" SunRice: Automatic Diagnosis of Rice Diseases using Deep Learning."

In Partial Fulfillment of the Requirements for the Degree of Bachelor of Science in Information Technology

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Approval Sheet

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ABSTRACT

Rice diseases significantly impact agricultural productivity, leading to considerable yield losses if not detected and managed promptly. Traditional methods of disease identification rely on manual inspection, which is often time-consuming, labor-intensive, and susceptible to inaccuracies. This study introduces SunRice, a mobile application that utilizes deep learning for the automated detection and classification of rice plant diseases. The system was developed using Google's Teachable Machine and trained on a dataset comprising 18,000 images representing five prevalent rice diseases (Brown Spot, Leaf Blast, Neck Blast, Stem Borer, and Tungro) alongside healthy rice plants. Data augmentation techniques were employed tota augmentation techniques, including image and flipping, were used to enhance model accuracy and

The study adopted an Agile development methodology, facilitating iterative improvements and optimizations throughout the development process. Twelve deep-learning models were trained and evaluated to determine the most effective model. The final model achieved exceptional classification accuracy, with 100% accuracy for the Stem Borer category and an average of 98% accuracy across other disease classifications. The confusion matrix analysis indicated minimal misclassifications, demonstrating the model's robustness and reliability. Additionally, accuracy per epoch analysis revealed that the model rapidly learned disease patterns, stabilizing within 20 training epochs. At the same time, end-user testing confirmed its usability and effectiveness in real-world agricultural settings.

The SunRice application enables real-time disease diagnosis, allowing farmers to capture or upload images of rice plants for immediate analysis and classification. By integrating deep learning and mobile technology, this system provides a cost-effective, scalable, and efficient solution for early disease detection. It ultimately improves decision-making in rice cultivation and mitigates potential crop losses. Future enhancements will focus on expanding the dataset, refining real-time analysis, and further integrating additional crop disease detection functionalities to support sustainable and technology-driven agriculture.

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CHAPTER I

INTRODUCTION

The total crop in agricultural products has gained importance with the increase in the world population. For this reason, the detection of plant diseases affecting the total crop has also become an important research topic. Plant diseases are one reason that reduces the yield and quality of agricultural products. If these diseases, which cause yield and quality decline, are not prevented, the total yield will be directly affected. The main problem with plant diseases is that plants cannot be monitored regularly [1]. It is essential to constantly check the diseases that can occur in the plant because they vary from year to year, depending on weather conditions. Plants growing in wetlands, such as the rice considered in this study, are more challenging to monitor than other plant species. This study deals with disease detection of rice consumed in almost all countries using image processing and artificial neural networks.

Agriculture is the main industry in the Philippines. The country's production covers domestic demand because it is located in Southeast Asia, where rainy and dry seasons alternate. According to the Food and Agriculture Organization of the United Nations, the Philippines was eighth in rice production in 2018 [2]. It is considered an essential commodity in the country. However, farmers lose about 37% of their annual rice yield to pests and diseases. Damages caused by pests and diseases constitute a significant part of crop losses. The study included expert plant health assessment and numerical estimates of worldwide production losses due to diseases and pests for five major crops, including rice [3]. Its result showed that the loss of rice production was probably 30%. On the other hand, crop management and early and correct diagnosis can significantly reduce losses. Plant protection experts advise and remind farmers that early diagnosis or recognition of rice diseases is the best way to prevent the possible spread and increase farmers' losses.

In agriculture, diagnosing rice diseases involves observing symptoms like leaf discoloration, lesions, or unusual growth patterns. Common diseases include blast, bacterial blight, sheath blight, and brown spot, whereas proper identification helps implement targeted management strategies like crop rotation, resistant varieties, and cultural practices. Furthermore, it is essential as it directly impacts crop health, yield, and quality. Early and accurate identification allows for timely intervention, preventing widespread outbreaks that can damage an entire field. Effective disease management strategies safeguard current harvests and contribute to long-term sustainability by reducing reliance on chemical treatments and preserving soil health. Lastly, proper diagnosis enables researchers to develop and improve varieties with enhanced disease resistance, ensuring the resilience of rice cultivation in the face of evolving pathogens and environmental challenges. [4]

Rice disease has a significant negative effect on yield, and correct diagnosis of this disease is crucial to avoid these effects. Currently, there are no precise and effective methods to diagnose rice disease, although special equipment is often needed. An automatic diagnostic method was developed for this study and used in a mobile application. Deep learning was used to develop this method from a huge image database. It is a promising technique to diagnose various crop diseases with high accuracy.

Company Overview

Jauod Rice Fields, situated in Purok 4, Mahayahay, Balisong-Cabayangan, Braulio E. Dujali, Davao del Norte, exemplifies excellence in sustainable agriculture. Operated by the Jauod family, consisting of ten siblings, the fields reflect decades of dedication to quality rice farming and environmental stewardship. The Jauod family integrates innovative practices into their traditional farming methods. By collaborating with the SunRice Application, they have improved crop monitoring and management. This technology enables early detection of rice plant diseases, allowing for precise interventions to optimize yields and maintain crop health.

Furthermore, Jauod Rice Fields actively contributes to agricultural research and development. Partnering with government agencies and agricultural experts provides fields for experimental studies that aim to benefit the broader farming community. Jauod Rice Fields is a model of progress that balances traditional farming values with modern innovations. Through their vision, the Jauod family continues to set high standards in rice production, inspiring other farmers and advancing agricultural practices for future generations.

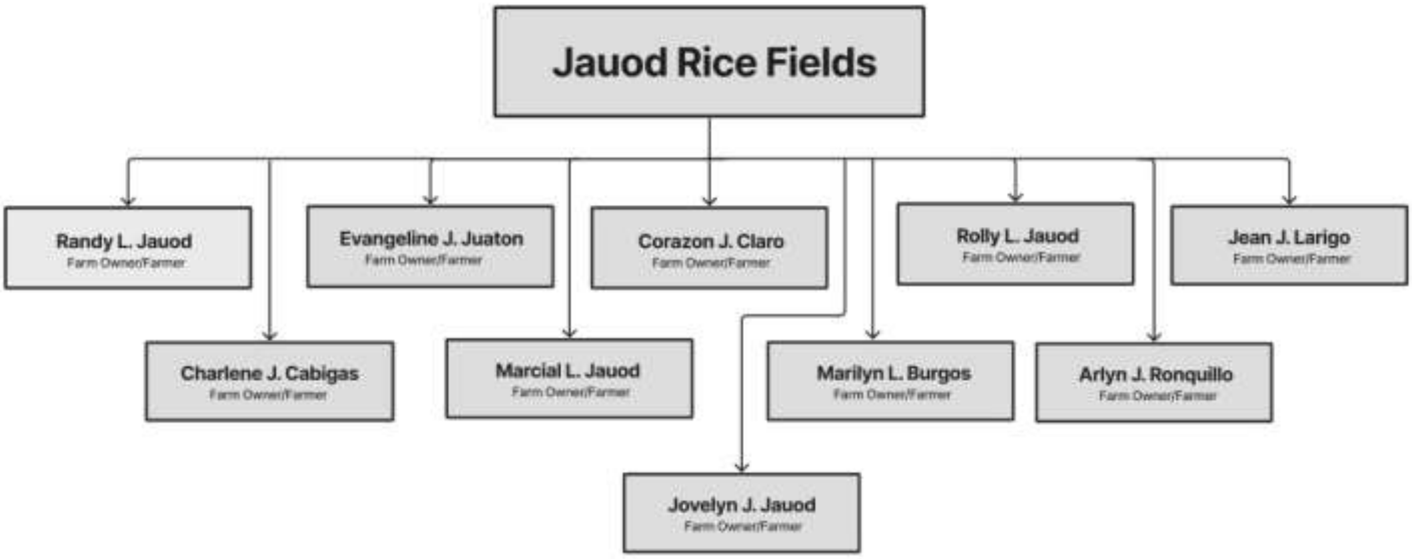

Figure 1. Jauod Rice Fields

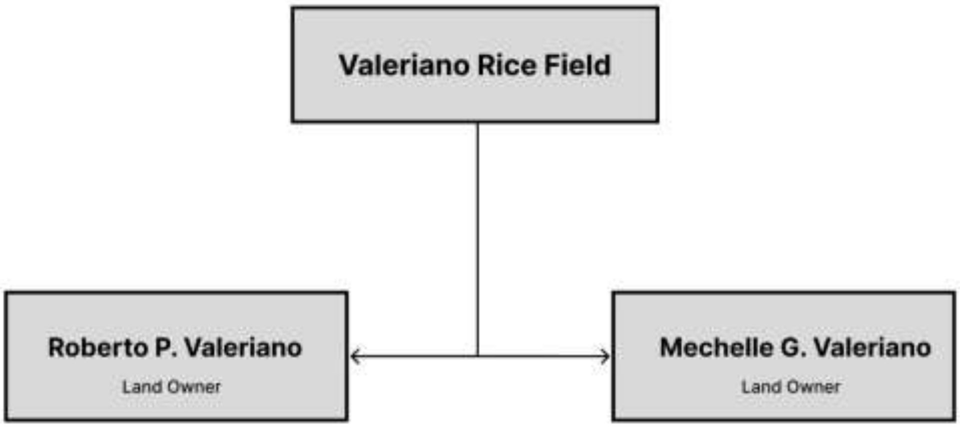

Figure 2. Valeriano Rice Field

The Valeriano Rice Fields, situated in CMRR+C8, Purok 7, Dujali, Braulio E. Dujali, 8106 Davao del Norte, are owned by Mr. Roberto P. Valeriano and Ms. Michelle G. Valeriano. The rice fields serve as a key agricultural area for cultivating and testing rice varieties, with support from the local government, which provides seeds to promote sustainable farming practices. The collaboration between the Valeriano Rice Fields and the municipal office of Braulio E. Dujali underscores their commitment to advancing agricultural research and development in the region.

Objectives of the Project

General Objectives

The main objective of this research is to develop an application that implements Automatic Diagnosis of Rice Diseases Using Deep Learning, allowing for timely intervention and management strategies to mitigate crop losses, improve agricultural productivity, and ensure global food security.

Specific Objectives

The specific objectives of the research on the Automatic Diagnosis of Rice Diseases Using Deep Learning may include:

1. To allow users to take and upload photos of rice plants to identify diseases.
2. To design an application that allows users to check rice plant details, such as disease description, information, cause-effect, and a guide on how to cure diseases.
3. To provide and gather a comprehensive dataset of images featuring healthy rice plants and various diseased states.
4. To develop a deep learning-based application capable of automated detecting and classifying diseases in rice plants.
5. To provide users with a complete record of their disease test results.

Scope and Limitations

The design development of SunRice**:** Automatic Diagnosis of Rice Diseases using Deep Learning is designed to aid in detecting and managing plant diseases through advanced image recognition technology.

Scope of the Study

1. The administrator is responsible for authorizing access to the system, which allows the input of details and images exhibiting signs of diseases.
2. Assessment of how image quality and diversity within the training datasets can impact disease detection accuracy.
3. The disease datasets only include conditions like neck blast, leaf blast, and brown spot, stem borer, and tungro.
4. The user manual provides users with information and instructions on how to effectively use the application. It offers guidelines for utilizing the application.
5. Procedures for continuous improvement are implemented to minimize mistakes and enhance the system's performance.

Limitation of the Study

1. The accuracy of the disease detection may be affected, such as poor image quality, and the percentage result of accuracy should exceed 70%.
2. The reliance on advanced image recognition technology could lead to potential technical glitches or limitations.
3. The training dataset's limited diversity might lead to misidentifying or overlooking certain diseases, such as Brown Spot, Neck Blast, and Leaf Blast, Stem Borer, Tungro.

4. An Android-powered smartphone is the only device that the user may use.

Significance of the Study

The result of this study will benefit the following:

To the Farmers. An autonomous diagnosis method for rice illnesses allows farmers to easily and quickly identify plant concerns, providing precise insights to manage their crops efficiently. Farmers can use technology to swiftly identify diseases damaging their rice plants, eliminating the need for substantial expertise or time-consuming human inspection.

To the Administrator. This study holds significant potential for administrators by offering valuable insights and tools to enhance administrative practices within the capstone project. By investigating best practices in data management, security protocols, and operational efficiency, administrators can improve decision-making processes and streamline workflows. Ultimately, the study aims to empower administrators with knowledge and strategies to optimize resource allocation and enhance overall project success.

To the Future Researcher. Future researchers can use the outcomes of this study on automatic rice disease diagnosis to gain a better understanding and increase their knowledge base. Our findings provide insights into the creation of automated systems for diagnosing rice diseases, which may be used as a reference point for future studies.

To the Student. This study offers students a valuable opportunity to deepen their understanding of cutting-edge agricultural technology and disease management techniques, equipping them with practical skills and knowledge for future endeavors in research or industry.

Definition of Terms

Different terms are defined herein to facilitate the understanding of this study.

Machine Learning. Machine learning is a branch of artificial intelligence that builds models that let machines do tasks like image classification, data analysis, and price prediction that would otherwise only be possible for humans by using algorithms trained on data sets. Machine learning is one of the most prevalent types of artificial intelligence in use today, powering many of the digital products and services we depend on daily [5].

Deep Learning. A technique in artificial intelligence (AI) called deep learning trains machines to process information in a manner modeled after the human brain. Deep learning models can generate precise insights and predictions by identifying intricate patterns in images, text, sounds, and other data types. Deep learning techniques can automate processes that generally call for human intelligence, like text transcription from audio files or picture descriptions [6].

Artificial Intelligence. The goal of the broad field of computer science known as artificial intelligence (AI) is to create machines that can carry out tasks that traditionally require human intelligence. Though AI is an interdisciplinary science with many different applications, developments in deep learning and machine learning, in particular, are revolutionizing almost every sector of the economy. Machines with artificial intelligence can match or even surpass human mental capabilities. AI is permeating more and more aspects of daily life, from the creation of self-driving automobiles to the spread of generative AI tools [7].

Neural Network. A neural network is an artificial intelligence technique that teaches machines to process information like that of the human brain. A particular kind of machine learning known as "deep learning" makes use of networked nodes or neurons arranged in a layered pattern to mimic the structure of the human brain. It builds an adaptive system that computers can use to grow continuously by learning from their errors. Artificial neural networks, therefore, make an effort to more accurately solve challenging problems, such as document summarization and face recognition [8].

Convolutional Network Neural Network. ConvNets, short for Convolutional Neural Networks, are a particular kind of deep learning algorithm that is primarily used for tasks requiring object recognition, such as image classification, detection, and segmentation. CNNs are used in many real-world applications, including security camera systems and driverless cars, among others [9].

Image Processing. Image processing is the process of converting an image to a digital format and carrying out specific operations on it in order to extract valuable data. When using particular preset signal processing techniques, the image processing system typically handles all images as 2D signals [10].

Pathogens. A pathogen is any living organism that spreads illness. Pathogens can include bacteria and viruses, but they can also take other forms. Any living thing has the potential to contract a pathogen, including bacteria. There are many pathogens in the world. According to expert estimates, the number of viruses on Earth surpasses the number of stars in the universe. The majority of these microorganisms have no detrimental effects on your health. A few even prove to be beneficial [11].

Mobile Application. The simple mobile application definition is a type of software designed specifically for use on a mobile device. Unlike traditional computer software, which is designed to run on desktop or laptop computers, mobile apps are developed to provide functionality tailored to the capabilities and limitations of mobile devices [12].

CHAPTER II

REVIEW RELATED LITERATURE

International Studies

The automated leaf disease diagnosis system is one of the most sophisticated tools used in precision agriculture. This system analyzes photos of infectious leaf diseases to identify diseases in plants. To identify diseases, it combines machine learning (ML), deep learning (DL), computer vision, and image processing algorithms. Leaf diseases were traditionally identified using human vision-based models, but these techniques can be costly and time-consuming. Furthermore, these models' performance is determined by the assessments of experts or individuals. By streamlining the diagnostic procedure, the automated leaf disease diagnosis system, on the other hand, enables farmers to decide on the state of their plants quickly and accurately. This can assist farmers in increasing crop yields and using resources more effectively [13].

Artificial intelligence technology is being used in some applications to diagnose diseases of plants. Among them is Pestoz [14]. Snapping pictures of illnesses and sending them to the diagnosis system is now possible for users. With recommendations for solutions, it will automatically process and return prediction results. Pest and disease identification on more than 30 plants is supported by an application called Plantix [15]. This tool can be used by farmers and agricultural officers to provide advice on crop prevention and appropriate management. Autonomous plant disease diagnosis still has limited applications, though. Each nation's plant species and disease types were taken into consideration when developing those applications, which served various functions.

Convolutional Neural Networks (CNNs) is the most appropriate model of Rice Disease Image Dataset since it uses image analysis. It was proven by [16] that convolutional neural networks (CNNs) have used in the field of computer vision for decades. Artificial intelligence (AI) techniques have a lot of potential to provide information in agriculture about the maximum probability of pest infestation, when and where to spray herbicide, and the quality of the soil. Around the world, farmers are using artificial intelligence (AI) techniques to monitor crop health more efficiently. They can be applied to practically any crop to control diseases. Crop management can now be done more accurately than ever before thanks to AI techniques that have been used to build and create intelligent machines [17]

Moreover, with the growing popularity of camera-equipped mobile devices, the number of mobile applications for image analysis has increased dramatically. There are several examples of mobile applications related to agricultural and plant diseases, which can be downloaded through the Google Play Store. For example, Rice Doctor [18] and Rice Expert (National Rice Research Institute, 2020) are mobile applications that offer both plant disease and pest diagnostics. They provide knowledge that displays images and text explanations. Also, keywords can be used to search for information and frequently asked questions.

Local Studies

Convolution Neural Networks and Deep Learning: This paper presents Convolution Neural Networks (CNNs) as a novel field of machine learning that is used to classify images in order to treat crop plant diseases. In order to categorize an image, the author [19] created a mobile application for diagnosing crop plants exhibiting symptoms of signature diseases. This application allows for the identification of signature diseases through the use of several rules pertaining to color, shape, and past weather information. Its foundation is mobile phone detection. An agriculturalist using the above-developed application can add to or modify the supported list of plant diseases [20].

Digital image analysis is used in this study to automate the disease detection process. Digital image analysis is becoming a widely used technique for task automation [21]. Additionally, automation reduces subjectivity and streamlines labor-intensive, time-consuming tasks. Every sample leaf goes through the same process, which improves accuracy, precision, and consistency. It is also possible to extract the shape features of the abnormal region in the rice leaf by using digital image analysis. Next, using these extracted features, the presence of brown spots and leaf scald—two of the most significant fungal diseases affecting rice—will be ascertained [22].

Enumerate rice diseases, such as leaf blasts and brown spots, which can be identified using various pattern recognition techniques. This is important because it helps to identify the infected disease. In order to classify images of diseased rice, they suggested using a neural network based on the Self Organising Map (SOM) in conjunction with a zooming algorithm. A satisfactory classification result was obtained by using boundary detection and spot detection techniques to extract features from the infected portions of the plant's leaves. Identifying a disease manually is challenging; however, with the development of an automated method, the process becomes simple [23].

Convolutional Neural Networks (CNNs) are deep learning algorithms that use images as input to a learnable process that can distinguish between different aspects of the image. A rice leaf is used as an input, and the database contains images of rice leaf diseases that correspond to the input. According to [24], a lot of researchers employ deep learning techniques to automatically classify images. Sorting items that will be observed into predefined categories is the aim of classification. Moreover, [25] mentioned that it would be highly intriguing to conduct more research on the detection method supported by basic image processing in the evidence. In order to complete the study, [26] the researcher also used the data processing method.

Neural networks have been used in related research to detect rice leaf disease. As stated in [27], "Using computational intelligence-based methods has shown to be effective for automated rice-disease detection in recent years". [28] According to a related study, "an automated system could have a feature on detection of diseases present in a rice leaf using color image analysis.". Additionally, it was stated in [29] that "the management of perennial fruit crops requires close monitoring, especially for the management of diseases that can significantly affect production and, consequently, the post-harvest life. Researchers developed a rice disease detection method that is correlated with the scenarios that were presented.

Functionalities	**Plantix**	**Rice Doctor**	**Peztoz**
Allows users to create an account or sign in to access the application's features.	/	/	
Enable users to capture and analyze images to detect any present image using processing techniques.	/	/	/
Users can upload pictures directly from their devices to the application.	/		/
The user knows the result of what disease in a crop.	/		/
The application shows the result percentage of the diseases of the crop.			
They provided detailed descriptions of various types of objects, including their characteristics, growth patterns, and common reasons for their susceptibility.	/	/	
Offers information on detected objects, including symptoms, causes, and recommended treatments for each identified object	/	/	
Suggests specific remedies or treatments for the detected object based on best practices and scientific research in agriculture.	/	/	

Table 1. Comparison Table

Table 1. shows a complete analysis of the image processing systems of existing projects. The report details the characteristics of the system that distinguish it from other systems and its fundamental similarity with existing projects. To highlight these differences and similarities, this system draws attention to the uniqueness of the project's contributions and potential progress. Comparison table of the system to other image processing projects.

CHAPTER III

METHODOLOGY

This research used a combination of methodologies. This chapter describes the methods used for this dissertation and the system development methodologies.

With an agile methodology, the developers are working on the project in phases to deliver a working application as soon as possible. They decided to develop the application using the Agile methodology since it allows for flexible and effective project planning, design, development, and implementation. The developers initiate the planning phase by determining the application's nature, focusing on the primary objectives and features. This straightforward and flexible approach to planning allows for adjustments as necessary. The developers craft the application to ensure easy comprehension and use for the users. This entails the creation of uncomplicated, user-friendly interfaces and layouts.

In the development phase, developers build the application in small parts or increments. Each part is developed, tested, and improved continuously. As developers complete each part, they implement it, gather feedback, and make necessary adjustments. This way, the application evolves and improves with each iteration. Using Agile, developers can adapt to changes quickly, involve users throughout the process, and ensure the final application meets their needs effectively.

Figure 3. Agile Software Development Method

Work Breakdown Structure

Figure 3. shows how to make work more manageable; developers often use a productivity tool called the Work Breakdown Structure (WBS). In the framework of the WBS, the project is divided into smaller, more manageable tasks. The breakdown makes it possible to focus on individual components of the project and not be bogged down by its complex nature. Each task may be planned and defined by the project team. They will be able to identify what is needed, who should do it, and what the anticipated results are going to be. This clarity is helping to establish timelines and appropriately allocate resources.

To arrange the scope and deliverables in such a way as to ensure coherence, the WBS shall assist. The hierarchy of each task provides an indication of the relationship among various tasks and their contribution to a given project objective. The WBS serves as the main source for scheduling project activities. It allows you to see all your tasks clearly, making it easy to monitor progress and make sure that everything is on time.

The use of the WBS as a monitoring and control tool is one of the most significant contributions of the WBS. They may be used by developers to monitor the progress of each task, identify any deviations from the plan, and adjust accordingly to keep the project on schedule. By using the WBS, developers can ensure a more organized, effective, and controlled approach to project management, which will lead to better results and higher quality.

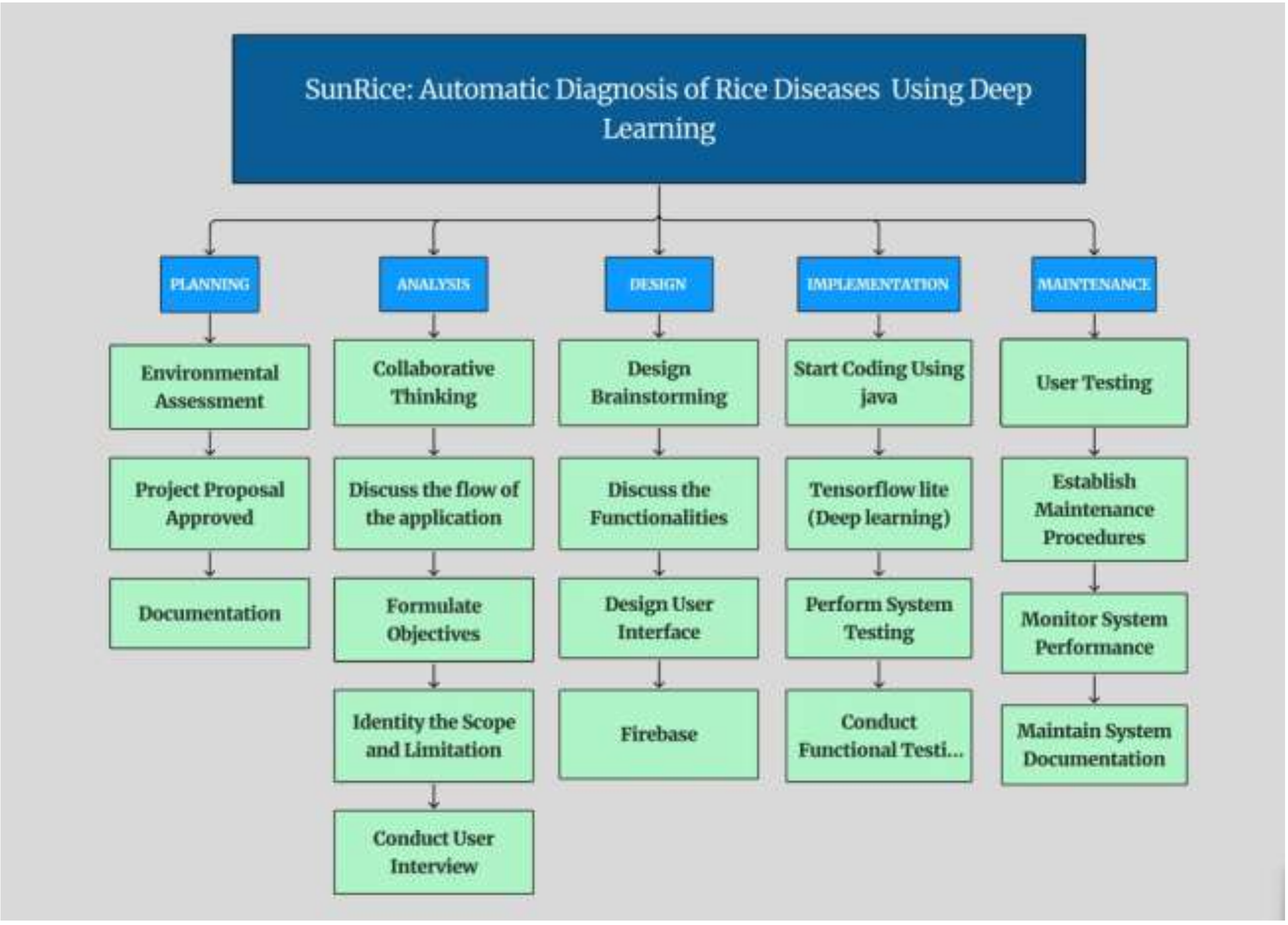

Figure 4. Work Breakdown Structure

System Planning

The researchers embarked on their project by conducting an extensive literature review to identify suitable deep-learning models for their objectives. Subsequently, they engaged in a structured planning phase, which involved selecting appropriate models, preparing training datasets, conducting experiments, and refining their approach based on the outcomes of these investigations. Additionally, they ventured to the Jaoud rice field to collect a dataset encompassing diseases prevalent in the area. During this field visit, they interviewed Mrs. Evangeline J. Jauod, one of the field owners, to gather insights into the diseases affecting their rice fields. Their findings revealed the presence of brown spots, neck blasts, leaf blasts, tungro, and stem borer among the prevalent diseases in the area.

Finding the affected rice paddy fields, a process influenced by some seasonal factors, was the first step in the training data preparation phase. By taking pictures of the afflicted fields, images of rice disease were obtained. To assure data quality, minimize duplication, and guarantee accurate labeling, farmers were given access to these images for review and validation. The authenticity of the disease photos was confirmed by farmers, who also helped classify the images according to the diseases that were visible in each image.

To verify the accuracy of these photographs, researchers have been working together with farmers. Although the pathogen types such as viruses, bacteria, and fungi could be broadly classified into rice leaf diseases, it has been recognized that each pathogen presents some specific physiological symptoms that require accurate identification. This collaboration has ensured that the training data set contains a wide range of disease manifestations, thereby strengthening the robustness of the deep learning model.

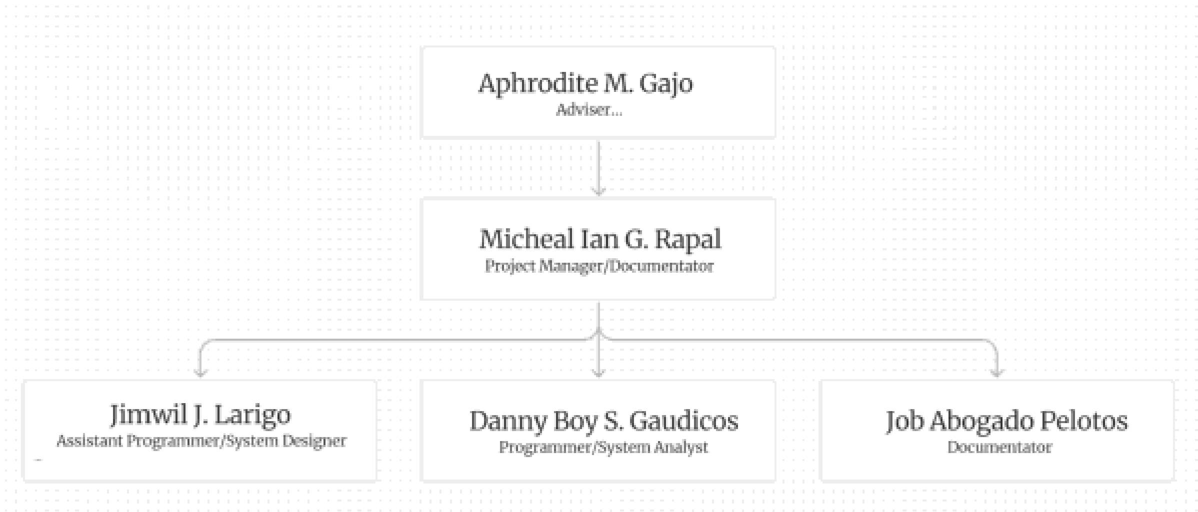

Figure 5. Project Team Organization

Rice Plant Diseases

This section of the study focuses on identifying the causes of various rice plant diseases, including Brown Spot, Leaf Blast, Neck Blast, Stem Borer, Tungro, and healthy rice plants. Examples of rice plant leaf diseases are illustrated in Figure 6 (sourced from Kaggle) and Figure 8 in SunRice, and the Healthy Rice Plant are illustrated in Figure 6 (sourced from Kaggle) and Figure 8 in SunRice.

Brown Spot is characterized by infections occurring just below the panicle, typically at the neck node. These infections can lead to harmful "neck rot" or "rotten neck blast" symptom in rice crops. If neck rot develops early, the entire panicle may perish prematurely, resulting in a blank, white appearance [30]. Leaf Blast is caused by the fungus *Magnaporthe oryzae*. It is recognized as one of the most significant rice diseases globally due to its widespread prevalence and substantial damage in favorable environments [31].

Neck Blast manifests through infections just below the panicle, typically at the neck node, leading to "neck rot" or "rotten neck blast" symptoms. If this condition arises early, the panicle may die prematurely, giving it a blank, white appearance [32]. Healthy rice is a protein source and rich in essential vitamins, such as thiamin and niacin, as well as minerals, including zinc and phosphorus. However, certain nutrients such as vitamin E, magnesium, potassium, and manganese are lost during the milling and polishing process that converts brown rice into white or polished rice. These nutrients remain exclusive to brown rice [33].

Tungro disease affects all phases of plant development, but symptoms are most pronounced during the vegetative phase [34]. Plants affected by tungro experienced leaf discoloration, stunted, reduced tillers, and delayed flowering accompanied by the presence of vectors of both imago, nymph, and eggs [35]. Damage caused by stem borers in rice cultivation results in the appearance of dead hearts, midge in the vegetative stage of the plant, and white heads in the flowering stage. Mechanically, the freshly hatched larvae bore into the stem and feed internally, causing the death of central shoot dead hearts in the vegetative stage and white head at the flowering stage, respectively. This results in chaffy grains. The larvae feed on the green tissue of the leaf sheath [36].

Data Collection and Datasets Overview

This research involved collecting rice leaf disease samples, encompassing five (5) distinct diseases Brown Spot, Leaf Blast, Neck Blast, Stem Borer, and Tungro as well as one (1) healthy rice plant. Data were gathered from Kaggle and SunRice, with additional collaboration from Jaoud and Valeriano Rice Fields. The SunRice dataset, as detailed in Table 3, consists of 18,000 images. This dataset provides an equal distribution of 3,000 images for each category: Brown Spot, Leaf Blast, Neck Blast, Stem Borer, Tungro, and Healthy Rice Plants.

The Kaggle dataset, summarized in Table 2, includes 4,122 training images. These comprise 653 images of Brown Spots, 981 images of Leaf Blast, 1,000 images of Neck Blast, and 1,488 images of Healthy Rice Plants. The PlantVillage dataset, provided under the Kaggle categories, included images exclusively of Corn species. It is a widely recognized and commonly utilized dataset for plant disease identification through leaf imagery [37]. Additionally, the *Dhan-Shomadhan: A Dataset of Rice Leaf Disease Classification for Bangladeshi Local Rice* was incorporated into this study [38].

Images from the Rice Brown Spot and Rice Leaf Blast classes were supplemented with leaf background images from their respective categories to augment the training samples. This enhancement aimed to increase the dataset's diversity and robustness. The dataset used in this study is licensed under CC BY 4.0 [39], and none of the images were altered or edited. Another vital resource utilized in this study, the "Rice Leafs" dataset, was sourced from Kaggle [40].

Data Augmentation

Data augmentation techniques were applied in this research stage to enhance the dataset images used for gathering data and testing rice diseases. The augmented datasets provided diverse samples, ensuring robust training and evaluation of the model developed for rice disease identification. The data augmentation process included creating variations such as Normal Image, Rotate Image, Slight Zoom, Adjust Brightness (Light and Dark), and Flip Image. These transformations ensured the model was exposed to various conditions, improving its robustness and generalizability.

Figure 7, obtained from Kaggle, illustrates sample images after applying data augmentation techniques. Similarly, Figure 9, derived from the SunRice dataset, presents additional examples of augmented images. These images were pivotal in building a comprehensive dataset, as Table 3 of the SunRice application outlines. Using Google's Teachable Machine, the dataset was trained to create a machine-learning model that effectively identified rice diseases. This process ensured the model's reliability and accuracy when integrated into the SunRice application, enabling efficient disease detection and diagnosis.

The automatic disease detection process involves several steps. It begins with data acquisition, where diseased images are collected using various devices, such as cameras, mobiles, image sensors, and spectral cameras. After data acquisition, data preprocessing is performed to enhance the quality of the images and prepare them for further analysis. This preprocessing stage may include noise reduction, image enhancement, segmentation [41] and data augmentation [42], standardization of the image size. Segmentation is the process of partitioning an image into multiple segments or regions based on certain criteria, such as color, intensity, texture, or semantic information.

Kaggle Rice Plant Diseases

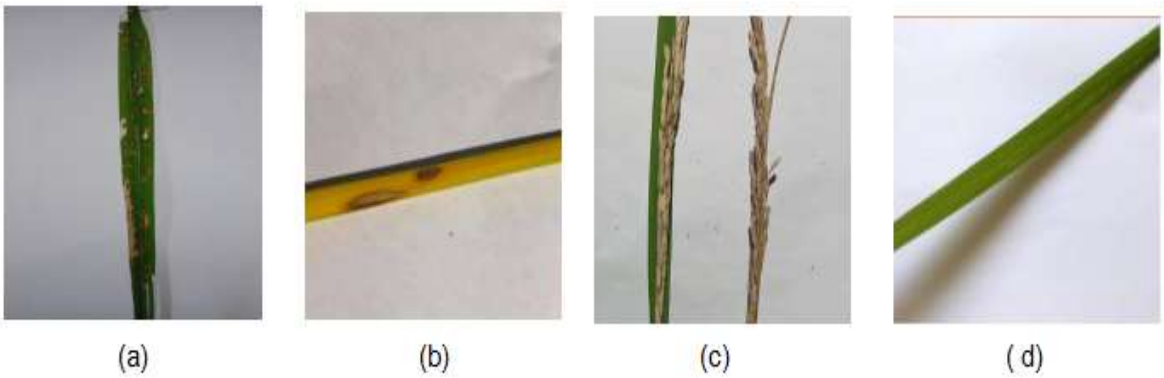

Figure 6. Kaggle Rice Plant Diseases Sample: **(a)** Brown Spot, **(b)** Leaf Blast, **(c)** Neck Blast**, (d)** Healthy.

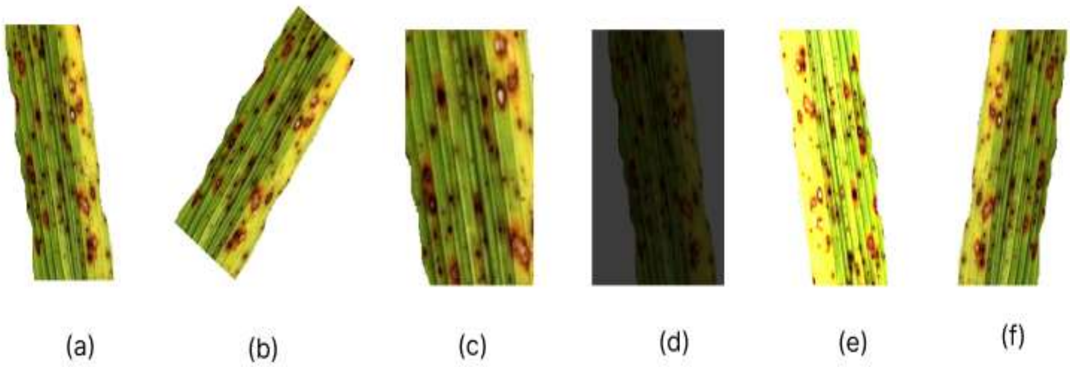

Figure 7. Kaggle Sample Images after Data Augmentation: **(a)** Normal Image, **(b)** Rotate Image, **(c)** Slight Zoom, **(d)** Adjust Brightness-Light, **(e)** Adjust Brightnesss-Dark**, (f)** Flip Image.

List of Rice Diseases	No. Of Images
Brown Spot	653
Leaf Blast	981
Neck Blast	1000
Healthy	1,488

Table 2. Kaggle Rice Plant Diseases Datasets

This table provides an overview of the Kaggle leaf diseases dataset, listing the categories of healthy and diseased rice leaves and the number of images for each category. This dataset would be used to train and evaluate a deep neural network model in the research [37].

SunRice Rice Plant Diseases

The research focused on building a comprehensive dataset for rice disease identification through systematic image collection and augmentation techniques.

Additionally, Table 3 outlines the rice fields involved in the study, specifically the Jaoud Rice Fields and Valeriano Rice Fields, detailing the number of datasets collected from each location. The combined efforts of field collection, laboratory imaging, and data augmentation ensured the development of a reliable and comprehensive dataset.

Figure 8. SunRice Rice Plant Diseases Sample: **(a)** Brown Spot, **(b)** Leaf Blast, **(c),** Neck Blast**, (d)** Stem Borer, **(e)** Tungro, **(f)** Healthy.

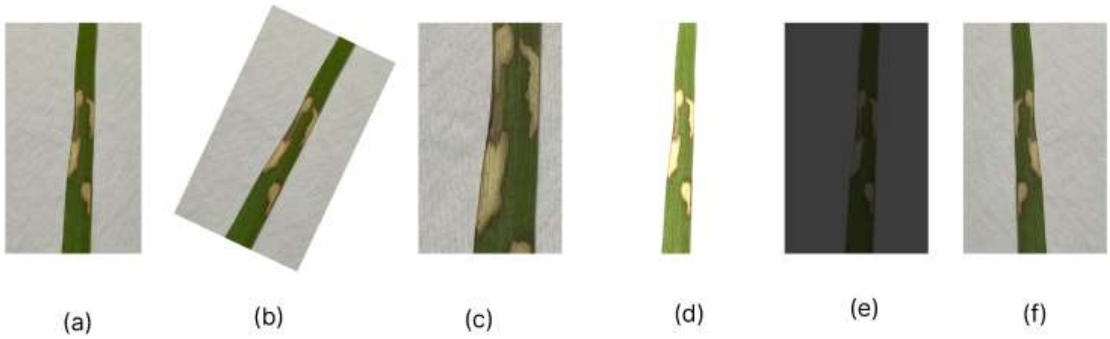

Figure 9. SunRice Sample Images after Data Augmentation: **(a)** Normal Image, **(b)** Rotate Image**, (c) Slightly Zoom, (d)** Adjust Brightness Light, **(e)** Adjust Brightness Dark, **(f)** Flip Image.

List of Rice Diseases	No. Of Images
Brown Spot	3,000
Leaf Blast	3,000
Neck Blast	3,000
Stem Borer	3,000
Tungro	3,000
Healthy	3,000

Table 3. SunRice Rice Plant Diseases Datasets

This table provides an overview of the SunRice leaf diseases dataset, listing the categories of healthy and diseased rice leaves and the number of images for each category. This dataset would be used to train and evaluate a deep neural network model in the research.

Rice Cultivation Timeline

The research also explored the cultivation practices applied in the Jaoud Rice Fields, focusing on direct-seeded and transplanted rice cultivation. Figures 10 and 11 illustrate these cultivation techniques, which the Jaoud Rice Fields employ due to their effectiveness during planting. These methods ensure efficient and productive rice cultivation when aligned with a structured rice planting schedule.

According to Ma'am Evangeline J. Juaton, one of the owners of the Jaoud Rice Fields, their cultivation process follows a systematic timeline. After harvesting, the land preparation phase takes approximately eight weeks to ensure the fields are ready for planting. Direct seeding is completed within one day, whereas transplanting requires 3-4 weeks.

The subsequent growth stages are carefully monitored. The vegetative stage typically lasts one week, followed by the reproductive stage, which spans three weeks. The ripening stage is calculated to take 2-3 weeks, after which the rice is ready for harvest. This structured and systematic approach to rice cultivation ensures optimal yields and maintains the efficiency of the planting process.

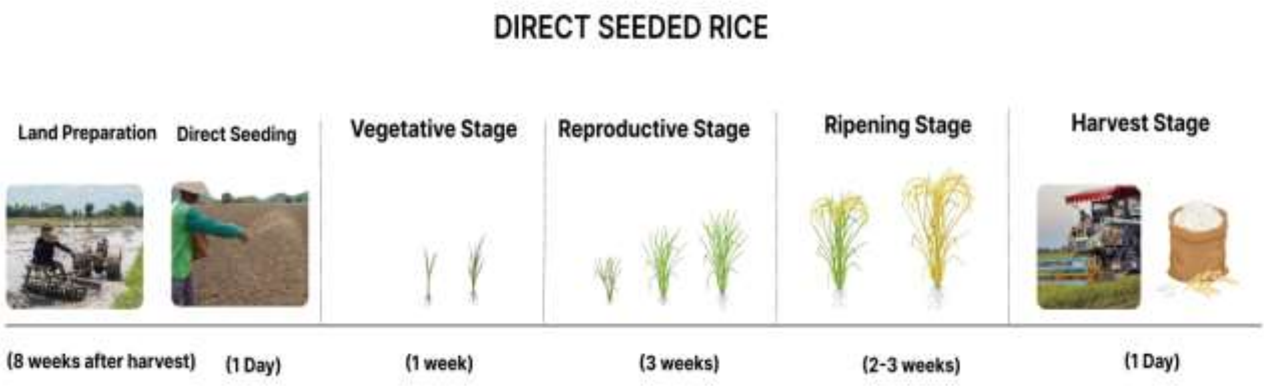

Figure 10. Direct Seeded Rice Cultivation

Figure 10 illustrates the direct-seeded rice cultivation process. It includes several stages: land preparation, where the soil is prepared for planting; direct seeding, where rice seeds are sown directly into the field; the vegetative stage, during which the plants grow; the reproductive stage, where flowering and grain formation take place; the ripening stage, when the grains mature; and the harvest stage when the rice is collected for processing. Each stage plays an essential role in the successful cultivation of rice.

DSR refers to establishing a rice crop by sowing seeds directly in the field rather than transplanting seedlings from the nursery. Direct seeding is the oldest method of rice establishment practiced by humankind for ages, but it was gradually replaced by puddled transplanting for various reasons [43]. Several Asian countries have been involved in direct seeding practices for decades, including Malaysia, Vietnam, Sri Lanka, Thailand, Cambodia, and the Philippines. DSR has also been practiced in India for a long time and has steadily increased in the last few decades. States in India having projected areas of uneven rainfall distribution and soil moisture limitations occurrence, like Tamil Nadu, Jharkhand, Chhattisgarh, parts of Bihar, Odisha, Karnataka, and eastern Uttar Pradesh, seem to have good potential for DSR cultivation [44].

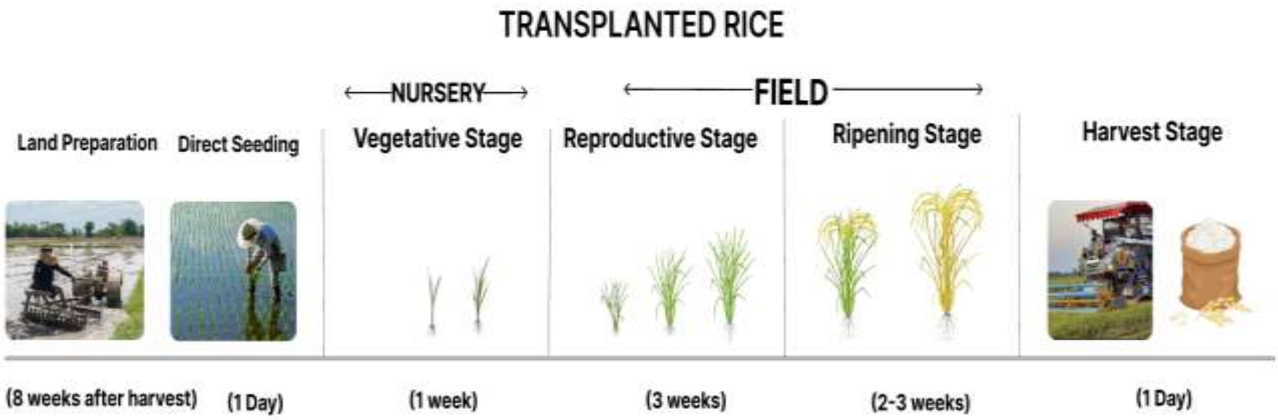

Figure 11. Transplanted Rice Cultivation

Figure 11 shows the steps in transplanted rice cultivation. It highlights important stages such as land preparation, direct seeding, the vegetative stage in the nursery, the reproductive stage, the ripening stage, and the harvest. Each step is crucial to understanding how transplanted rice grows and what affects its successful cultivation.

The transplanted rice production system is more common than the broadcasted one in some areas of the tropics. The broadcasting method, the direct seeding technique, ascribes a rice production system by sowing seeds on the rice field rather than transplanting rice seedlings from the nursery. The quality of rice seedlings in the nursery before transplanting into rice fields is commonly good. Transplanting causes uniform spacing and plant growth, limits competition between rice crops for nutrients and space, and reduces weed growth. However, transplanted rice production requires a higher cost but generates lower profit [45][46].

Gantt Chart

Figure 12. illustrates the process of improving project management, developers use a Work Breakdown Structure WBS along with a Gantt chart. To help clarify what is needed, who should do it, and what the expected results will be, WBS provides a complete breakdown of the project into small but achievable tasks. This clarity facilitates the establishment of deadlines and the efficient allocation of resources. To ensure that the scope and deliverables are coherent and well organized, the hierarchical structure of the WBS also shows the relationship between different tasks and their contribution to the overall objectives of the project.

As a result of the structured breakdown, the Gantt chart can be drawn up by plotting these WBS-derived tasks according to time series. A task is represented by each bar in the Gantt chart, showing its start and end dates so that you can see how much time it takes to complete a task. This visual representation facilitates the efficient management of projects and their timely completion, providing developers with a better view of progress, identification of overlaps in crucial paths, and understanding the activities.

The developers can promote better communication between team members and stakeholders, ensuring that everyone is in line with the project schedule and progress by combining the detailed planning of the WBS with the visual schedule of the Gantt chart. This integrated approach results in a more organized, effective, and efficient project management process that will ultimately lead to improved quality outcomes.

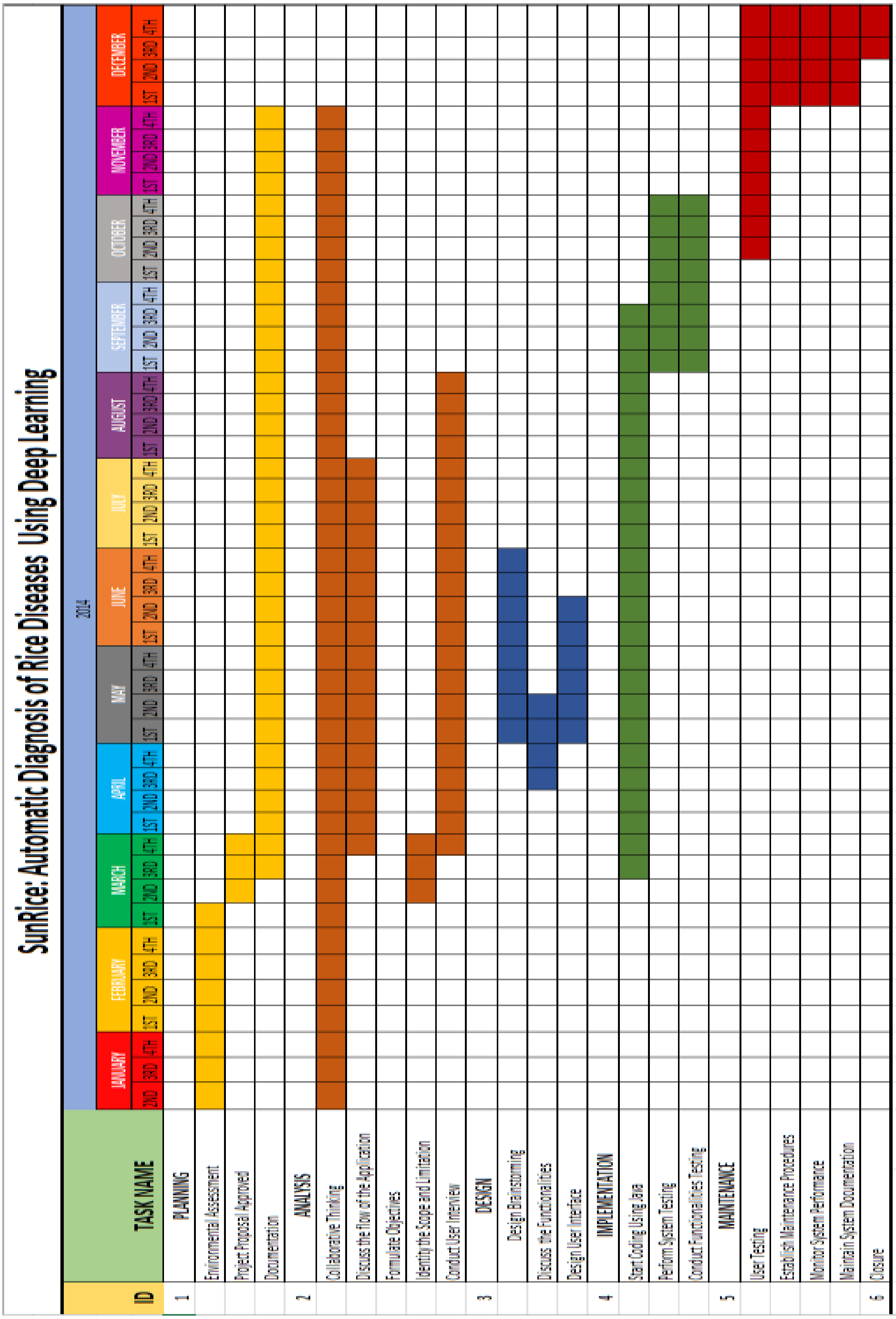

Figure 12. Gantt Chart

Technology and Tools

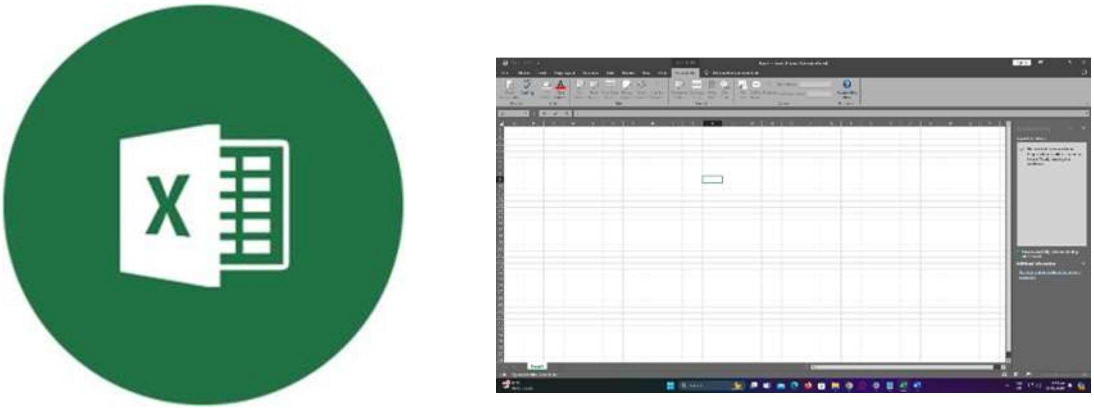

Figure 13. Microsoft Excel

Excel is a powerful tool that allows users to manipulate, analyze, and visualize large amounts of data quickly and easily [47]. Excel is used by the researcher for data administration, analysis, and visualization. It is an effective tool for data organization and analysis, as seen in the creation of gantt charts for task monitoring and scheduling and data dictionaries for organizing the formats and types of data.

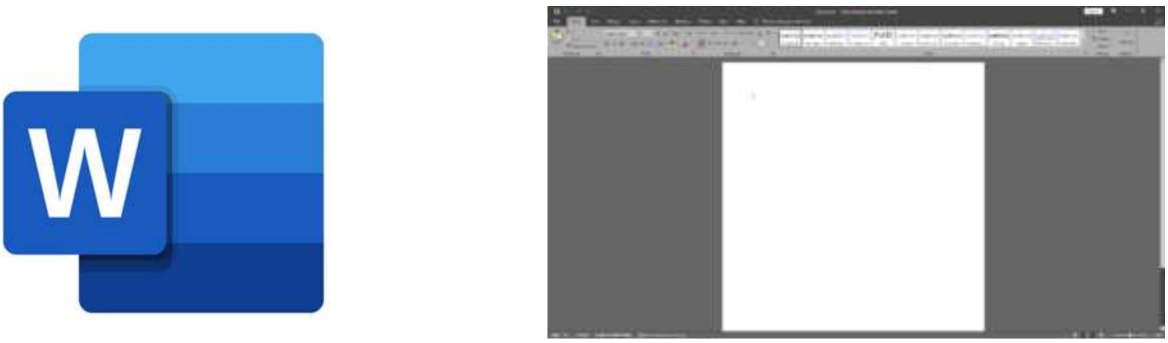

Figure 14. Microsoft Word

Microsoft Word is a word-processing program that allows the creation of simple and complex documents. [48]. With the help of Microsoft Word's features, researchers can easily organize and format their research papers, including creating tables, figures, and citations.

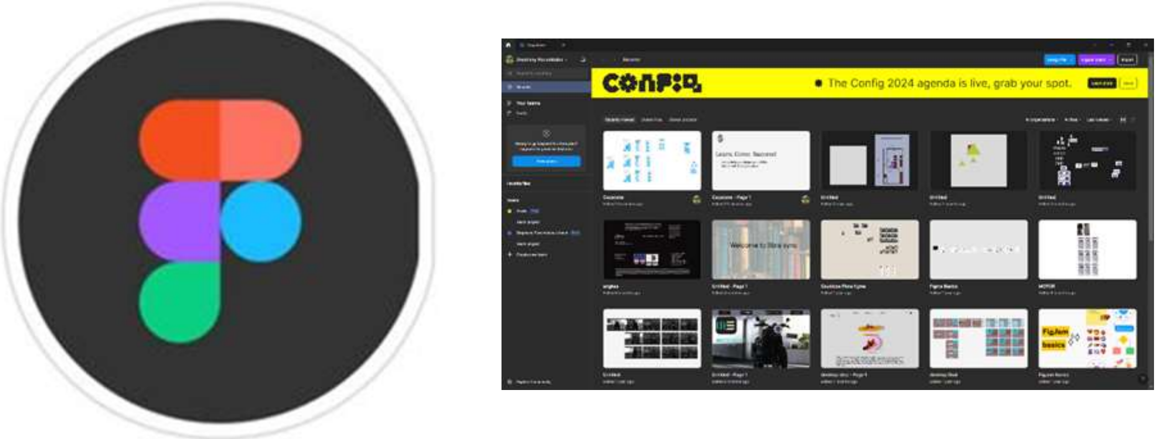

Figure 15. Figma

Figma is a cloud-based design tool like Sketch in functionality and features but with significant differences that make it better for team collaboration [49]. Figma is a tool that researchers can use to create interactive prototypes. It assists researchers and developers in designing user interfaces for applications and in creating diagrams that analyze data and functions related to the operation of the applications.

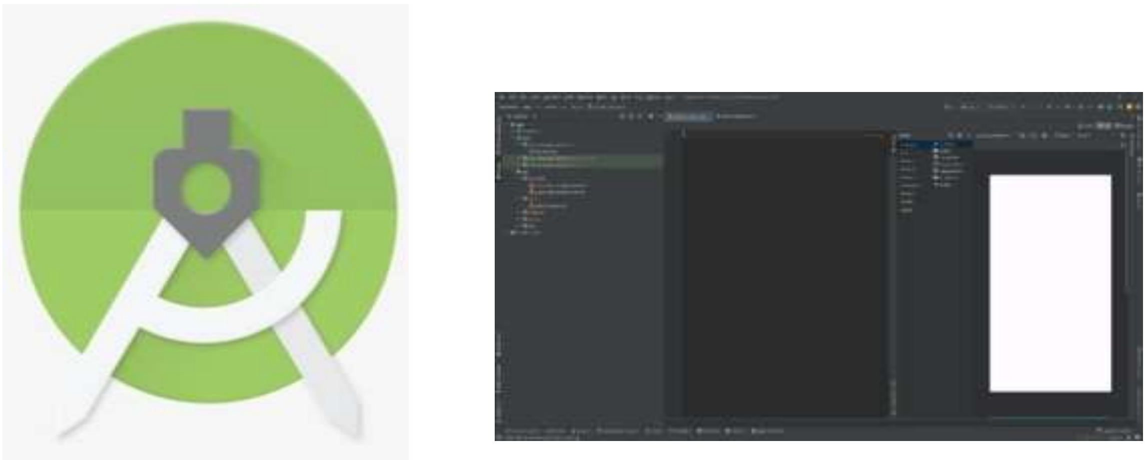

Figure 16. Android Studio

Android Studio is the official integrated development environment for Android applications. It's based on the Java-integrated software development environment IntelliJ IDEA and includes code editing and development tools [50]. The Android studio provides a user-friendly interface for writing code, debugging, and optimizing performance; it allows the developers to make an application.

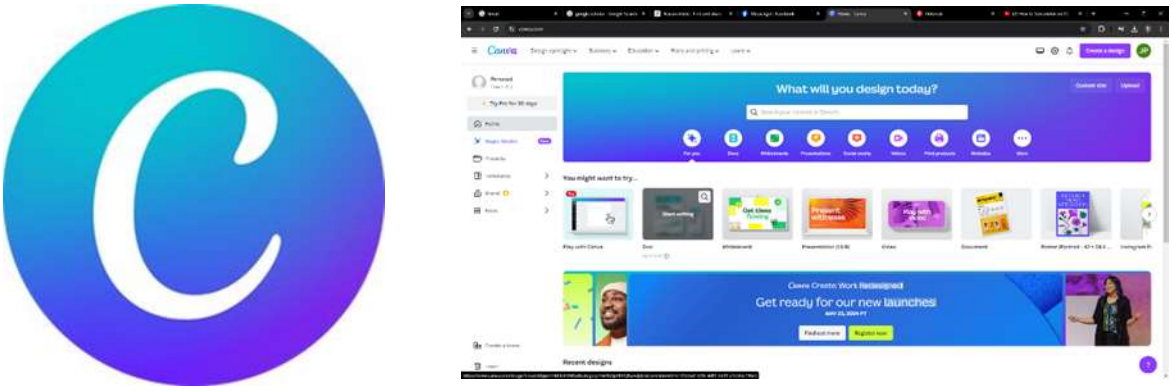

Figure 17. Canva

Canva is a graphic design tool created in 2012 by Australian entrepreneur Melanie Perkins. It utilizes a drag-and-drop format familiar to the average user and design professionals. It features fonts, graphics, vectors, and templates [51]. The researchers utilize Canva to design visually appealing presentations, banners, and logos. The developers use it to create prototypes and user interfaces for their applications, facilitating teamwork between researchers and developers to collaborate on ideas and findings.

Figure 18. Java Language

The Java programming language was developed by James Gosling in 1995. Java has become widely popular as a class-based, object-oriented, and high-level programming language. It is designed to enable the “write once, run anywhere” (WORA) feature, which allows compiled Java code to run without further compilation on all platforms that support Java [52]. The SunRice application is programmed in the Java programming language by the developers using Android Studio. This allows them to successfully create an app that aids farmers in identifying rice plant diseases. rephrase what just said.

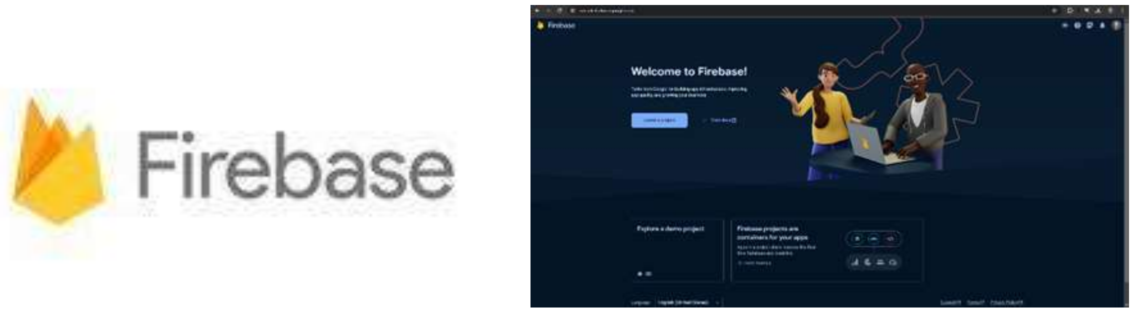

Figure 19. Firebase

Firebase is a comprehensive mobile and web application development platform developed by Google. It provides developers with a suite of cloud-based tools and services designed to help create, maintain, and improve applications [53]. The developer uses a firebase for real-time database, authentication, and security of the data, and researchers can analyze and visualize the data result on the firebase.

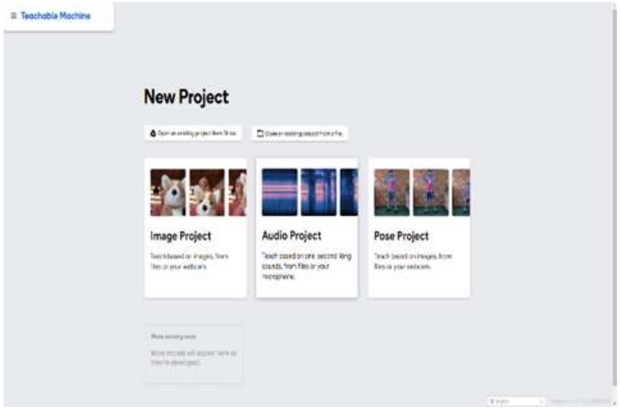

Figure 20. Teachable Machine

The Teachable Machine is a website tool that makes creating machine learning models for your projects easy and quick without any coding required. Train your computer to recognize images, sounds, and poses. Then, export a model for websites, applications, or more [54]. By entering an object dataset, developers can use teachable learning to create models for a variety of tasks, like image processing. They can then label the models, determine the accuracy of the results, and determine the percentage or result.

Figure 21. LucidChart: Intelligent Diagramming

The developer uses LucidChart to make a flowchart to understand the application's flow, which makes it easier for them to see their workflow. The researchers' and developers' concepts, plans, and procedures can be visually communicated with effectiveness.

Figure 22. Mobile Phone

A mobile phone is a wireless handheld device that allows users to make and receive calls [55]. A mobile phone helps the researcher employ creative data collection techniques, and it also enables the developer to test applications to see if they are functioning.

Operating System	Android Version 11, Galaxy Wide 4, One UI Version 3.1
Random Access Memory (RAM)	3 GB 1866MHz
Read Only Memory (ROM)	32 GB
Screen Display	6.4 in, Super AMOLED, 720 X 1560 pixels, 24bit
Camera	4160 x 3120 pixels, 1920 x 1080 pixels, 30fps

Table 4. Specs and System Requirements for Mobile Phone

Table 4 shows the system specifications and requirements for the mobile phone used in this research are as follows: The device operates on Android Version 11, with One UI Version 3.1, and is the Galaxy Wide 4 model. It has 3 GB of Random Access Memory (RAM) running at 1866 MHz, ensuring sufficient speed for basic tasks and app performance. The phone has 32 GB of Read Only Memory (ROM), providing ample storage for applications, data, and media. The screen features a 6.4-inch Super AMOLED display with a 720 x 1560 pixels resolution and 24-bit color depth, delivering clear and vibrant visuals. The camera supports a high resolution of 4160 x 3120 pixels for photos and 1920 x 1080 pixels at 30 frames per second for video recording, ensuring quality imaging capabilities for research purposes.

System Analysis

In this stage, we will focus on system analysis within the automated rice plant detection methodology utilizing deep learning techniques. With a growing demand for efficient agricultural methods, notably in rice farming, leveraging the power of artificial intelligence promises significant improvements in crop monitoring and management. Our work includes thoroughly studying existing systems to determine their strengths, shortcomings, and possibilities for improvement. Through careful system analysis, we delve into the many layers of data collecting, processing, and model optimization, setting the framework for a robust and scalable solution designed exclusively for automated rice plant detection.

This capstone project takes a systematic approach, using several approaches within system analysis to handle the multifaceted issues inherent in automated rice plant detection. By separating critical components such as picture preprocessing, feature extraction, and model training, we want to create a streamlined pipeline that maximizes accuracy and efficiency. Developers aim to improve our system through rigorous testing and validation iteratively, assuring its adaptability to a wide range of climatic conditions and operating scenarios. Finally, the goal is to advance the field of agricultural automation and provide farmers with a trustworthy instrument for increasing productivity and sustainability in rice farming.

Deep learning, a family of machine learning algorithms inspired by the biological process of neural networks, is gaining traction in various applications and outperforming traditional machine learning algorithms [56]. It is only because of their ability to generate faster and more precise outcomes. It aims to model high-level abstraction in data using a set of algorithms [57]. Deep learning techniques involve direct learning from data for all model features. It begins with low-level features that provide an appropriate representation of the data. It then gives higher-level abstractions for each problem to which it is applied. Deep learning becomes increasingly valuable as the amount of training data increases. The development of deep learning models has increased with the software and hardware infrastructure [58].

Use Case Diagram

In Figure 23 provides an overview of the interaction between two main user types within the SunRice application system: the admin and the farmer. As the primary end-user, the farmer must register an account upon their first application use. Once registration is complete, the user's information is sent to Firebase, the platform for storing and verifying account data. The admin is then responsible for reviewing the registration request. The admin can approve or reject the request if the account meets the necessary criteria. Once approved, the user's account status is updated accordingly, granting the farmer access to the full features of the application. The admin, in contrast, has direct login access to SunRice without needing approval and serves a vital role in managing the application's ecosystem. The admin can monitor and maintain user accounts and accept or reject incoming registration requests, ensuring that only verified users can interact with the system.

After a successful login, the farmer can utilize the core functionality of SunRice—image-based disease detection for rice plants. Through the application, the user can capture and upload an image of a rice crop suspected to be affected by disease. This image is then transmitted to the SunRice model, which is designed to perform classification based on a trained algorithm. The model processes the image and identifies the type of disease, if any, present in the plant. Once classification is complete, the results are delivered back to the farmer through the application interface. This provides the user with a detailed response regarding the health condition of their crop. The interaction between the user and the model allows for real-time disease identification, which empowers farmers to take timely and appropriate action in managing their crops. This structured system enhances the reliability and usability of the application, offering a seamless process from user registration to disease diagnosis while delineating the roles and responsibilities of both the admin and the farmer.

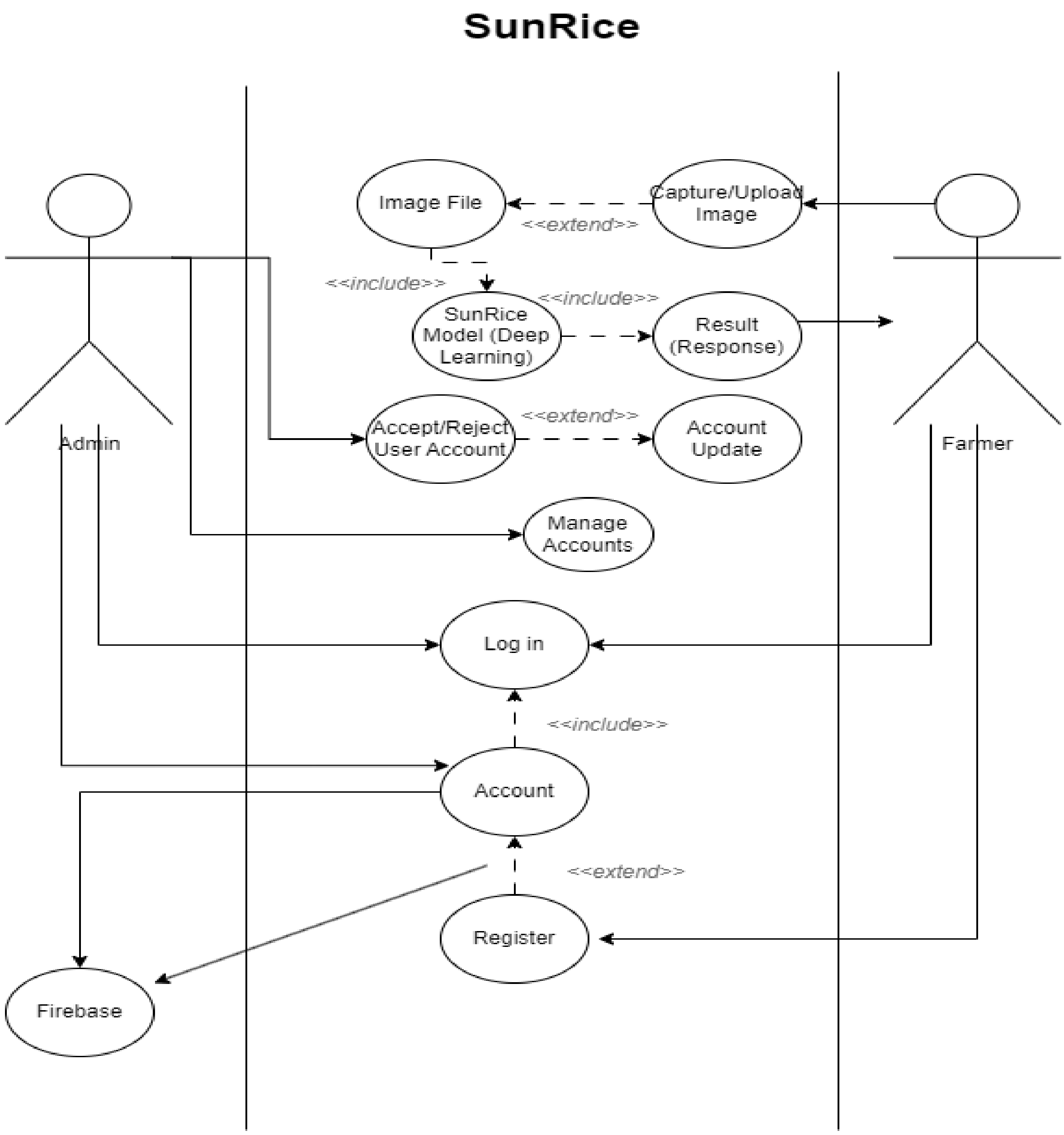

Figure 23. Use Case Diagram

Context Flow Diagram

In Figure 24 illustrates the overall system flow and interactions within the SunRice application, a digital solution developed for the automated diagnosis of rice diseases through deep learning. The system begins with the farmer, who serves as the primary user. The farmer can capture and upload images of suspected rice diseases through the application. Upon submission, the system processes the image and provides an automated diagnostic result, helping farmers quickly identify the type of disease affecting their crops. This functionality is designed to streamline the diagnostic process, reduce the reliance on manual inspection, and support timely decision-making in agricultural practices.

In addition to the farmer's interaction, the system also includes administrative functions. The admin plays a crucial role in overseeing the application's performance and maintaining the integrity of the data by managing activity logs generated within SunRice. The application is integrated with Firebase, the cloud backend for storing data and transmitting diagnostic results. When a farmer uploads an image, the data is processed to Firebase. After the deep learning model evaluates the image, Firebase transmits the diagnosis to the SunRice application, displaying the results to the user. This seamless communication between the application and Firebase ensures users' and administrators' efficiency, accuracy, and real-time access to critical information.

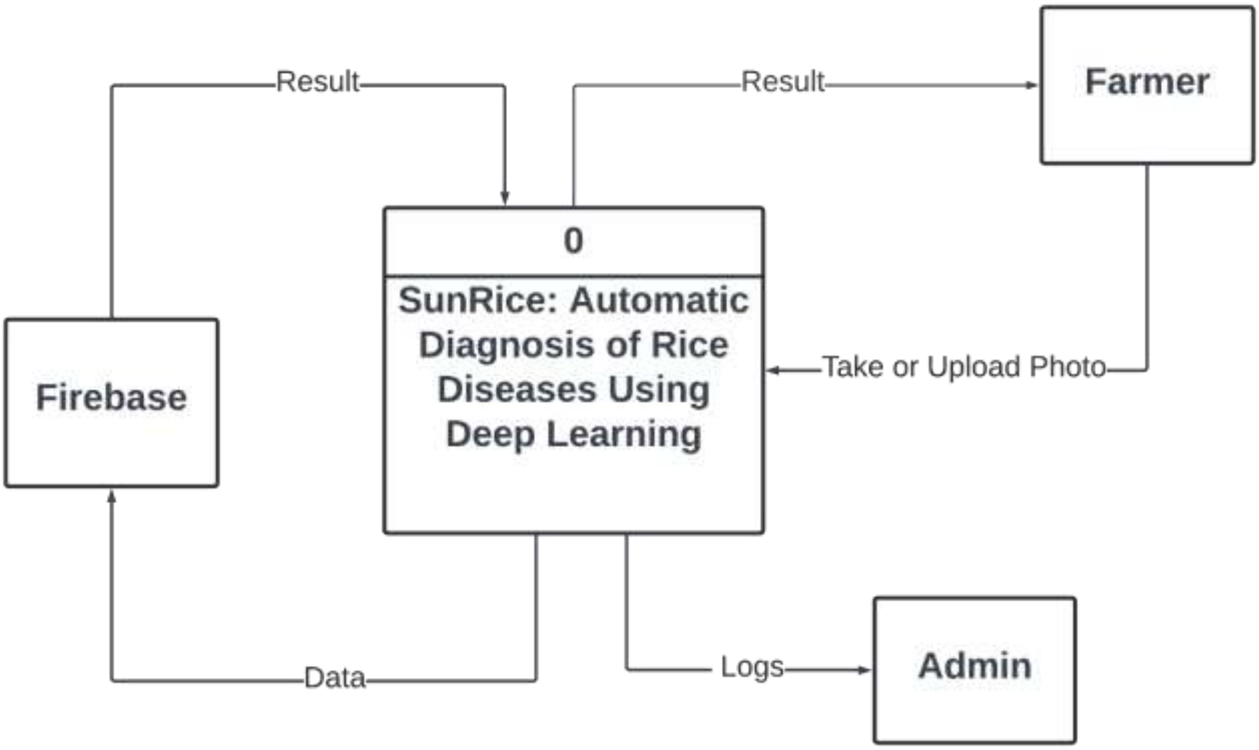

Figure 24. Context Flow Diagram

Data Flow Diagram

In Figure 25, presents a comprehensive overview of the system's data processes and interactions. The flow begins at the registration phase (1.0), where users—primarily farmers—input essential account details to gain access to the platform. Once the registration is completed successfully, an account is created within the SunRice system. Users with an existing account may proceed directly to the login process (2.0), where the credentials they provide are validated to ensure secure access. This initial part of the flow highlights the system's commitment to user authentication and proper data handling right from the entry point.

Upon successful login, users are granted access to core functionalities, including capturing or updating images (3.0), which serve as vital input data for the application.

These images, often of crops or rice-related elements, are subsequently processed through the scanning module (4.0). During this phase, the image is analyzed to extract relevant datasets and convert them into meaningful results for the user. This process reflects the application’s intelligent use of image recognition and data analysis to provide immediate feedback, assisting farmers in making informed decisions based on real-time agricultural data.

Once the image data has been scanned and interpreted, the output is not only displayed to the user. Still, it is also directed into the recording module (5.0), where all image-related information is securely stored in Firebase. Additionally, the system logs these details (6.0), including the image metadata and associated user information, into the admin panel for monitoring and tracking purposes. This final segment of the flow emphasizes data preservation, transparency, and accountability within the SunRice application, ensuring that every interaction is documented for operational integrity and potential system audits. Overall, the DFD captures the logical structure and data dynamics of SunRice, enabling a clear understanding of how information is managed throughout the application.

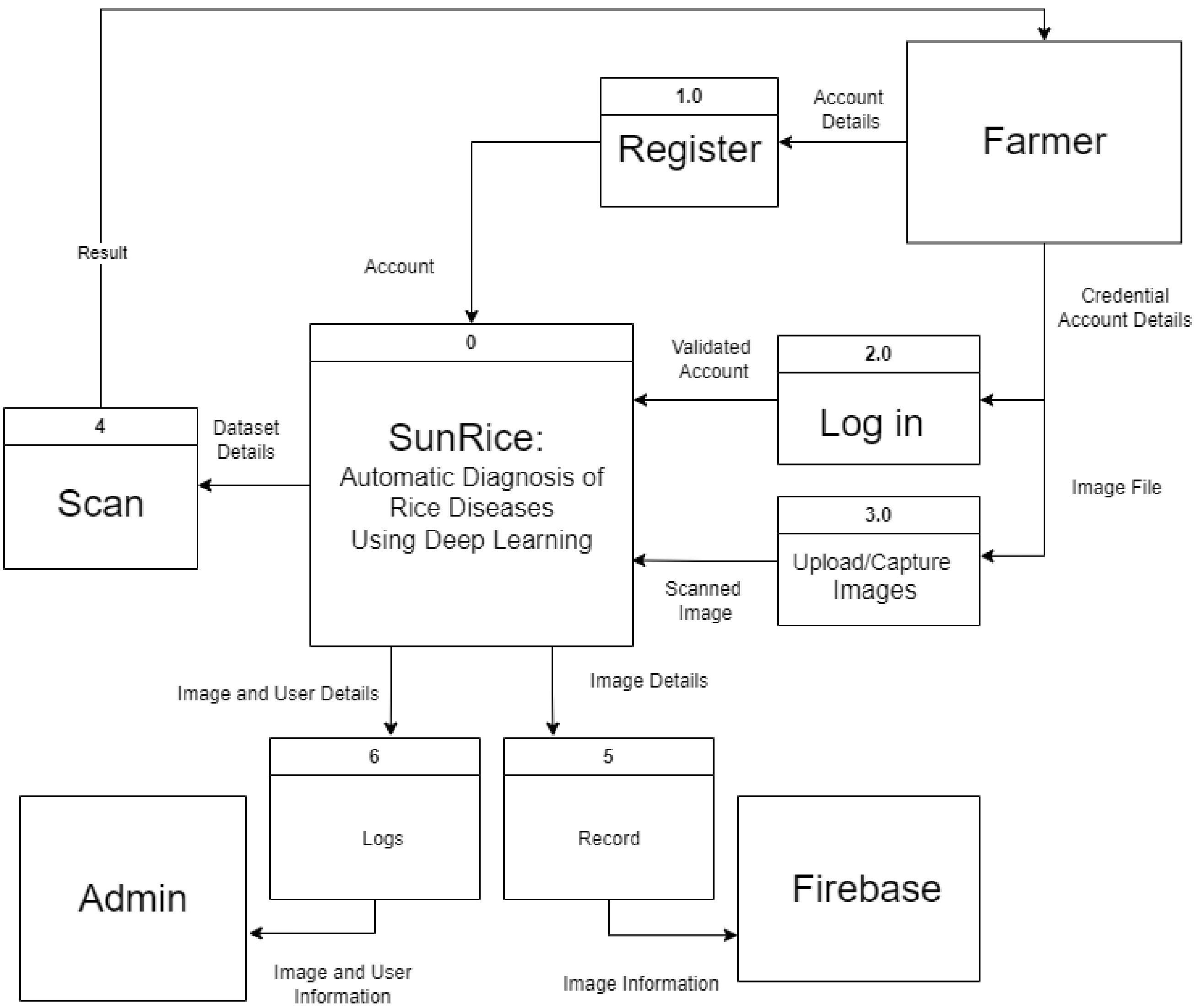

Figure 25. Data Flow Diagram

Deep Learning

Deep learning, a family of machine learning algorithms, is inspired by the biological process of neural networks, and it dominates many applications and proves to be an advantage over conventional machine learning algorithms [59]. It is only because of their capability to produce faster and more accurate results. It attempts to model high-level abstraction in databases on a set of algorithms [60]. In deep learning techniques, there is direct learning from the data for all aspects of the model. It starts with the lowest-level features that present a suitable representation of the data. It then provides higher-level abstractions for each of the specific problems in which it is applied. Deep learning becomes more useful when the amount of training data increases. The development of deep learning models has increased with the increase in the software and hardware infrastructure [61].

Deep learning models use multiple layers, which are the composition of multiple linear and non-linear transformations. With the increase in the size of data, or with the developments in the field of big data, conventional machine learning techniques have shown their limitation in analysis with the size of data [62]. Deep learning techniques have been giving better results in this task of analysis. This technique has been introduced worldwide as a breakthrough technology because it has differentiated machine learning techniques working on old and traditional algorithms by exploiting more human brain capabilities [63]. It is useful in modeling the complex relationships among data. Instead of working on task-specific algorithms, it is based on learning data representations. This learning can be supervised, unsupervised, or semi-supervised.

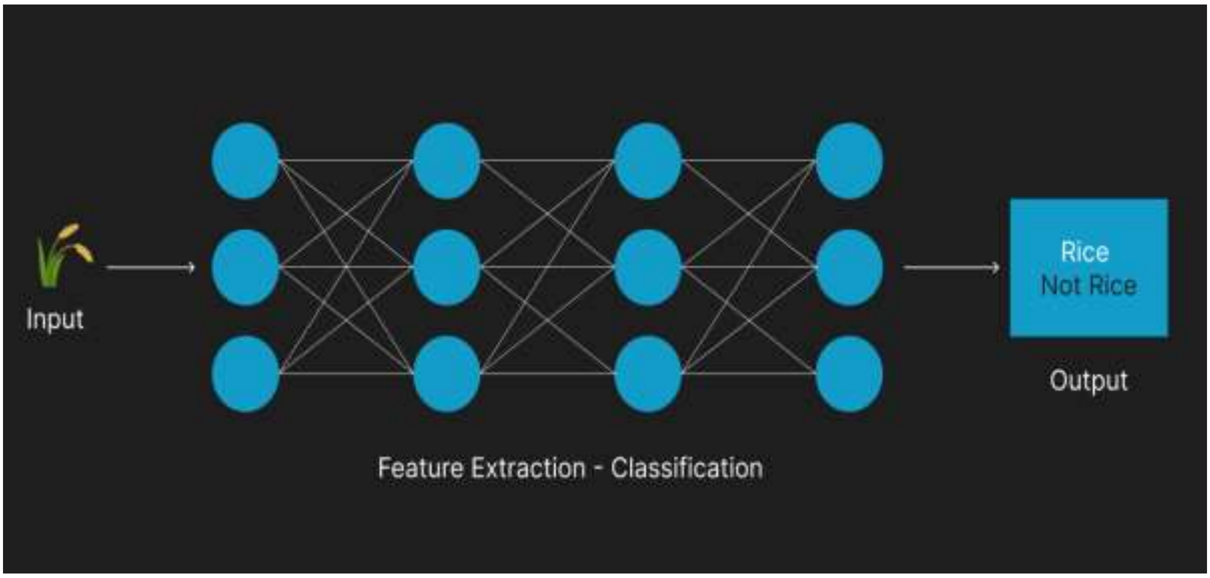

Figure 26. Deep Learning

The feature extraction and transformation process in deep learning models involves multiple layers of nonlinear processing units. Each layer takes the output of the preceding layer as its input and can be utilized in both supervised and unsupervised approaches for solving classification and pattern analysis challenges. Deep generative models are organized layer by layer, while deep learning models primarily rely on artificial neural networks. The interaction of layered factors results in the generation of observed data, forming the basis of distributed representation and creating a concept hierarchy for high-level abstraction.

Deep Neural Network

A deep neural network is a variant of a multilayer feed-forward artificial neural network. It has more than one hidden layer between the input layer and the output layer [64] The number of neurons is similar in each of the hidden layers. Initially, the number of neurons is fixed randomly, and it is adjusted manually during the network training. A larger number of nodes at the hidden layer may result in an increase in the complexity and, hence, a decrease in the training performance. So, the selection of a number of nodes at this layer is carefully considered. This architecture devises a compositional model in which the object is referred to as the layered composition of primitives. It has the capability to model complex non-linear relationships in the training data. The benefit of using extra hidden layers in the network is that it enables the composition of features from lower layers. These features potentially model complex data with fewer units [65].

There are two issues also associated with deep neural networks. First, the issue of overfitting, which is common in many neural network models, and second, the issue of computation time. The problem of overfitting has more chances to arise in deep neural networks due to the use of extra layers. Due to this issue, it models the rare dependencies in the training data. The network gave better results on training data and degraded accuracy on validation data. To avoid the issue of overfitting in deep neural networks, regularization methods like weight decay or sparsity can be used during training, which excludes the modeling of rare dependencies. The increase in smaller training sets can also overcome the problem of overfitting. The computation time of the learning model depends on many parameters, such as the layer size, the learning rate, and the initially chosen weights [66]. The number of nodes in the hidden layers increases the complexity of the system, and it requires more computational time. It should be carefully considered while selecting all these parameters.

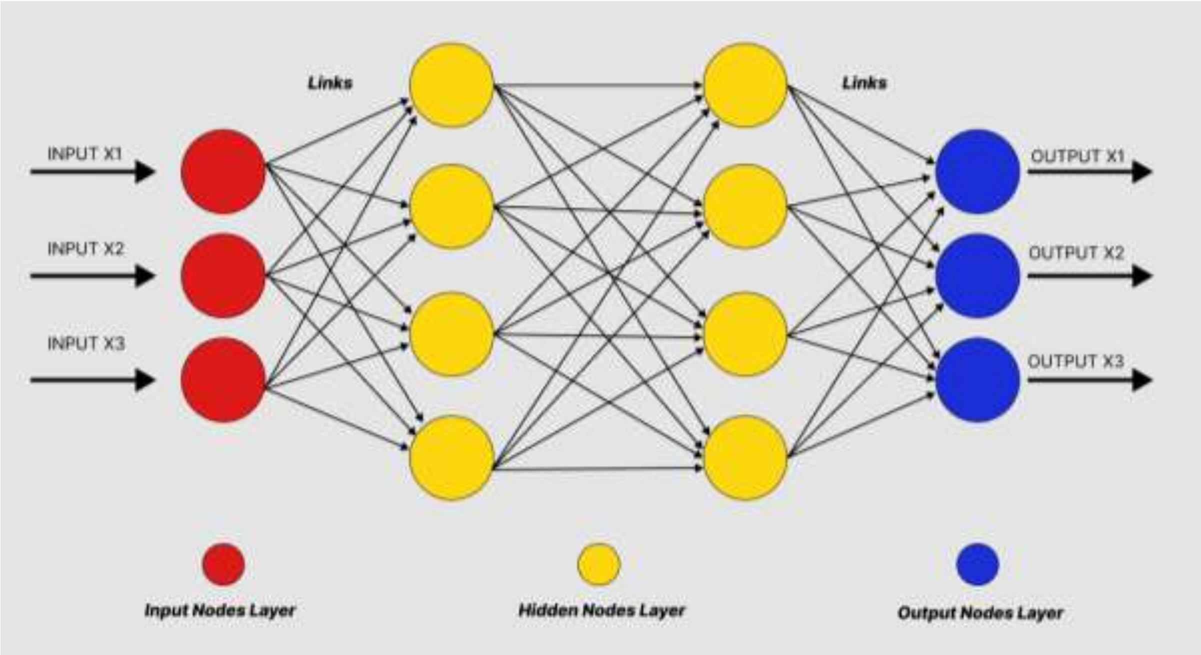

Figure 27. Deep Neural Network

The identification of rice plant diseases using a deep neural network involves several stages. To begin with, the network takes in images of the plants at the input layer. These images are transformed into matrices of pixel values and then proceed through different hidden layers that contain neurons. In these hidden layers, the neurons perform complex calculations to extract characteristics such as color, texture, and patterns that indicate diseases. For instance, the initial hidden layer could identify edges and basic shapes, while subsequent layers recognize more intricate patterns.

With a Teachable Machine model, the network undergoes training using labeled images of healthy and diseased rice plants under supervised learning. During this training process, the weights of the neurons are adjusted to minimize classification errors. Ultimately, the output layer, which consists of neurons representing different disease categories and healthy plants, provides the final diagnosis. The number of neurons in each layer and the overall architecture can differ, but generally, the input layer corresponds to the pixel count of the image; hidden layers may contain tens to hundreds of neurons.

System Flowchart

In Figure 28 presents an overview of the SunRice application's process flow, beginning from the user's login or registration and extending through the core functionalities accessible via both user and admin dashboards. The flow initiates with the user's interaction with the login interface; if the user does not have an existing account, they must complete a registration form to proceed. Once authenticated, users are directed to the dashboard, where a structured navigation menu is displayed, offering access to various features such as Home, Profile, History, Disease Library, About Us, and FAQs. Within the Home section, the application provides two main options for detecting rice plant disease: capturing an image in real-time or uploading an existing one. The selected image undergoes a diagnostic analysis, and the resulting output includes detailed information about the detected disease, which is presented through the Disease Library Result section for the user's reference.

On the administrative side, the flowchart details a distinct process following an admin login, directing them to the admin dashboard. From this interface, administrators are granted extended privileges and access to the same navigational structure Home, Profile, Disease Library, About Us, and FAQs, however, with the added capability to add, update, and delete content across these sections. Furthermore, the admin holds authority over user management operations, which includes viewing and managing user activity logs, approving or rejecting newly registered accounts pending verification, and manually adding new user accounts into the system. Administrators, like users, can also log out of the application after completing their tasks, ensuring secure session management and privacy for all involved parties.

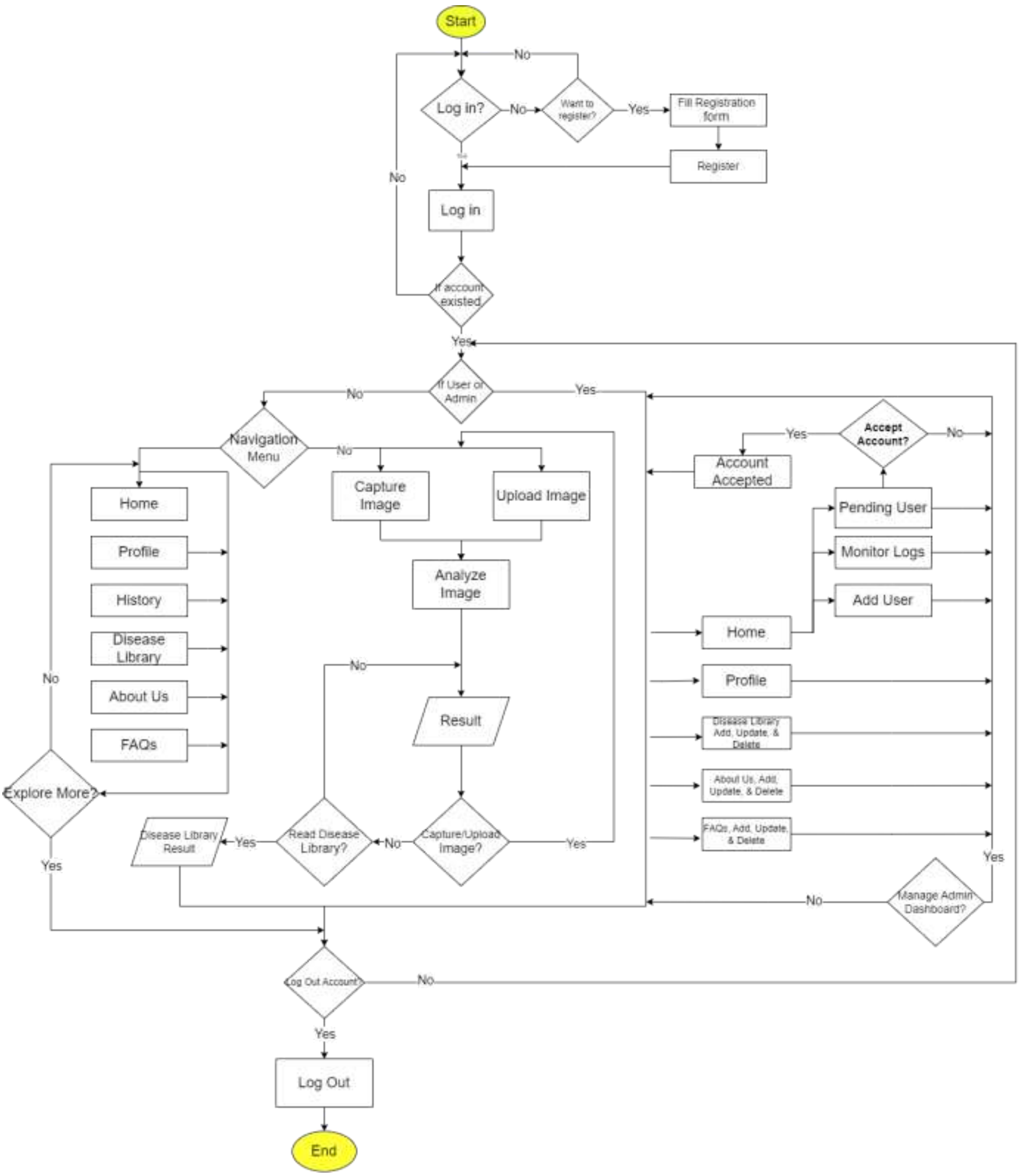

Figure 28. Flowchart

Entity Relationship Diagram

In Figure 29 illustrates the structure of a Firebase-based application designed to handle user management, health information, and historical activity records. At the center of the system is the USERS entity, which stores key details such as usernames, passwords, profile pictures, login attempts, and references to user history. Each user can generate multiple entries in the HISTORY entity, which logs the results of user interactions or scans, including confidence level, image URLs, timestamps, and diagnostic outcomes. Deleted history records are not permanently removed but transferred to the HISTORYRECYCLEBIN, allowing for data recovery or tracking. The ADMIN entity is also connected to the recycle bin, signifying that administrators have the authority to manage and oversee deleted records.

The diagram also features supporting entities that enhance the system's functionality. The DISEASE LIBRARY is a reference source for information such as disease names, causes, symptoms, preventive methods, and available chemical and organic treatments. Additionally, the PENDING USERS entity holds account information for individuals awaiting verification before accessing the central system.

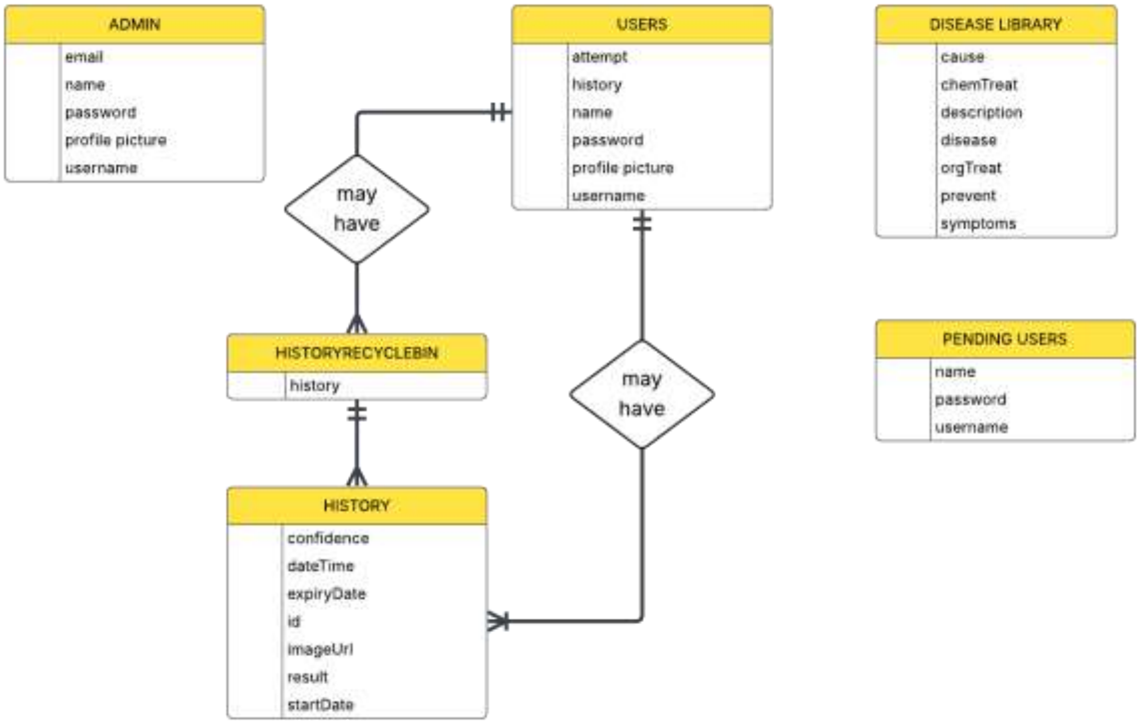

Figure 29. Entity Relationship Diagram

Data Dictionary

This section of the research paper shows the structured information about various fields used in the system's database. It illustrates key components such as the Admin, Disease Library, History Recyclebin, History, Users, and Pending Users. Each element has distinct attributes critical for understanding how the system operates and stores data. For instance, the Admin section, shown in Figure 30, provides specific fields such as the admin's email, name, password, profile picture, and unique username, all essential for identifying and securing admin access to the system.

In Figure 31, the Disease Library section is presented, detailing the various fields associated with the information stored for each disease. This includes the cause of the disease, chemical and organic treatment methods, descriptions, symptoms, and prevention strategies. These fields provide a comprehensive record for each disease, allowing users to access vital information to manage plant diseases. The data types and field sizes for these attributes help ensure that the data is correctly structured and can be easily retrieved by the system.

The History Recyclebin, illustrated in Figure 32, contains the deleted history logs essential for tracking the system's activities. This field type preserves logs in an array format, enabling users to recover previous entries if necessary. Similarly, the History section in Figure 33 presents crucial information about the detected disease or analysis, including confidence levels, timestamps, expiration dates, and result classifications, which are vital for documenting the history of disease monitoring and detection.

Figures 34 and 35 show the structure for Users and Pending Users, respectively. The Users section includes fields for the user's name, password, profile picture, username, and history of previous diagnosis results, ensuring that all relevant data for system users is stored securely. The Pending Users section outlines the data for users awaiting approval, with fields for their name, password, and chosen username. These sections demonstrate how the system organizes user data, ensuring operational efficiency and security.

Admin				
Field Name	**Data Type**	**Field Size**	**Description**	**Example**
email	String	50	Admin's email address	admin@gmail.com
name	String	30	Full name of the admin	Jim Larigo
password	String	100	Hashed password	$2a$12$N...
profilePictue	String(URL	200	Link to profile image	https://img.com/admin.jpg
username	String	30	Admin's unique username	admin_jim

Figure 30. Admin

Disease Library				
Field Name	**Data Type**	**Field Size**	**Description**	**Example**
cause	String	200	Main cause of the disease	Fungal infection
chemtreat	String	200	Chemical treatment methods	Cooper-bases fungicide
description	String	500	Description of the disease	A disease affecting rice plants
disease	String	100	Name of the disease	Brown Spot
orgTreat	String	200	Organic treatment solutions	Neem oil spray
prevent	String	200	Prevention methods	Proper spacing of plants
symptoms	String	300	Symptoms shown by affected plants	Brown lesions on leaves

Figure 31. Disease Library

History Recyclebin				
Field Name	**Data Type**	**Field Size**	**Description**	**Example**
history	Array	N/A	Deleted history logs	[{ "id": "..."}]

Figure 32. History Recylebin

History				
Field Name	**Data Type**	**Field Size**	**Description**	**Example**
confidence	Number (Float)	N/A	Confidence level of detection (AI, etc.)	95
dateTime	Timestamp	N/A	Date and Time of the entry	2024-04-08T10:15:00Z
expiryDate	Date	N/A	Date expiration date	08/04/2025
id	String	50	Unique ID of the record	hist123
imageURL	String(URL)	200	Link to the image used for analysis	https://img.com/leaf.jpg
result	String	100	Result of classification	Leaf Blast
startDate	Date	N/A	Starting date of analysis or monitoring	10/08/2024

Figure 33. History

Users				
Field Name	**Data Type**	**Field Size**	**Description**	**Example**
attempt	Number(Integer)	N/A	Number of images attempt	2
history	Array	N/A	Previous diagnosis result	[{ "id": "..."}]
name	String	30	Full name of the user	Job Pelotos
password	String	100	Hashed password	$2a$12$...
profilePicture	String(URL)	200	Link to user's profile picture	https://img.com/user.jpg
username	String	30	User's unique username	JobWorld

Figure 34. Users

Pending Users				
Field Name	**Data Type**	**Field Size**	**Description**	**Example**
name	String	30	Name of the pending user	Ian Rapal
password	String	100	Hashed password	$2a$12$...
username	String	30	Pending user's chosen username	Ian123345

Figure 35. Pending Users

Prototype / Mockup

Figure 36. Logo

Figure 36 illustrates the initial screen displayed when users open the SunRice app. It prominently features the SunRice logo and the tagline "Say Cheese, Say Leaves." This screen serves as the welcoming interface, introducing the brand Identity and creating an engaging first impression for users.

Figure 37. Welcome to SunRice

Figure 37 illustrates a prototype mockup of the welcome screen for the SunRice platform. The screen prominently displays a friendly and inviting message, "Welcome to SunRice!" This message is designed to create a positive first impression and engage users as they interact with the platform.

Figure 38. Step 1: Capture an Image

Figure 38 illustrates the initial step in guiding users to capture an image using the application. It demonstrates that users should tap the camera icon on the main screen to activate the camera. Then, they are instructed to position the device over the plant, ensuring proper lighting and focusing on the diseased area for a clear image. Finally, users must press the capture button to take the photo. This step aims to ensure accurate and high-quality images for further analysis.

Figure 39. Step 2: Upload Existing Image

Figure 39 illustrates the second step of the process, "Upload an Existing Image." In this step, the user taps the upload icon on the main screen, which allows them to select an image from their device's gallery. The chosen image should display the diseased part of the rice plant. Once the image is selected, the user confirms that the upload will proceed.

Figure 40. Step 3: Get a Diagnosis

Figure 40 illustrates the third step of the process, which involves obtaining a diagnosis. After capturing or uploading an image, the SunRice system analyzes it using advanced AI technology. Within a few moments, the system provides an identification of the disease or a list of potential diagnoses, offering quick and accurate results.

Figure 41. Tips for Best Results

Figure 41 provides valuable tips for achieving the best results when identifying a rice plant disease. It emphasizes the importance of ensuring that the images are clear and recommends capturing the plant from multiple angles, if possible, to improve accuracy. Additionally, users are encouraged to regularly update the app to access the latest features and improvements, ensuring the most up-to-date and effective disease identification process.

Figure 42. Get Started

Figure 42 features a "Get Started" button, which serves as the initial action for users. When clicked, the button directs users to the login or sign-up page, allowing them to begin using the SunRice application by logging into an existing account or creating a new one.

Figure 43. Sign up

Figure 43 illustrates to get started; the user will need to create a new account if you don’t have one. the required fields on the registration form, including your name, email address, and a secure password. After completing the form, click the "Sign Up" button to create your account.

Figure 44. Log in

Once the user account is set up, you can enter your username or email address in the designated field, followed by your password in the corresponding field. Once done, click the "Log In" button. If your credentials are correct, you will be granted access to your account.

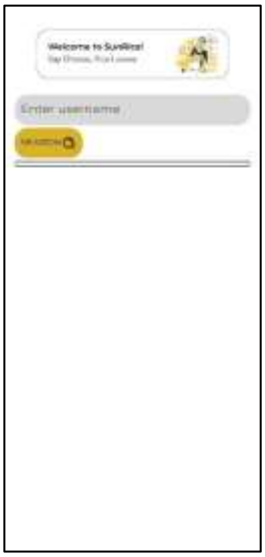

Figure 45. Search User Account

Figure 45 illustrates the password recovery process. When users forget their password, they can click the "Forgot Password" button shown in Figure 42. Upon clicking, the user must enter their username in the search bar. A "User not found" message will appear if the entered username does not exist.

Figure 46. User Verification via Image Selection

Figure 46 illustrates a user verification process where the system displays random images when users search for their username. The user must select an image they previously took or one saved in their history. If they choose the wrong image, they must re-enter their username to generate another set of random images. The user has a total of three attempts. After three incorrect attempts, the account is automatically blocked and requires admin approval for reactivation.

Figure 47. User Account Verified

Figure 47 illustrates the verification process. The user selects the correct image. Upon successful selection, a message saying "Successfully Verified" appears. Users can then click the "Change Password" button to update their password.

Figure 48. User Change New Password

Figure 48 illustrates the password reset process after account verification. Once the user verifies their account, they can enter a new password. After typing the new password, they must click the "Save New Password" button to confirm the change. Once the password is successfully updated, the user can log in to their account using the new credentials.

Figure 49. User Home Page

Figure 49 illustrates the user interface after logging in, which directs you to the Home page. At the top, you will see the SunRice logo, where the results are displayed. Two buttons are available: "Capture and Image" and "Upload an Image." These buttons allow users to choose between capturing or uploading an image to identify rice diseases. The user’s name is shown on the top-left side, alongside a navigation menu button, for easy access to other features.

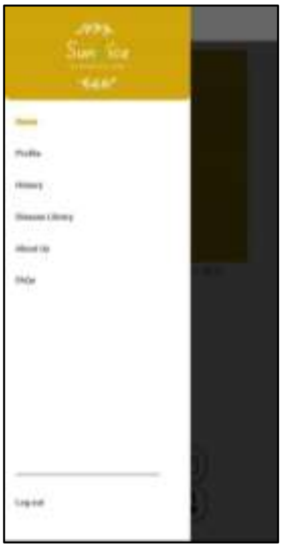

Figure 50. User Navigation Menu

Figure 50 displays the navigation menu, which includes options for Home, Profile, History, Disease Library, About Us, FAQs, and Log Out. This menu allows users to easily navigate the application, providing quick access to key sections for a smooth and efficient user experience.

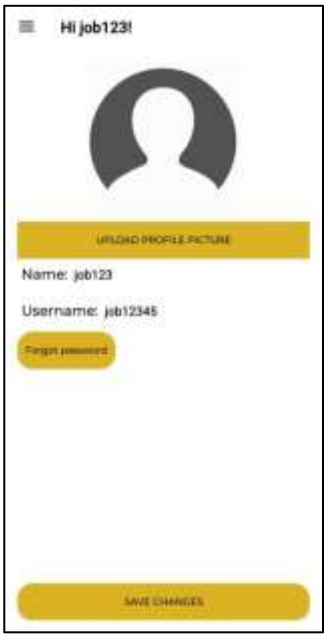

Figure 51. User Profile

Figure 51 illustrates to access your profile, navigate to the navigation menu, then click on the Profile button located in the top-Left corner of the page. This will redirect you to your personal profile page, where you can view and update your information as needed.

Figure 52. User Results History

Figure 52 illustrates that after completing your profile, you can proceed to the history section to provide a brief overview of relevant past experiences by capturing disease. Also, in History, the user can delete, clear, recover the results, and sort the data.

Figure 53. User Disease Library

Figure 53 illustrates that after clicking on "History," you will be redirected to the Disease Library. Here, you can explore a wide range of information about various diseases, their causes, symptoms, and treatment options. you can also browse through categories to find the relevant disease information you need.

Figure 54. User Rice Disease

Figure 54 illustrates a rice disease, providing essential details such as the disease name, its causes, symptoms, prevention methods, chemical treatments, and organic treatments. The figure serves as a visual guide to understanding the disease and its management.

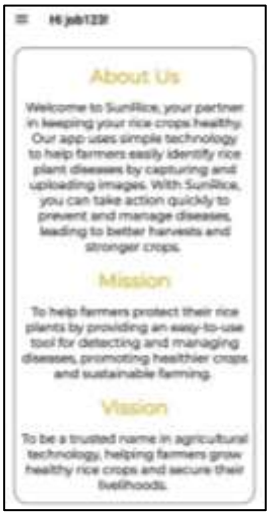

Figure 55. User About Us

Figure 55 displays the "About Us" section, providing detailed information about the SunRice Company. It includes an overview of the company's background, mission, and vision statements. At the bottom, users can find the contact information, which allows them to reach out to the company with any concerns, especially in case they encounter issues while using the SunRice Application

Figure 56. User FAQs

Figure 56 presents the FAQ section of the SunRice application, where users can find answers to common questions related to the app. This section allows users to easily access information about the app's features and functionality. Additionally, at the bottom of the FAQ page, a QR code is provided, offering quick access to the User Manual available in both English and Tagalog versions, guiding users on how to use the application effectively.

Figure 57. Admin Navigation Menu

Figure 57 illustrates the admin navigation menu, including options for Home, Profile, Disease Library, About Us, FAQs, and a Logout button. This menu provides administrators with easy access to key sections of the system for efficient navigation and management.

Figure 58. Admin Home Page

The Admin Home Page allows administrators to monitor user logs efficiently. It features a search bar for finding user accounts, an "eye" button to view user profiles, and a delete option to remove accounts. Administrators can also manage pending accounts by clicking "Show Pending User" and adding new users with the "Add User" button.

Figure 59. Admin User Logs

Figure 59 illustrates the admin can view all user activities, search for a specific user by username, and access detailed user profiles by clicking the eye button. If needed, the admin can delete a user account with a single click on the recycle bin button.

Figure 60. Admin List of Pending Users

Figure 60 illustrates a user management system where the admin can view all pending user accounts. Users cannot log in without admin approval. The admin can approve an account by clicking the check button or delete it by clicking the button.

Figure 61. Admin Add User Account

Figure 61 showcases the admin interface for adding user accounts. The admin can input the Name, Username, and Password in the provided fields. Once all details are entered, clicking the Add User button creates the user account.

Figure 62. Admin Profile

Figure 62 illustrates the admin profile interface. It displays the admin's profile picture, name, and username. The admin can update their profile picture by clicking the "Upload Profile Picture" button. After changing the profile information, the admin can click the "Save Changes" button to save the updates.

Figure 63. Admin Rice Disease Library

Figure 63 illustrates the Admin Rice Disease Library, where users can view a comprehensive list of rice diseases. It is a centralized database for managing and displaying detailed information on various rice diseases, making it easier for administrators to access and update the library.

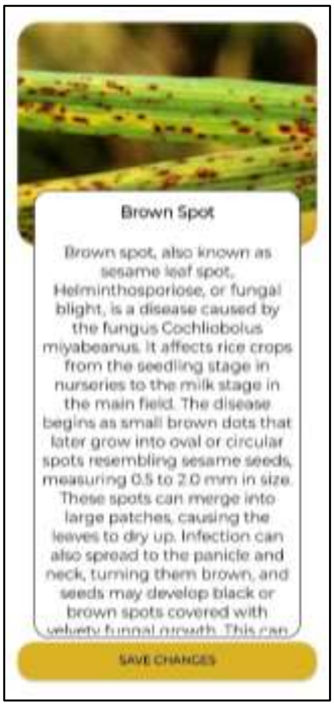

Figure 64. Admin Rice Disease

It illustrates an admin interface where the admin can select a specific rice disease. In this section, the admin can modify or update the information related to the selected rice disease, allowing for easy management and adjustment of disease details.

Figure 65. Admin About Us

The "About Us" section of the SunRice prototype allows the admin to easily update and manage information about the company, including its history, values, and key details. Additionally, the admin can update the company's mission and vision statements, ensuring the content stays current and relevant.

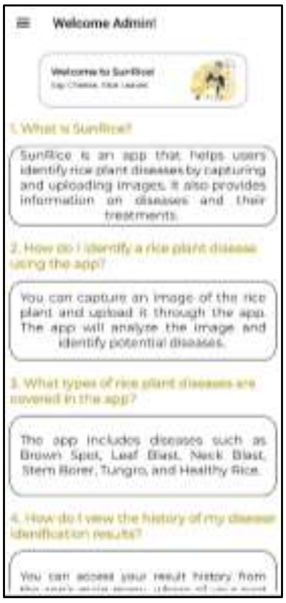

Figure 66. Admin FAQS

It illustrates an admin interface for managing FAQs related to SunRice. It features a user-friendly dashboard where the admin can easily update existing information or add new questions. The design includes fields for inputting question titles, answers, and categories, allowing for efficient organization and management of frequently asked questions.

CHAPTER IV

RESULTS AND DISCUSSION

Teachable Machine and Deep Learning Process

The researchers utilized deep learning techniques in the SunRice application to identify rice diseases by analyzing visual data, such as images of diseased rice leaves. A model was trained using Google's Teachable Machine tool, as illustrated in Figure 8. For this process, the researchers organized the training dataset into classes based on the names of specific rice diseases and uploaded sample images corresponding to each disease. Table 3 presents the SunRice Plant Diseases Dataset, which includes a list of rice diseases and the number of images per class,

Once the dataset was uploaded, the training process was initiated. Upon completion of the training, the user clicked "Export," followed by selecting "TensorFlow Lite" and choosing the floating-point option to export the model. This process generated a model, which was then integrated into the SunRice application. The trained model enables end-users to effectively identify rice diseases. The researchers set a target of achieving at least 70% accuracy for disease identification within the application, and the results indicate that the model successfully met this target, demonstrating its efficacy.

Model Performance Analysis

Accuracy per class

CLASS	ACCURACY	# SAMPLES
Brown spot	0.98	450
Leaf Blast	0.98	450
Neck blast	0.98	450
Stem borer	1.00	450
Tungro	0.98	450
Healthy	0.98	450

Figure 67. Accuracy per class

Figure 67 illustrates the results from the Teachable Machine's accuracy per class analysis, revealing strong performance across all rice disease categories in the model. The model achieved a high accuracy rate for each class, with the highest being Stem Borer, which reached an accuracy of 1.00 based on 450 samples. Other diseases, including Brown Spot, Leaf Blast, Neck Blast, and Tungro, all demonstrated an accuracy of 0.98, with 450 samples each. The Healthy class also achieved an accuracy of 0.98, indicating that the model can effectively distinguish healthy rice plants from diseased ones. These results suggest that the model is effective in classifying various rice diseases and healthy plants, with minimal errors in its predictions.

The results analysis shows that the model performed exceptionally well in identifying rice diseases, with accuracy rates approaching or reaching 100% for most disease categories. Specifically, the Stem Borer category achieved perfect accuracy. Other disease categories, such as Brown Spot, Leaf Blast, Neck Blast, and Tungro, exhibited consistent accuracy rates of 0.98, demonstrating reliable performance across a broad range of diseases. Additionally, the model showed strong capabilities in identifying healthy rice plants, with an accuracy rate of 0.98. The uniformity in accuracy across various categories, combined with the substantial number of samples used for training (450 per class), highlights the model's reliability in accurately classifying both diseased and healthy rice plants.

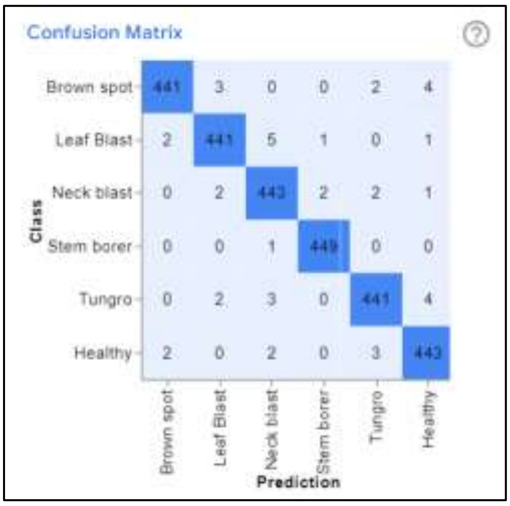

Figure 68. Confusion Matrix

Based on the confusion matrix shown in the image, the results provide detailed insights into the model's performance in classifying rice diseases and healthy plants. The matrix illustrates how the model's predictions align with the actual classes. In the case of the Brown Spot class, it was correctly identified 441 times, with a few misclassifications (3 times as Leaf Blast and 2 times as Neck Blast). Similarly, the Leaf Blast class was predicted correctly 441 times, with a few errors (5 times misclassified as Neck Blast and 1 time as Healthy). The Stem Borer class was the most accurately predicted, with all 450 samples classified correctly. Other classes, such as Tungro and Healthy, also showed high accuracy with minimal misclassifications.

The confusion matrix clearly represents the model's classification performance. The diagonal values indicate correct predictions, while the off-diagonal values represent misclassifications. The model performed well across all disease categories, with the Stem Borer class being classified without errors. The Brown Spot, Leaf Blast, Neck Blast, and Tungro classes were mostly classified correctly, with occasional misclassifications into neighboring classes. The Healthy class also exhibited high accuracy, with minimal errors in predicting diseased plants as healthy. In summary, the confusion matrix shows that the model is accurate and performs well, though there is still room for improvement in distinguishing between certain disease categories.

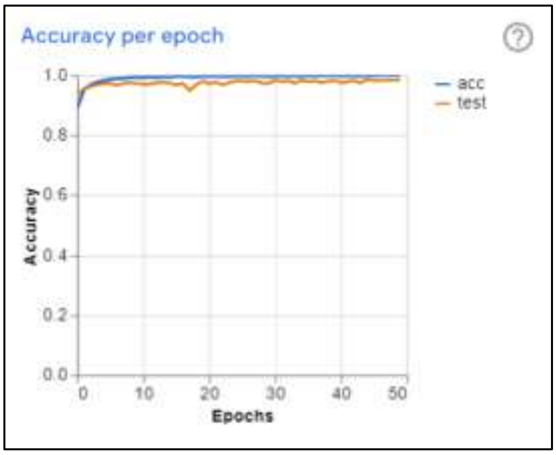

Figure 69. Accuracy per epoch

Figure 69 shows the progression of training and testing accuracy throughout the model's training process. The blue line represents the training accuracy (acc), while the orange line represents the testing accuracy (test). As seen, both the training and testing accuracies increase rapidly during the initial epochs, eventually stabilizing near 1.0 (100%) after a relatively small number of epochs. This suggests that the model quickly learned to classify rice diseases and healthy plants accurately. The minimal gap between the training and testing accuracy indicates that the model is well-balanced and generalizes effectively to new, unseen data. The graph demonstrates the learning curve of the model during training. Both the training and testing accuracies converge towards an optimal value of 1.0, indicating effective learning and successful generalization. The model achieves its maximum accuracy relatively early in the training process, with both curves stabilizing and showing minimal fluctuation after approximately 20 epochs.

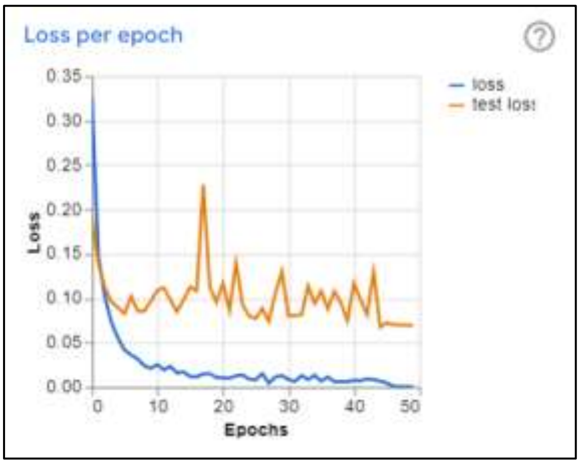

Figure 70. Loss per epoch

Figure 70 displays the loss values for training and testing data during the model's training process. The blue line represents the training loss, and the orange line represents the test loss. Initially, the training loss decreases significantly, indicating that the model learns effectively during the early epochs. After approximately 20 epochs, the training loss stabilizes at a very low value, suggesting that the model has reached a point where further improvement in loss is minimal.

However, the test loss (orange line) shows more fluctuations and remains slightly higher than the training loss, although it also decreases and stabilizes over time.

The graph shows the model's loss values during training. A sharp drop in the training loss during the early epochs indicates that the model quickly learned the correct patterns. The test loss shows more variation but follows a similar downward trend, suggesting that the model generalizes well to unseen data, though it could be more consistent with the training process. The relatively low and stable training and test loss values after around 20 epochs indicate that the model has reached an optimal state of learning and is performing well on both the training and testing datasets, with minimal risk of overfitting.

Trained Model Summary

The researcher trained twelve (12) machine learning models using Teachable Machine to develop and deploy a machine learning application designed for specific tasks, such as image classification. The primary objective was to enable the identification of objects in images, including the detection of rice diseases. The experimental phase lasted six months, during which these models were tested and refined. Initially, the goal was to train models using a large dataset of over 5,000 images. However, during the training process, Teachable Machine experienced frequent crashes and lags, necessitating a reduction in dataset size to 4,000 images and then further down to 3,000 images. Table 3 presents the SunRice Plant Disease Datasets, outlining the datasets used in this research. The limitations of the tool-imposed constraints on the dataset size, leading to adjustments that ensured the successful training and deployment of the models within the SunRice system.

Figure 9 presents sample images from the SunRice dataset following data augmentation. These augmented images were crucial to the training process and included techniques such as image rotation, brightness adjustment, slight zooming, and flipping. The images were captured using an Apple iPhone 11, with a 4:3 aspect ratio, a resolution of 3024 x 4032 pixels, and various angles to enhance compatibility with images captured by end users. For comparison, [67] created a dataset comprising healthy rice samples collected from fields in West Bengal and diseased samples obtained from the Internet. Their methodology involved using a Canon camera, background removal, and data augmentation. These comparative studies highlight the diverse approaches and preprocessing techniques employed in constructing robust datasets for rice disease detection. Distinguishing between different rice diseases with visually similar symptoms is a significant challenge in rice disease classification. Since deep learning models primarily rely on visual features to identify diseases, they often struggle to differentiate between diseases with similar visual characteristics. To overcome this challenge, additional information, such as weather conditions, plant health data, or other spectral bands like infrared, may be necessary. Despite these efforts, ambiguities in disease identification may still require laboratory analysis, making perfect accuracy unrealistic under field conditions [68].

Another critical challenge is the lack of robustness and generalizability of trained models. While most of the deep learning models proposed in the literature perform well on the datasets they were trained on, they often fail to deliver similar performance on other datasets [69]. This limitation means that these models are not sufficiently robust and cannot generalize to new, unseen data. To be effective, trained models must be able to apply their knowledge to data captured under various settings and environments when exposed to data outside their training domain [70]. The unavailability of adequate high-quality data for model training presents another significant challenge. Deep learning models require a large volume of high-quality data to train effectively, but collecting such data, particularly for leaf diseases, is often difficult [71]. Low-quality images with poor contrast lack the necessary details for accurate disease identification [72]. When image quality is compromised, it becomes challenging to apply machine learning techniques effectively, making it harder to diagnose diseases with precision.

Classification Performance Analysis

Figure 71 presents the results of the SunRice Success analysis, which includes samples of rice disease classification during testing. The findings indicate that the SunRice model achieved over 70% accuracy in identifying rice diseases, demonstrating its effectiveness in detecting and classifying these diseases. The results were obtained from the researchers' testing account. Notably, in sample (f), the model classified the image as "disease unidentified" with an accuracy exceeding 70%. This outcome is correct, as the image does not represent any rice disease, accurately showcasing the model's ability to distinguish between diseased and non-diseased images. This ability to differentiate non-disease-related images highlights the reliability and accuracy of the model.

However, Figure 72 illustrates the SunRice Error Analysis, highlighting instances where the system produced incorrect results during testing. While the model performed well in most cases, there were still some misclassifications. For example, in sample (a), the image depicted tungro disease, but the system incorrectly identified it as neck blast. Similarly, in sample (c), the system misclassified tungro disease as leaf blast. Additionally, in sample (f), which did not show any rice disease, the system mistakenly identified the image as brown spot disease instead of correctly marking it as "disease unidentified." These errors suggest areas where the model's accuracy can improve, particularly in distinguishing between similar disease symptoms and recognizing non-diseased plants. These challenges are common in plant disease detection, as demonstrated in studies where machine learning approaches have been tailored for similar tasks. For instance, the authors of [73] explored supervised machine learning techniques like Naive Bayes (NB), Decision Tree (DT), K-Nearest Neighbor (KNN), Support Vector Machine (SVM), and Random Forest (RF) for detecting maize plant diseases from plant images. These classification techniques were analyzed and compared to identify the most accurate model for disease prediction. Among the various algorithms tested, the RF algorithm achieved the highest accuracy of 79.23%.

The authors of [74] developed a custom Convolutional Neural Network (CNN) called M-Net, based on the AlexNet architecture. M-Net, with fewer layers than AlexNet, demonstrated faster performance and achieved an accuracy of 71%, which was competitive when compared to benchmarked models. Similarly, Tejaswini et al. [75] implemented a five-layer CNN and achieved an accuracy of 78.2%, showcasing the effectiveness of CNN-based models in plant disease detection, aligning with the need to enhance accuracy and performance, as observed in the SunRice model.

Other studies have tailored the analysis of color and texture features for plant disease detection. Using a dataset of 110 RGB images, the authors extracted features such as the mean and standard deviation of RGB and YCbCr channels, grey level co-occurrence matrix (GLCM) features, and the mean and standard deviation of images processed with a Gabor filter. A Support Vector Machine (SVM) classifier was employed for classification. The results indicated that GLCM features were effective for detecting normal leaves, while color features and Gabor filter features proved to be the most effective for identifying anthracnose-affected leaves and leaf spot disease, respectively. The highest accuracy achieved was 73.34% using all the extracted features [76], suggesting that the integration of such features could further improve the SunRice model's performance.

The authors explored supervised machine learning techniques for maize plant disease detection, comparing the performance of NB, DT, KNN, SVM, and RF algorithms. Their findings confirmed that the RF algorithm achieved the highest accuracy of 79.23%, further underscoring its suitability for plant disease prediction [77].

Figure 71. SunRice Success Analysis

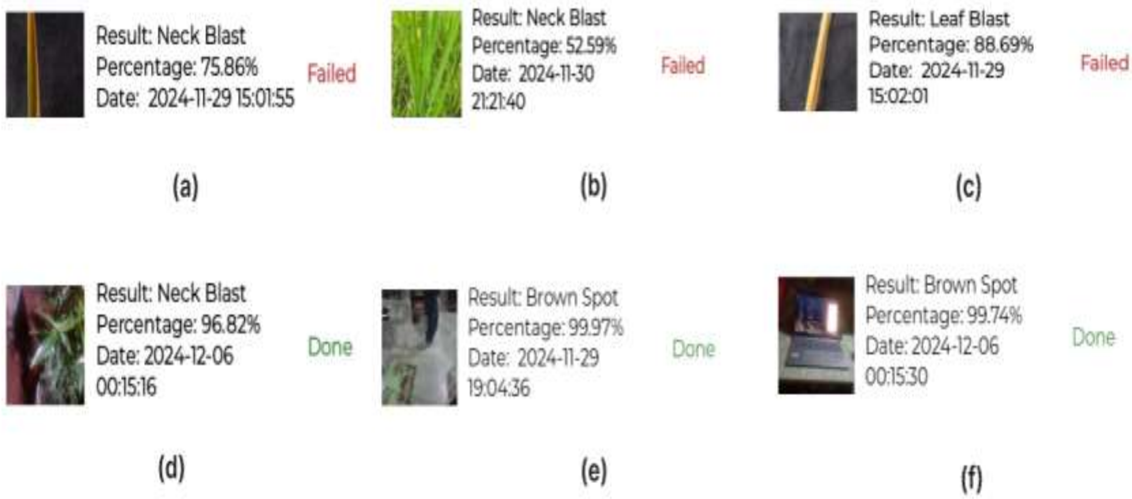

Figure 72. SunRice Error Analysis

End-user Response Analysis

The end-user response analysis provides an overview of both the success and error outcomes observed during the implementation and testing phase of the SunRice application. Figure 73 presents the success analysis results, showcasing the application's positive feedback and effective performance when end-users attempted to identify rice diseases. These images, collected by the researcher in the history, reflect the accuracy and usability of the application, highlighting areas where users successfully detected and diagnosed rice diseases. This demonstrates the application's effectiveness and ease of use in real-world scenarios.

In contrast, Figure 74 illustrates the error analysis results, where the application failed to provide accurate results in certain instances. The images reveal areas where the application's performance could have been improved, indicating potential limitations in the disease identification process. These errors highlight the application's challenges in complex or variable conditions, providing valuable insights for further improvements. Optical sensing-based phenotyping (OSP) has become a common approach in nondestructive rice disease detection, with methods such as charge-coupled device (CCD) cameras being used to analyze various features of rice diseases, including color [78], shape [79], texture [80], and spectral reflectance [81]. However, these technologies have limitations in handling large sample sizes, limited feature extraction capabilities, inaccurate segmentation, and noise suppression, which affect their accuracy in complex backgrounds and with unknown samples [82].

Figure 73. Success Analysis

Figure 74*.* Error Analysis

This chapter presents the results, interpretations, and discussion of the SunRice application development, emphasizing the achievements and challenges encountered during its implementation and testing phases.

The SunRice application utilizes deep learning techniques to identify rice diseases by analyzing visual data, such as images of diseased rice plants. The researchers used Google's Teachable Machine to train a model that accurately classifies rice diseases. The training process involved organizing dataset classes, with the researchers ensuring an equal number of datasets to avoid biases and experimenting with twelve models using sample images outlined in Table 3. The researchers targeted an accuracy rate exceeding 70% for disease identification, with the final model achieving this objective, as demonstrated in Figures 67–70. These figures highlight the model's performance analysis, showcasing the potential of deep learning and Teachable Machine technology for agricultural applications.

The implementation phase involved collaboration with the company, including the Jauod and Valeriano Rice Fields, to address real-world agricultural needs. Researchers interviewed end-users to understand the challenges of diagnosing rice diseases better. A dataset of thousands of images, shown in Figure 8, was prepared, and data augmentation techniques, as illustrated in Figure 9, were applied to enhance the model's ability to generalize across diverse scenarios. During data collection, challenges arose due to seasonal constraints in the rice cultivation timeline. There were instances when researchers could not gather data after the farmers harvested the rice, forcing them to wait a few months for the rice plants to ripen again, as illustrated in Figures 10 and 11. Despite these obstacles, the research team conducted multiple experiments to optimize the training process and ensure the model's reliability.

During deployment on September 21, 2024, user testing was conducted in the Jauod and Valeriano Rice Fields to evaluate the system's effectiveness. End-users provided valuable feedback, reporting issues such as delayed button responses, system failures, and device compatibility concerns when installing the application. These insights led to iterative improvements in the application. A monitoring system was implemented to ensure consistent performance, and researchers conducted maintenance procedures to address user concerns, ultimately enhancing the overall user experience; the deployment ended on December 11, 2024.

The researchers introduced significant upgrades to improve the application's functionality and usability in response to user feedback. (Figures 37–41) showcase the redesigned guidelines interface, which now includes Next and Back buttons to help users navigate the steps more effectively, enhancing the overall user experience. The navigation menu (Figure 50) was updated to include an About Us section (Figure 55), providing detailed information about SunRice, such as its mission, vision, and contact details. This lets users easily reach out with concerns or questions, fostering better communication. A new FAQ section (Figure 56) was added to assist users further, addressing common queries and offering troubleshooting tips. Furthermore, a QR code linked to a soft copy of the User Manual was integrated, giving users easy access to more detailed guidance and instructional materials, helping them to maximize the application's features and functionality.

The Rice Disease (Figure 54) was enriched with more detailed and reliable descriptions of rice diseases, offering users a more comprehensive resource for disease identification. To improve accessibility, the font size was increased to accommodate users over 30 who reported difficulties reading smaller text. In the History Section (Figure 52), new features were added to enhance user experience and data management. A Sorting Button (Today, Week, Month) was introduced, allowing users to organize their data more efficiently, while the Clear and Recover buttons provided additional control over the data history. A delete function was also incorporated, enabling users to long-press on the specific rice disease entry to delete it. To improve security, passwords were encrypted, and a new account approval system was implemented, requiring admin authorization before new users could log in. This ensured that only verified users had access to the application. In Figures 45 to 48, the researcher incorporated a "Forgot Password" feature that allows users to recover their accounts through a verification challenge based on their previous results. Users are given three attempts to successfully recover their account and reset their password, enhancing the application's security and user-friendliness. These enhancements reflect the research team's commitment to improving the functionality and security of the SunRice application, ensuring a more seamless and secure user experience.

These upgrades, guided by user feedback gathered through evaluation sheets and interviews (Table 5), resulted in a qualitative evaluation of "Efficient," with an overall score of 3.65. This outcome suggests that the system effectively meets the average requirements of its objectives while also identifying areas for future improvement. The feedback highlights key aspects that could be further optimized to ensure the system remains relevant and practical for end-users. Future upgrades and ongoing application maintenance will focus on refining the application's performance and usability, enhancing its reliability, and ensuring it provides user-friendly solutions that adapt to evolving needs.

Assessment Descriptions	Final AWM	Descriptive Equivalent
How clear and easy-to-follow are the steps provided for using the SunRice application?	3.8	Efficient
How effective is the application in capturing and uploading images for disease identification?	3.4	Efficient
How accurate are the results provided by the application in identifying rice diseases?	2.6	Moderately Efficient
How easy is it to read and understand the information in the disease library?	3.6	Efficient
How useful is the disease library in providing detailed and relevant information about rice diseases?	4.2	Efficient
How helpful is the history feature in allowing users to check past results and disease diagnoses?	4.4	Efficient
How easy is the application to navigate based on its design?	3.8	Efficient
How satisfied are you with the SunRice application based on your overall experience?	3.4	Moderately Efficient
Total	**3.65**	**Efficient**

Table 5. Summary of Qualitative Results for SunRice: Automatic Diagnosis of Rice Diseases using Deep Learning

Table 5 shows the qualitative evaluation of the SunRice application based on end-user feedback, which demonstrated that the system is "efficient." This indicates that the application meets more than the average requirements of its stated objectives, particularly in accurately identifying rice diseases. However, while the application fulfills its primary goals, the feedback also highlighted areas for potential improvement. Future upgrades could include refining the accuracy of disease classification and incorporating additional features requested by end-users. By addressing these opportunities, the SunRice application can continue evolving, enhancing its performance and usability to provide even better user support.

No.	Assessment Description	Rating					Final AWM
		1	2	3	4	5	
1.	How clear and easy-to-follow are the steps provided for using the SunRice application?			0.6	3.2		3.8
2.	How effective is the application in capturing and uploading images for disease identification?			1.8	1.6		3.4
3.	How accurate are the results provided by the application in identifying rice diseases?		0.8	1.8			2.6
4.	How easy is it to read and understand the information in the disease library?			1.2	2.4		3.6
5.	How useful is the disease library in providing detailed and relevant information about rice diseases?				3.2	1	4.2
6.	How helpful is the history feature in allowing users to check past results and disease diagnoses?				2.4	2	4.4
7.	How easy is the application to navigate based on its design?			1.2	1.6	1	3.8
8.	How satisfied are you with the SunRice application based on your overall experience?			0.4	0.6	2.4	3.4
Total			**0.8**	**7**	**15**	**6.4**	**3.65**

Table 5.1 Summary of Qualitative Results for SunRice: Automatic Diagnosis of Rice Diseases using Deep Learning.

Through a careful analysis and tabulation of the statistical data from the evaluation sheets presented in Table 5, along with the feedback provided by end-users, it has been determined that the implementation of the SunRice application has effectively achieved its intended benefits and functions.

1. How clear and easy to follow are the steps provided for using the SunRice application?

The application received a mean score of 3.8, with a descriptive equivalent of "Efficient." This result demonstrates that the guidelines and steps are clear and easy for end-users to follow.

2. How effective is the application in capturing and uploading images for disease identification?

The evaluation revealed a mean score of 3.4, with a descriptive equivalent of "Moderately Efficient." This result suggests that the application is effective in capturing and uploading images for disease identification, though there may be room for improvement.

3. How accurate are the results provided by the application in identifying rice diseases?

The application received a mean score of 2.6, with a descriptive equivalent of "Moderately Efficient." This suggests that the accuracy of disease identification needs improvement. There are instances where the results are not accurate, and researchers should consider improving the application by using a more robust model for accurate results.

4. How easy is it to read and understand the information in the disease library?

The evaluation received a mean score of 3.6, with a descriptive equivalent of "Efficient." The results indicate that the disease library is easy to read and understand.

5. How useful is the disease library in providing detailed and relevant information about rice diseases?

The application received a mean score of 4.2, with a descriptive equivalent of "Efficient." This result highlights the effectiveness of the disease library in offering detailed and relevant information.

6. How helpful is the history feature in allowing users to check past results and disease diagnoses?

The application received a mean score of 4.4, with a descriptive equivalent of "Efficient." This demonstrates that the history feature is highly beneficial, allowing users to track past diagnoses and results.

7. How easy is the application to navigate based on its design?

Based on the evaluation, the application received a mean score of 3.8, with a descriptive equivalent of "Efficient." This indicates that end-users find the application design easy to navigate.

8. How satisfied are you with the SunRice application based on your overall experience?

The application received a mean score of 3.4, with a descriptive equivalent of "Moderately Efficient." This result reflects user satisfaction and suggests that the application meets more than the average requirements of its objectives. However, researchers should improve certain aspects of the application to enhance the end-user experience.

Rating	Range Interval	Descriptive Equivalence	Description
5	4.5 – 5.0	Very Efficient	The system meets all the requirements of the system's objectives.
4	3.5 – 4.49	Efficient	The system meets more than the average requirements of the system's objectives
3	2.5 – 3.49	Moderately Efficient	The system meets the minimum requirements of the system's objectives.
2	1.5 – 2.49	Less Efficient	The system meets less than the minimum requirements of the system's objectives.
1	1.0 – 1.49	Poor	The system does not meet the requirements of the system's objectives.

Table 6. Table Sheet Rating Scale

In Table 6 shows the evaluation of the system's performance based on its ability to meet its objectives, a scale ranging from 1 to 5 was used. A rating of 4.5 to 5.0 indicates that the system is efficient and fully satisfies all the intended requirements. Scores between 3.5 and 4.49 reflect an efficient system that exceeds average expectations. A moderately efficient rating, ranging from 2.5 to 3.49, means the system meets only the basic or minimum objectives. When the score falls between 1.5 and 2.49, the system is considered less efficient, fulfilling fewer than the minimum expected requirements. Finally, a rating of 1.0 to 1.49 is categorized as poor, signifying that the system fails to meet its intended objectives.

CHAPTER V

CONCLUSION AND RECOMMENDATION

Conclusion

In conclusion, the SunRice application has successfully met its primary goal of providing an automated, reliable tool for diagnosing rice diseases using deep learning techniques. Using the Teachable Machine platform, the application achieved an accuracy rate of over 70%, proving its robustness in real-world agricultural applications. This capability empowers farmers and farming experts to enhance rice disease management, supporting improved crop protection and more informed decision-making. The development and testing phases demonstrated the system's potential to address critical agricultural challenges and contribute to better rice cultivation practices.

Users have received The application positively, with feedback confirming its efficiency in achieving the core objectives. Features like the disease library, image capture, and disease identification were highlighted for their effectiveness, ease of use, and practical relevance. Additionally, the history feature, which allows users to monitor and manage recurring diseases, provides valuable continuity in disease management. The educational component of the disease library, which offers detailed information on prevention and treatment, is particularly beneficial, ensuring that users are equipped with the knowledge necessary to make informed decisions for disease control and crop health. While the application meets its minimum requirements, feedback also highlighted areas for improvement, such as further enhancing the accuracy of disease classification and addressing issues with device compatibility and navigation. These insights will inform future updates and continuous improvements to the application, optimizing its performance and usability.

The SunRice application not only aids in diagnosing rice disease but also plays a key role in fostering sustainable farming practices by providing easy-to-use, technology-driven solutions. By streamlining disease detection and offering educational resources, the application supports farmers in producing healthy, high-quality rice and advancing food security. In this way, SunRice is a vital tool in the agricultural sector, contributing to sustainable farming practices and laying the groundwork for future innovations in agricultural technology.

Recommendation

The researchers recommend adopting the SunRice application in rice farming communities because it can potentially improve rice disease diagnosis and management. The application leverages deep learning technology to analyze images of rice plants and provide accurate disease diagnoses. By integrating this tool into daily agricultural practices, farmers can identify rice diseases more efficiently and take timely action to mitigate crop loss. The researchers believe the SunRice application can be a valuable resource in supporting rice farmers by offering an accessible, user-friendly disease detection and management solution.

Based on end-user feedback, the researchers suggest that future application versions include an expanded database of rice diseases to improve its diagnostic capabilities. Currently, the application identifies a range of common diseases, but increasing the number of diseases covered will make the tool even more helpful for farmers facing diverse agricultural challenges. Additional disease categories will enhance the application's relevance and effectiveness in different geographical regions with varying rice disease profiles.

Furthermore, the researchers emphasize the importance of user feedback for continuous application improvement. They encourage end-users to report any issues or errors they encounter while using the SunRice application, as this feedback will be crucial for troubleshooting and ensuring the application's reliability. In particular, the researchers suggest that users ensure a stable Internet connection when using the app, as connectivity issues can affect performance, especially when uploading images for disease analysis. Addressing these technical challenges will contribute to optimizing the application's overall functionality.

The researchers remain open to further suggestions and improvements from end-users. They acknowledge that farmers' evolving needs require the continuous refinement of agricultural tools. By incorporating user feedback, the SunRice application can be enhanced to better support sustainable rice farming practices, ultimately improving crop health, yield, and productivity. The researchers believe that ongoing collaboration with users will ensure the application remains a valuable tool for farmers and contributes to the advancement of agricultural technology.

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Appendix A. Documentation

SunRice Application Deployment

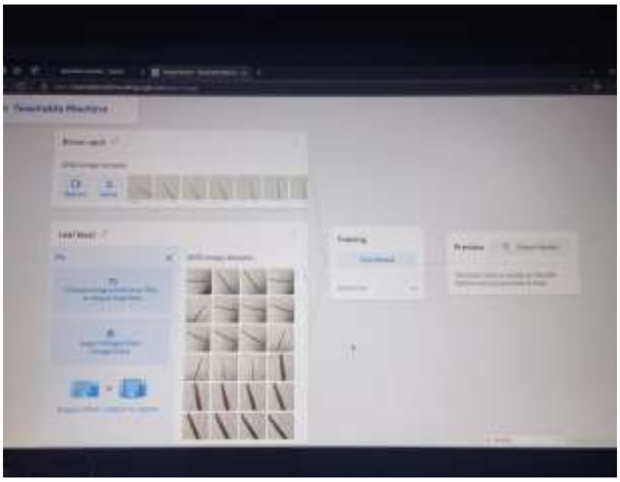
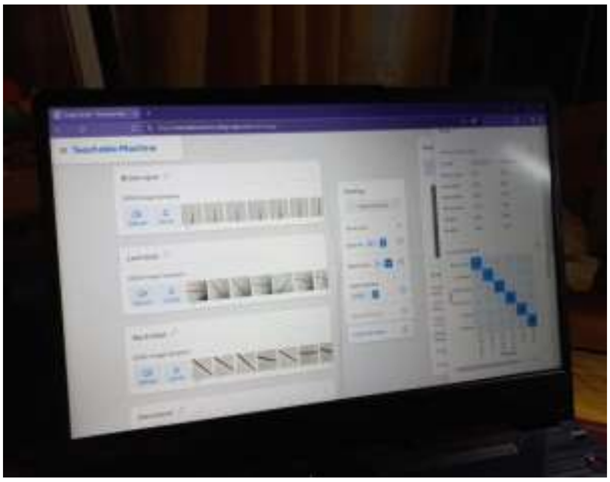
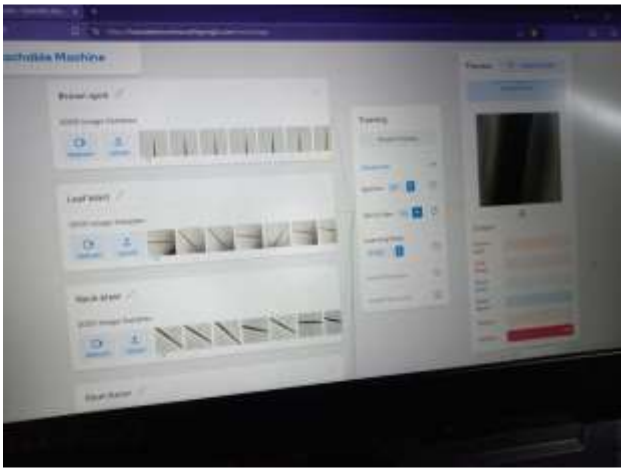
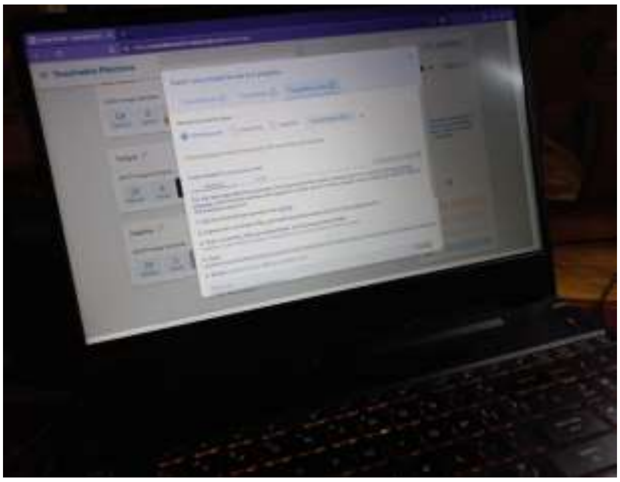





User Testing

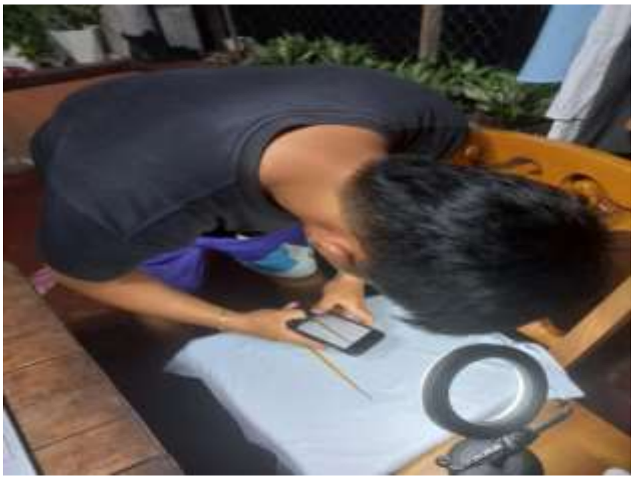
Assesssment Evaluation

Training Rice Disease Model with Teachable Machine

Data Gathering






Appendix C. User Manual

“User Manual Hard Copy”

SCAN ME

User Manual Link:

https://docs.google.com/document/d/1d406tbvStbHVgtMcMfNSa04HayYnCRn59JJP
tT1bYI/edit?usp=sharing

Trained Model

SCAN ME

Trained Model Link:

https://drive.google.com/drive/folders/1JdFpla8EtZZsl6bjR9vzlrCVzWWKlHjq?usp=dr
ive_link

SunRice Datasets Samples

SunRice Datasets Samples Link:

https://drive.google.com/drive/folders/1m0T9pt_giBrUeECH0Crq03gH1wCZGtNy?usp=drive_link

Appendix D. Letters

Appendix E. Source Code

Appendix F. Curriculum Vitae

Danny Boy S Gaudicos

09633433209

uchihadanzkiegaudicos@gmail.com

Prk. 2B Nuevo Iloco Mawab, Davao de Oro

February 2, 2002

Nuevo Iloco Mawab, Davao de Oro

ABOUT ME

Objective / About Me:

Tech-savvy and detail-oriented IT student with strong skills in software proficiency, data management, and communication. Experienced in using Microsoft Office, Google Workspace, and various industry-specific tools to organize and analyze information efficiently. Adept at engaging with customers, handling sales communication, and drafting professional reports and documentation. Highly adaptable, quick to learn new technologies, and eager to contribute to a dynamic work environment.

EDUCATION

Nuevo Iloco Elementary School
Nuevo Iloco Mawab
2009 - 2014

Nuevo Iloco National High School
Nuevo Iloco Mawab
2013 - 2018

Nuevo Iloco National High School
Nuevo Iloco Mawab
2017 - 2020

Aces Tagum College, Inc
Prk. Pag-ibig, Mankilam Tagum City
2019 - 2025

SKILLS

Software Proficiency - Experienced in using Microsoft Office, Google Workspace, and industry-specific software.

Data Management - Skilled in organizing, analyzing, and maintaining data using Google Sheets, Excel and Airtable.

Sales Communication - Strong ability to engage customers, handle objections, and close sales effectively.

Adaptability - Able to quickly understand and apply new instructions, tools, or working conditions efficiently.

Written Communication – Skilled in drafting clear, professional, and persuasive content, including reports, emails, and documentation.

Jimwil Jauod Larigo

09361112032 | jimwillarigo2021@gmail.com | Prk. Uraya, Mankilam Tagum City

May 9, 2003 | Regional Hospital Tagum City

ABOUT ME

Motivated and detail-oriented professional seeking to leverage my skills and experience to contribute effectively to a dynamic organization. Eager to apply my knowledge, adaptability, and strong work ethic in a challenging environment that fosters growth and development while delivering high-quality results.

EDUCATION

Magugpo Pilot Central Elementary School
Mabini Street Tagum City
2009 - 2015

Tagum City National Comprehensive High School
Aala Road, Mankilam Tagum City
2015 - 2019

Aces Tagum College, Inc
Prk. Pag-ibig, Mankilam Tagum City
2019 - 2021

Aces Tagum College, Inc
Prk. Pag-ibig, Mankilam Tagum City
2021 - 2025

WORK EXPERIENCE

Student Assistant of Aces Tagum College, Inc.

SKILLS

Figma Designer

AFFILIATIONS

2021 - 2025
Computer Society Club Member

Job Abogado Pelotos

09855289190
pelotosjob@gmail.com
Prk. 4A Upper Mabini, Magatos, Asuncion, Davao del Norte
June 03, 2002
Taguig City

ABOUT ME

As a fresh graduate, I am eager to apply my knowledge, skills, and enthusiasm to real-world challenges. I am a quick learner, adaptable, and committed to continuous growth, both personally and professionally. With a strong foundation in my field of study, I aim to develop my expertise, contribute effectively to a team, and make a positive impact in any organization I become a part of. My goal is to build a successful career while embracing opportunities that enhance my skills and knowledge.

EDUCATION

Kapt. Eddie T. Reyes Integrated School
Pinagsama Village Phase 2, Taguig, 1630 Metro
2009 - 2014

Diosdado Macapagal High School
Katuparan 8th Taguig, 1630
2013 - 2018

MCA Montessori School
Bonifacio 10 E Adevoso St Taguig, 1630
2017 - 2020

Aces Tagum College, Inc
Prk. Pag-ibig, Mankilam Tagum City
2021 - 2025

WORK EXPERIENCE

Chicken Chopper, Roaster, and Fryer Cooker

Store Cashier

Carwash Boy

Catering Staff

SKILLS

Housekeeping
Figma Designer
Multitasking

AFFILIATIONS

2014 - 2019
Computer Society Club Member

2021 - 2025
Youth Ministry

Michael Ian Gillamac Rapal

09065617691 michaelrapal21@gmail.com B11 L7 Villa Magsanoc, Mankilam Tagum City

September 21, 1999 Regional Hospital Tagum City

ABOUT ME

I am a dedicated and goal-driven student leader with a strong background in leadership, computer literacy, and problem-solving. With years of experience in student governance, I have developed excellent decision-making and organizational skills. Passionate about technology and innovation, I continuously enhance my coding and programming abilities while actively contributing to student organizations. I strive to create a positive impact in both academic and leadership roles, fostering growth and collaboration within my community.

EDUCATION

New Leyte Elementary School
Prk. 1 New Leyte Maco, Davao de Oro
2007 - 2013

New Leyte National Highschool
Prk. 1 New Leyte Maco, Davao de Oro
2013 - 2017

Aces Tagum College, Inc
Prk. Pag-ibig, Mankilam Tagum City
2017 - 2019

Aces Tagum College, Inc
Prk. Pag-ibig, Mankilam Tagum City
2019 - 2025

SKILLS

Leadership

Computer Literacy

Coding/ Programming

Decision and Problem Solving

AFFILIATIONS

2015 - 2016
SSG President

2015-2016
SSG Auditor (Municpal Level)

2016-2017
SSG President

2018-2019
SSG President

2018 - 2019
Tagum City Youth Leader

2022-2023
SSC President

2023-2024
SSC President

2024-2025
IICT Governor

2022-2025
Computer Society Member