to precise instructions and references. He included usage instructions, data flow, API endpoints, and system architecture in his well-organized documentation. The development process was expedited and team members' ability to collaborate seamlessly was enhanced by his meticulous attention to detail. He regularly engaged in team meetings, offering insights and answering questions in addition to documenting. His dedication to upholding a culture of open communication and encouraging teamwork was admirable. His individual documentation efforts made a substantial difference in our project's ability to identify paddy diseases, which benefited farmers and enhanced crop health.

Resources Allocation Summary

Index	Name	Work distribution
10899186	Lanka Pathmakumara	Machine Learning model
10899275	Senadheerage Dinethmin	Mobile application
10899423	Thuseya Rankelum	Documentation and API
10899412	Kenath Kapilarathna	API and Mobile application
10898869	Liyanage Perera	UI / UX
10899212	Thuduwa Silva	Documentation

4 Resources Allocation