RICE PLANT DISEASE DETECTOR AND SEVERITY CALCULATOR USING MACHINE LEARNING AND VISUAL COMPUTING

A Proposal
Presented to the Faculty of the
College of Computer Studies and Information Technology,
Southern Leyte State University

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

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DEDICATON

Above all, this study is dedicated to our Almighty God for giving us guidance, motivations and strengths in doing this whole project.

To the Instructors, who guided and prepared us to reach our dreams in the future.

To our parents and relatives, who gave us all the support and helped us in our struggles and also gave us inspiration in all the good times and bad times.

To the members of this team, who never falter to push through all the challenges that we have encountered in this college life.

To our Capstone Adviser, who gave her time available just to guide us, teach us and give us motivation to continue doing this study.

And lastly to our Alma Mater, Southern Leyte State University that sheltered and molded us to become a person that we are today.

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CHAPTER I

INTRODUCTION

2.1 Project Context

Rice production in the Philippines is important to the food supply in the country and economy. The Philippines is the 9th largest rice producer in the world, accounting for 2.8% of global rice production. The Philippines was also the world's largest rice importer in 2010. Additionally, rice is the staple food in the Philippines which is significant to the economy and people at lower income levels. It has been the major crop in the country which many farmers cultivate and nearly all consumers eat.

With the exponential increase in population, rice demand in the country is expected to grow faster than production. In this situation, damage to rice crops by any means is unacceptable. Rice diseases have a devastating effect on rice production. Many diseases hamper the growth and productivity of plants which lead to great ecological, economical losses, and food security threats.

There are many diseases that hamper the growth and productivity in rice which lead to great ecological and economical losses. Some of the known types of rice plant diseases and its corresponding characteristics are:

1. Leaf Blast√ (LB): The indication of the disease is black dots to oval dots, with reddish brown and gray or white points.

2. Brown Spot √ (BS): The disease infected on the leaves of rice. The indication of disease is round to oval, with dark brown lesions.

3. Sheath Blight (SB): This infection suggests itself on both leaves and stems. The indication is oval, white or straw-colored show in center with reddish brown spots [8].

4. Leaf scald (LS): The symptoms are narrow reddish-brown wide bands. Sometimes the lesion is on the edge of the leaf, the border is yellow or gold.

5. Bacterial Leaf Blight √ (BLB):The indication have elongated lesions at the tip of the leaf, which are several centimeters long, and change from white to yellow due to the action of the bacterium.

6. Rice Blast (RB): It is because of the fungus Magnaporthe Oryza. The white to gray-green lesions or blemishes have a dark green border on the first time. The more obvious lesions on the leaves are oval or spindle-shaped, whitish to gray center, red to brown or necrotic edge. Usually, the spots are elongated and point at both ends.

7. Sheath Rot (SR): It was created by two fungal species, Sarocladium Oryza and sacroladium tensum. Typical casing root begins with the upper sheath of the spikelet. It looks like an oblong or asymmetrical stain with dark red, Brown edges, gray midpoint or brownish gray generally, more spots are experiential, these spots will expand, and rise can cover most of the leaf sheath. The panics remain in the cloak or may appear partially. The diseased leaflets showed a large amount of white, powdery fungal increase (mycelia) on outer surface. The panicles did not rot or small flowers changed from reddish brown to dark brown.

Detection of rice plant disease and its severity has always been challenging considering the similarities of symptoms. Locally, the only available technique in diagnosing the rice disease and determining the severity of leaf spot disease was naked eye observation or visual analysis. As the visual analysis requires constant human observations and manual measurements, the process tends to be very costly, tiresome, and time-consuming and can lead to errors especially when dealing with large areas of plants. This also requires continuous monitoring of experts which might be expensive.

It is important to detect the plants disease at early stage and accurate diagnosis the infectious disease is critically important because diagnosis can improve the effectiveness of treatments and avoid long-term complications for the infected patient plant. Undiagnosed patients' plant can unknowingly transmit the disease to others. Furthermore, estimating or measuring the severity of disease on plants is fundamental to many studies in plant pathology and has practical applications where disease control is needed, including crop disease surveys, decision making, comparing crop management approaches, understanding and estimating yield loss, and rating germplasm for crop breeding purposes. With this, the use of emerging technologies like computer vision and machine learning would be promising so that early and accurate identification and detection of plant diseases for early and timely implementation and application of corresponding remedial measures.

Image processing techniques and machine learning are proved accurate and economic practices for measuring the parameters related to various plant diseases to avoid losses in the number of agricultural products and yields (Ramesh et.al. 2020). Recent advances in computer vision particularly machine learning techniques have been applied in agriculture to extract information from the images and to represent this information effectively and efficiently.

Hence, in this study, the authors employed one of the most popular learning algorithms at present and most applied to analyze visual imagery - the convolutional neural network and visual computing. A computer-based rice disease detector and severity calculator will be implemented to facilitate the experts and the farmers in diagnosing rice diseases.

1.1 Purpose and Description

The main purpose of this study is to create a method for recognizing the diseases of rice plants using their images. Considering the challenges of every farmer in their food production this system may help their technique and method to provide development to increase productivity and overcome the challenges of rice disease to create a better accumulation in their rice crop against the rice plant disease. This project will also help the farmers to enables to identify the types of diseases to make the right decision and to select proper treatment. One of the advantages of using machine learning based method is that it performs tasks more consistently than human experts. The proposition of this project is in task of gathering available data set of rice plant using image processing in which this data will be use for the creation of the system which can be able to distinguish the types of rice plant disease and select the proper treatment.

This system accepts an image input from the user. This image undergoes object detection and image preprocessing in which it will classify all the characteristics of rice plant disease that is present in the system image. This project is designed to provide an important benefit for automated plant identification and can improve low-performance plant classification.

1.2 **Objectives of the Project**

Generally, this study aims to develop a computer application that recognizes rice diseases and measures the severity level of disease using visual computing and machine learning. Specifically, this study aims to attain the following objectives:

1. To implement image analysis technique in measuring the severity level of rice disease and a machine learning algorithm in recognizing rice diseases.
2. To design and develop an easy-to-use application of the rice plant disease leaf image processor; and
3. To evaluate the accuracy of the software in recognizing rice plant diseases.

1.3 Scope and Limitation of the Project

For this project to be realized, the proponents prepared and studied the requirements that were needed for building this project. First is to gather datasets that are available locally and in web and train it so it can classify and recognized diseases of a rice plant with high accuracy using deep learning algorithm. This project used Python programming language and other libraries.

This project will only focus on rice plant diseases. The system in this study is only capable of recognizing rice plant diseases and will ignore other kinds of plant. And lastly the system will only allow one image at a time and will not allow multiple images at a time.

CHAPTER II

REVIEW OF RELATED LITERATURE

2.1 Related Literature/Theoretical Background

Technology is one of the helpful tools in making peoples life easier and comfortable to live in. on this thought this study aims to produce an application using image analysis that well help identify the different disease ion the plants. In modern societies, technology is the medium of daily existence. Every major technological advance has ramifications on many levels, including economics, politics, religion, and culture (Feenberg et al., 2012). Those technology has its widespread effect to the community; it may help one in their life or may cause disturbance. One of the better uses of the technology is through the identification of different diseases in various plants and crops. Since the last ten years, researchers have been interested in how to diagnose plant disease using image processing techniques. In a wide range of crops, several disease detections, identification, and quantification approaches have been developed and implemented (Sethya et.al., 2019). In which this proves that this technology is implemented to help farmers in the process.

In the Philippines, rice is an essential staple meal. It meets more than 45 percent of Filipinos' total daily calorie needs, with an average rice consumption of 118.6 kilograms per year (Bautista et al., 2010). Rice is planted and harvested twice a year, the first season runs from December to May, and the second season runs from June to November. Because there is usually no rain during the first cropping season, it is known as the dry season. During this time, irrigation is largely dependent on rainfall during the growth season. Rice is a labor-intensive crop in the Philippines. The amount of human effort used in each stage of rice production is far greater than the energy consumed by machines. Approximately 37% of the entire labor force was employed in the agricultural industry. In the Philippines, there are three major sources of available power: human work, animal labor, and mechanical power. Their application is usually determined by the size of the farm, cultural practices, soil conditions, and geography.

According to (Sethya, et.al, 2019), rice is an important source of food for the rural people, and it is also the world's second most produced cereal crop. Rice is Asia's most well-known low-cost and nutrient-dense cuisine. Specifically, rice is the staple foods that Asian people are consumed every day. Also, rice is the primary source of nutrition for half of the world's population (Sharma et al., 2012). Rice plant disease detection and severity assessment has always been difficult. Until recently, the sole method for diagnosing rice illness was naked eye observation (visual analysis). This technique necessitates regular agricultural field monitoring for an expert in this sector to accurately estimate illness. On that thought illness in the rice plant can only be identify if an accurate and well process technology is made. With that Image processing techniques have proven to be one of the most accurate and cost-effective methods for determining the factors associated with a variety of plant diseases. As a result, this study includes a thorough examination and comparison of various image processing algorithms that can be used to diagnose plant diseases.

Disease in plants is caused by fungus and bacteria. Leaf blast, Brown spot, Sheath blight, and Leaf scald are some of the diseases that affect rice plants. Farmers are sometimes unable to pay attention to diseases or have trouble diagnosing infections, resulting in crop loss. Every disease has a different remedy to work out. The current disease detection method is manual, which means farmers rely primarily on guide books or personal expertise to identify diseases. There are various stages of development for each plant disease. And this type of diseases are Leaf blast causes a black spot to an oval patch on the leaf with narrow reddish-brown borders and a gray or white center. Brown spot is a disease that affects rice plant leaves. The disease manifests itself as round to oval lesions that are dark brown in color. Sheath blight is a disease that affects both the leaves and the stems. Oval, white- or straw-colored regions in the center with reddish brown dots are the symptoms. Leaf scald causes narrow reddish-brown broad streaks on the leaves. Lesions near the leaf edges with yellow or golden borders are common. Symptoms of bacterial leaf blight include elongated lesions on the leaf tip that are several inches long and turn yellow from white due to the bacteria's action.

Moreover, diseases in the rice plant are mostly made of fungal pathogens that can be seen by the naked eye. Rice blast (RB), which is caused by the fungus Magnaporthe oryzae, is the most severe and prevalent disease in rice-growing areas around the world (Deng et al., 2017). In chilly and rainy summers, RB outbreaks can last the full growing season of rice (Fang et al., 2019; Kobayashi et al., 2001). Magnaporthe oryzae, a fungal pathogen, can induce two primary pathosystems, rice leaf blast (RLB) and rice panicle blast (RPB), depending on the affected organs (RPB). The pathogen infects the leaves primarily during the tillering and jointing stages, as well as the panicles following heading (Kobayashi et al., 2001). The microorganisms that cause panicle infection are spread by spores that develop on the leaf wounds (Kobayashi et al., 2001). Furthermore, when a pathogen infects leaves, the leaf tissue is severely destroyed, and photosynthesis is harmed (Talbot et al., 2003). Early diagnosis of RLB infection is crucial for limiting the spread and minimizing the potential for greater consequences. RLB detection has always relied on visual assessment by experts in the field. For accurately recognizing RLB at an early stage, a more effective approach is required. For detecting agricultural diseases across multiple spatial scales, remote sensing has been shown to be an effective and non-destructive technology (Franceschini et al., 2019; Huang et al., 2014; Mahlein et al., 2013; Rumpf et al., 2010; Shi et al., 2018b; Zhang et al., 2012).

As stated by (Zhan-yu et. al., 2008), rice brown spot leaf disease severity was measured in the lab by measuring the percentage of infected surface area of rice leaves using a phytopathologist's observation. There are 3 steps on how to estimate leaf disease severity of rice plant. The first phase involved experimenting with various spectral transformation approaches. The second phase was to use principal component analysis (PCA) to extract principle components (PCs) from the above modified spectra in order to minimize the hyperspectral reflectance spectra dimensions and simplify the data structure. And the last step is the resampling and PCs spectra were entered as input vectors into the Radial Basis Function neural network (RBFN), and the disease severity of rice brown spot was entered as target vectors into the RBFN. The RBFN distributed factors and various data processing algorithms were thoroughly examined. PCs spectra based on the first-order derivative using the RBFN model produced the best prediction result, with a modest root mean square of prediction error (RMSE) in the testing dataset (7.73%), and resampling spectra with an RMSE of 8.75 percent.

Based on the information of rice diseases obtained from different sources, rice diseases can be forecasted before their outbreak during the process of rice production. The conventional identification of rice diseases is mainly based on visual observations of experienced producers or rice experts in the field. This requires continuous monitoring of experts which might be prohibitively expensive in large farms. Nevertheless, with the rapid development of image processing and pattern recognition technologies, the new way for plant disease recognition and diagnosis is provided. The image recognition and machine learning are the essential research topics as they may prove beneficial in monitoring large fields of crops, and thus automatically detect the symptoms of diseases as soon as they appear on plant leaves. (Junde Chen et. al., 2020)

The most important thing in agriculture that affects the quantity and quality of crops is plant diseases. In general, a farmer knows that his plant is attacked by a disease through direct vision. However, this process is sometimes inaccurate. With the development of machine learning technology, plant disease detection can be done automatically using deep learning. deep learning-based rice disease detection system that have developed, which consists of a machine learning application on a cloud server and an application on a smartphone. The smartphone application functions to capture images of rice plant leaves, send them to the application on the cloud server, and receive classification results in the form of information on the types of plant diseases. The results showed that the smartphone-based rice plant disease detection application functioned well, which was able to detect diseases in rice plants. The performance of the rice plant disease detection system with VGG16 architecture has a train accuracy value of 100% and a test accuracy value of 60%. The test accuracy value can be improved by adding the number of datasets and increasing the quality of the dataset. (Heri Andrianto et. al., 2020)

2.2 Related Studies

(T. Islam et al., 2018) reported a faster rice disease detection technique. The green pixel masking with Naïve Bayes' classifier used for detection of bacterial blight, rice brown spot & rice blast with accuracy of 89%, 90% & 90% respectively. (Sarangdhar et al. ,2017) illustrated a SVM of regression system for detection and characterization of different cotton leaf disease. (P K... Sethy et al., 2017) reported a mineral deficiency identification method for rice crop by use of SVM in association with two feature extraction method such as K-means clustering and FCM clustering. Here the overall identification accuracy of N, P, K, Mg & Zn deficient rice leaf by use of SVM with K-means clustering and FCM are 85.05% and 95% respectively.

(S. Phadikar et al., 2012) reported a methodology for classification of rice leaf diseases based on leaf complexion. The image samples of 1000 number both healthy & disease affected leaf were collected using Nikon COOLPIX P4 digital camera in macro mode. Then classification is done in two phases. First healthy and affected rice leaf are classified. Then brown spot & leaf blast are classified. The classification is done by two classifiers i.e., Bayes' classifier and SVM with tenfold cross validation and achieved accuracy of 79.5% and 68.1%respectively.

(P. Sanyal et al., 2007) tried to identify different mineral deficient rice leaf by used of multilayer perceptron neural network (MLP-NN) based on color& texture feature. For experimentation the image of healthy & mineral deficient rice leaf was collected (IRRI, Philippines) and 80% sample used for training & 20% for testing. The MLP-NN classifier have 40 hidden layers for texture feature and 70 hidden layers for color feature. The proposed technique successfully identified five types of mineral deficient rice leaf such as boron, iron, magnesium, manganese, nitrogen & potassium with overall accuracy of 88.565.

Thelma D Palaoag et.al Rice pest and disease detection using convolutional neural network. The study proposed an application that will help farmers in detecting rice insect pests and diseases using Convolutional Neural Network (CNN) and image processing. It looked into the different pests that attack rice fields; information on how they can be controlled and managed was considered; farmers' knowledge in different rice pests and diseases, and how they control these pests. The searching and comparison of captured images to a stack of rice pest images was implemented using a model based on CNN. Collected images were pre-processed and were used in training the model. The model was able to achieve a final training accuracy of 90.9 percent. Cross-entropy was low, which implies that the trained model can perform prediction or can classify images with low percentage of error.

(Sachin B Jadhav) Convolutional neural networks for leaf image-based plant disease classification. The study proposes an efficient soybean disease identification method based on a transfer learning approach by using a pre-trained convolutional neural network (CNN's). The proposed convolutional neural networks were trained using 1200 plant village image dataset of diseased and healthy soybean leaves, to identify three soybean diseases out of healthy leaves. Pre-trained CNN used to enable a fast and easy system implementation in practice. It used the five-fold cross-validation strategy to analyze the performance of networks. They also used a pre-trained convolutional neural network as feature extractors and classifiers. The experimental results for the identification of soybean diseases indicated that the proposed networks model achieves the highest accuracy.

CHAPTER III

TECHNICAL BACKGROUND

3.1 Technicality of the Project

The Rice Plant Disease Detector and Severity Calculator as shown in Figure 1 is a computer-based web-application that identifies the disease of a rice plant and it severity. The user can upload an image of a rice plant leaves so that the system can process and evaluate its use. The system can identify rice plant disease and can also calculate the severity of the disease infected on a rice plant. The proponents aimed for this software to be capable of running without the use of an internet connection. This goal was achieved with the help of the model that was created to train the datasets so that it can classify and identify the rice plant diseases. And the proponents design the application in a python library called Streamlit, it is used for creating Computer-Based web applications using Python Programming language.

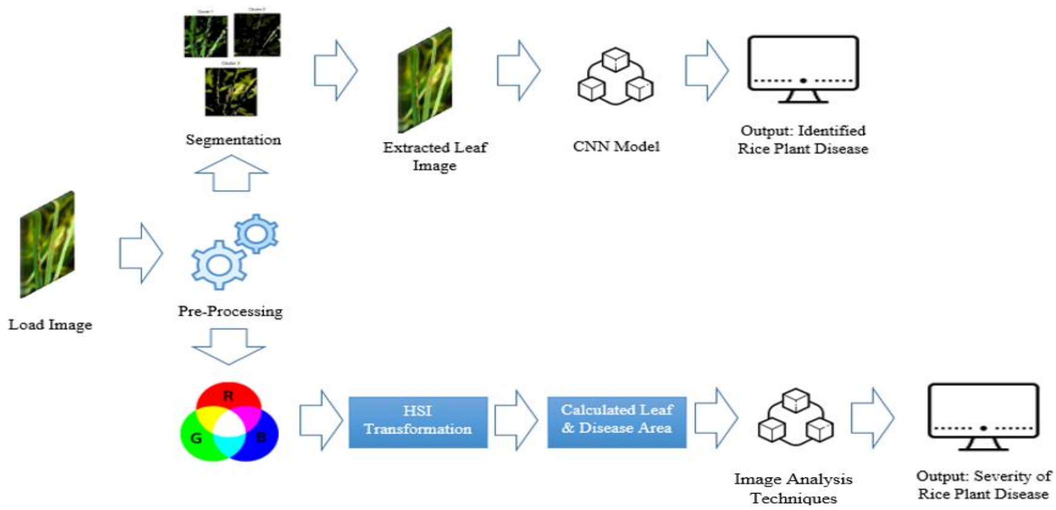

Figure 1. Conceptual Framework of the Study

Figure 1 shows the conceptual framework of the study. As you can see in the diagram, it needs an image of rice leaf that will be loaded to the system, after the image is loaded it will undergo image pre-processing. For the Rice Leaf Disease Detector part, after image pre-processing the images will undergo image segmentation. Once the image is segmented it will be extracted and will be utilized in the CNN model for training and utilizing the extracted features to classify and identify the disease infected to the rice plant. And for the Severity calculator part same thing after the image is uploaded it will also undergo image-processing and segmentation after that process the RGB values that has been extracted will be converted into HSI representation for calculation of the leaf area and the infected area. After it will use image analysis technique to identify the severity of the rice plant disease

3.2 Details of the Technologies to be Used

In developing the project, the following technology tools will be used:

- Python (latest version)

- NumPy - A library for the Python programming language, adding support for large, multi-dimensional arrays and matrices, along with a large collection of high-level mathematical functions to operate on these arrays.
- Cv2 (OpenCV) - OpenCV is a library of bindings designed to solve computer vision problems.
- Keras - Keras is an open-source neural network library written in Python. Designed to enable fast experimentation with deep neural networks, it focuses on being user-friendly, modular, and extensible.
- Matlplotlib - A plotting library for the Python programming language and its numerical mathematics extension.
- Tensorflow – a backend framework for running Keras.
- Jupyter – for editing and running documents that contains codes
- Streamlit – a Python library for developing acustom web application for machine learning
- Html- a standard markup language for documents designed displayed in web browser
- CSS – a style sheet language use for describing the written document in HTML

Necessary installations of libraries, packages and frameworks will be made in order for this project to be realized and to support the system to be suitable for identifying corn disease for which the trained model will be going to be deployed for actual implementation.

How the Project Will Work

The project is a Computer-Based application in which the user will provide rice leaf images that will be acquired using a 13.0 megapixels' camera or higher for taking pictures if the image is already existing you will just be uploading this image into the system. For the Disease Severity Calculator after the image is uploaded the leaf images will be cropped and cleared for extraneous objects. Then after that, the leaf images will undergo image segmentation to separate the region of the leaves from the background using the Otsu method. And once the image has been segmented, the RGB images will be transformed into HSI color representation. After the conversion of RGB to HSI, the system will now perform feature extraction which will be extracting color and texture features from the images. The color feature of the image will be segmented into two regions which will be representing the healthy part of the leaf and the infected part of the leaf. After the calculation of the infected region, it will use the image analysis technique to be able to classify it accordingly to get its severity calculation presented in the study.

And for the Leaf Spot Disease Recognizer the loaded image will undergo image segmentation wherein the region of interest will be partitioned through segmentation. This will be done by finding the threshold value using the known Otsu method. And once the image is segmented, it will proceed to feature extraction, extracting the color features and morphological features from the rice leaf digital image. Using the extracted features, it will then be loaded to the training system which is utilizing the convolutional neural network machine learning algorithm. With the trained system it is then the system will be able to recognize the type of disease based on the rice leaf that is uploaded to the system.

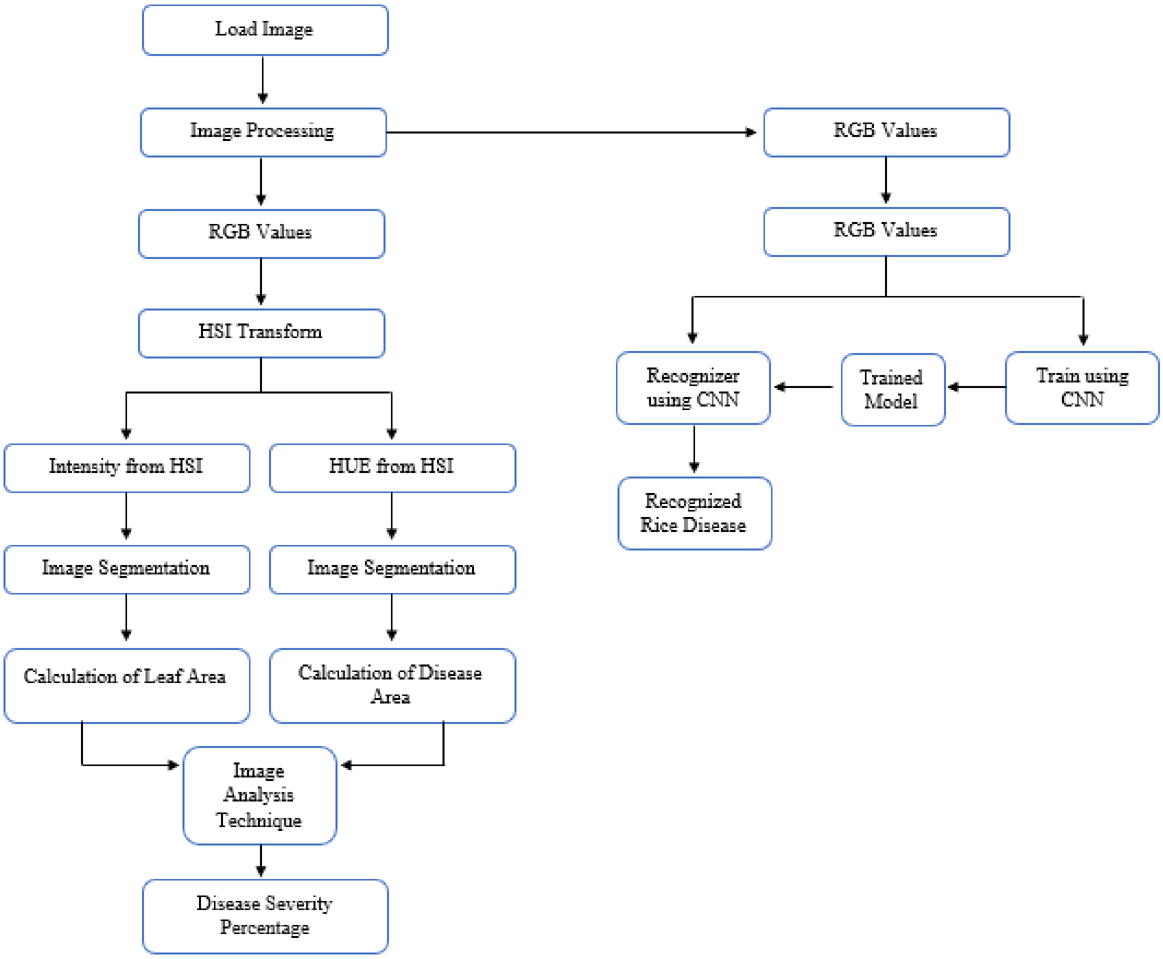

Figure 2. Process Flowchart

CHAPTER IV

METHODOLOGY

4.1 Requirement Specification

4.1.1 Operational Feasibility

Fishbone Diagram

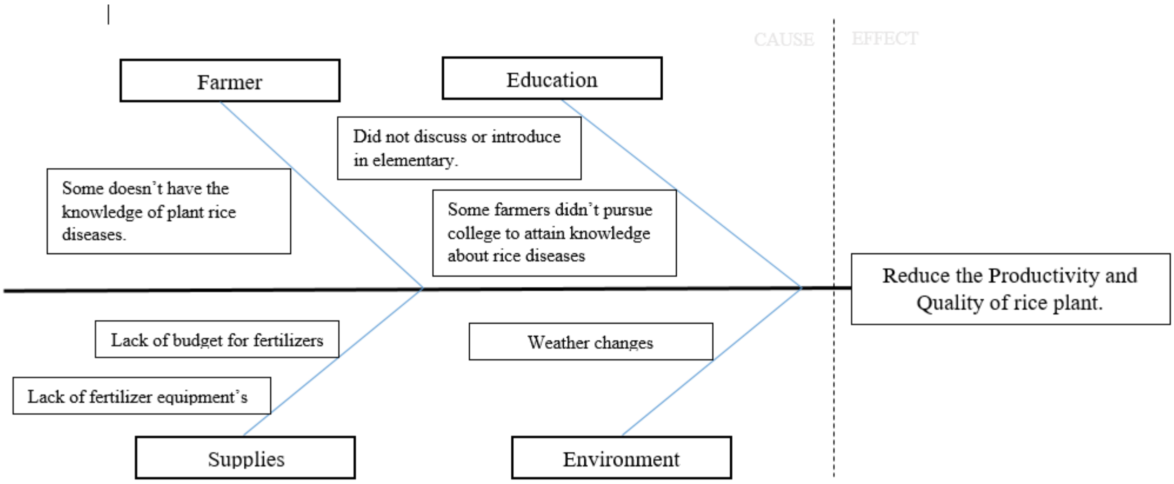

Figure 3. Fishbone Diagram

The diagram shows the causes on why some Farmers are unfamiliar with rice plant diseases. These following factors affects the productivity and quality of rice plants.

Function Decomposition Diagram

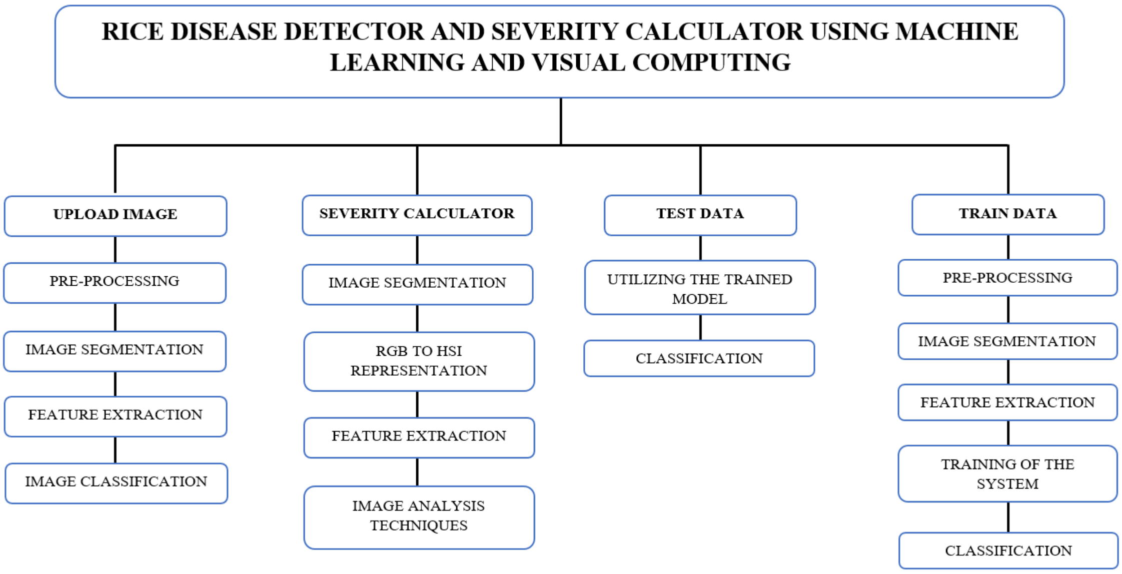

Figure 4. Function Decomposition Diagram

Detailed discussion of the different functions

Functional Decomposition Diagram shows all the major functions that can be encountered in the system.

Uploading of image

In this function the image of rice leaf will be uploaded. The user will provide rice leaf images that will be acquired using a 13.0 megapixels camera or much higher megapixels for taking pictures or if the image is already existed it must be high resolution for a better-quality image.

Pre-processing

In this function the leaf image will be cropped and cleaned for extraneous objects.

Image Segmentation

The region of interest, which is the rice leaf, and the dark background will be partitioned through image segmentation. This will be done by finding the threshold value using the known Otsu method. Thresholding is a technique applied to image segmentation. The basic objective is to classify the pixels of a given image into two classes: those pertaining to the object and those pertaining to the background.

Feature Extraction

Feature extraction refers to taking measurements, geometric or otherwise, of possibly segmented, meaningful regions in the image. Features such as color and texture need to extract from the image. In this function the color and morphological features will be extracted from the individual rice leaf digital image.

Color Feature

Color is an important feature that human perceives when viewing an image. Human vision system is more sensitive to color information than gray levels, so color is the first candidate used as the feature (Pazoki *et. al.*, 2013). To study the effect of color features on rice plant disease identification performance, two transformations of RGB (red, green, and blue) color space were evaluated. The hue, saturation, and value (HSV) and the luminance, and the two chrominance components (YCbCr).

RGB The RGB color space is the most used color space for image representation on computers. An RGB image, sometimes referred as the true color image, is stored as (alpha, red, green, blue) in a 32-bit pixel. Each component is 8 bits in size, thus, the range of values it can represent is between 0 to 255 inclusive.

HSI from the RGB color bands of an image, Hue (H), Saturation (S) and Value (V) will be calculated using the following equations (Image Processing Toolbox, 2007):

$$\boldsymbol{Max} = \text{Max}\ (R, G, B) \qquad (7)$$

$$\boldsymbol{Min} = \text{Min}\ (R, G, B) \qquad (8)$$

$$\boldsymbol{V} = \text{Max} \qquad (9)$$

$$\boldsymbol{S} = \frac{Max - Min}{Max} \qquad (10)$$

$$\frac{1}{6}\frac{G - B}{Max - Min}\text{V- R}$$

$\boldsymbol{H} = \frac{1}{6}\frac{B-R}{Max-Min} + \frac{1}{3}$V- G (11)

$\frac{1}{6}\frac{R-G}{Max-Min} + \frac{2}{3}$ V- B

If H<0 then H = H + 1

YCbCr The Y element represents the luminance component and the Cb; Cr elements represent the two chrominance components. Equations below represent the YCbCr transformation of RGB color space (Umbaugh, 2005).

Y= 0.299R + 0.587G + 0.114B (12)

Cb = – 0.1687R – 0.3313G + 0.500B + 128 (13)

Cr = 0.500R – 0.4187G – 0.0813B + 128 (14)

Texture Features

The Gray Level Coocurrence Matrix (GLCM) method is a way of extracting second order statistical texture features *(P. Mohanaiah, 2013).* The Gray Level Co-occurrence Matrix (GLCM) is a statistical calculation of how often different combination of gray level pixel values occur in an image. It has been the workhorse for textural analysis of image since the inception of the technique. GLCM matrix describes the frequency of occurrence of one gray level with another gray level in a linear relationship within a defined area. The GLCM is a matrix where the number of rows and column are equivalent to the number of gray levels of an image. The matrix element P(i,j|ΔxΔy) is the relative frequency in which two pixels, separated by a pixel distance (ΔxΔy), occur within a given neighborhood, one with intensity i and the other with intensity j *(Chaki et. al. 2015).* Equation 15-21 shows the computation of the SGDM properties.

Angular moment: Angular moment is a measure of image homogeneity

$$asm = \sum_{i=0}^{Ng^{-1}} \sum_{j=0}^{Ng^{-1}} [p(i,j)]^2 \qquad (15)$$

Mean Intensity Level: Mean intensity level is a measure of image brightness

$$mean = (\mu_x + \mu_y)/2 \qquad (16)$$

$$\mu_x = \sum_{i=0}^{G-1} iP_x(i) \text{ and } \mu_y = \sum_{j=0}^{G-1} jP_y(j)$$

Correlation: Correlation is a measure of intensity of linear dependence

$$\sum_{i=0}^{G-1}\sum_{j=0}^{G-1} \frac{\{i \times j\} \times P(i,j) - \{\mu_x \times \mu_y\}}{\sigma_x \times \sigma_y}$$ *correlation =*

(17)

$$\sigma_x^2 = \sum_{i=0}^{G-1} (P_x(i) - \mu_x(i))^2$$

Where:

$$\sigma_y^2 = \sum_{j=0}^{G-1} (P_y(j) - \mu_y(j))^2$$

Variance Texture Features: Measure of variation of intensity

$$Variance = \sum_{i=0}^{Ng^{-1}} \sum_{j=0}^{Ng^{-1}} (i - mean)^2 P_{x(i,j)}$$

(18)

Inverse Difference Moment: Contrast of an image is measured by the inverse difference moment

$$Idm = \sum_{i=0}^{Ng^{-1}} \sum_{j=0}^{Ng^{-1}} \frac{P(i,j)}{1+(i-j)^2} \qquad (19)$$

Covariance of the Intensity: Produce moment is analogous to the covariance of the intensity

$$covariance = \sum_{i=0}^{Ng^{-1}} \sum_{j=0}^{Ng^{-1}} (i - mean)(j - mean)P(i,j)$$

(20)

Entropy: The entropy feature is a measure of the amount of order in an image

$$Entropy = -\sum_{i=0}^{Ng^{-1}} \sum_{j=0}^{Ng^{-1}} p(i,j) \text{ x } \log (\mathrm{P(i,j)}) \qquad (21)$$

Severity calculation

Segmentation

The region of interest, which is the rice leaf, and the dark background will be partitioned through image segmentation. This will be done by finding the threshold value using the known Otsu method. Thresholding is a technique applied to image segmentation. The basic objective is to classify the pixels of a given image into two classes: those pertaining to the object and those pertaining to the background.

RGB to HSI color representation

This process is for the conversion of RGB image to HSI color representation, the RGB images were converted into HSI colors pace representation and were computed as follows:

$$H = \text{arcos}\frac{\frac{1}{2}[(R-G)+(R-B)]}{[(R-G)^2+(R-B)(G-B)]^{\frac{1}{2}}} \qquad (1)$$

$$S = 1 - \frac{3}{R+G+B}[\min(R,G,B)] \qquad (2)$$

$$I = \frac{1}{3}(R+G+B) \qquad (3)$$

$$g(x,y) = \frac{0\ iff(x,y)>T}{1\ iff(x,y)\leq T} \qquad (4)$$

Where g(x,y) is the segmented image, f(x,y) is the gray-level histogram at pixels (x,y) and T is the threshold value computed using the triangle method. The disease severity is converted using the following formula:

$$\%DS = \left(\frac{AD}{AL}\right)\ x\ 100 \qquad (5)$$

where:

DS = disease severity in percentage

AD = the number of pixels in the disease area of the leaf

AL = the number of pixels of the leaf

The computed DS value were matched with the severity value using the diseases severity scale developed by Horsfall and Heuberger (1942).

Image Analysis Techniques Function

In this function after the calculation of the infected region of rice plant leaf, it will be analyzed by image analysis techniques to be able to classify it accordingly to get its severity calculation presented in the study.

Train Data

In this function the extracted features will then be loaded to the training system which will be utilized by convolutional neural network (CNN) machine learning algorithm. In this function after the extracted features loaded to the training system utilized by the convolutional neural network machine learning algorithm. CNNs are equipped with an input layer, an output layer, and hidden layers, all of which help process and classify images. The hidden layers comprise convolutional layers, ReLU layers, pooling layers, and fully connected layers, all of which play a crucial role on classifying the different types of rice plant diseases.

4.1.2 Technical Feasibility

Compatibility Checking (Hardware/Software)

The software in the study is a Computer-Based application that can be installed in any Microsoft Operating System computers. The software is runnable without the need of internet connection as long as the needed software of the program is also installed in the computer. This system only needs a high-quality resolution image for the data input.

Relevance of Technologies

A computer is the most needed device or technology that we can use in running this system because it is a Computer-Based application, and all the operation should be done in the computer. And it also needs HD images that we can use as our input data so we can generate more accurate result.

4.1.3 Schedule Feasibility

PROJECT TITLE: RICE PLANT DISEASE DETECTOR USING IMAGE PROCESSING

TEAM NAME: TEAM KAKAYANIN

PROJECT LEADEAR: OCLARIT

					MARCH,2021				APRIL,2021				MAY,2021				JUNE,2021				JULY,2021			
MARCH - JULY 2021					1	2	3	4	1	2	3	4	1	2	3	4	1	2	3	4	1	2	3	4
TASK	ASSIGNED TO	PROGRESS	START	END																				
Project Title Brainstorming	Whole Team	100%																						
Creating Formal Proposal	Project Manager	100%																						
Chapter 1	Technical Writer	100%																						
Chapter 2	Technical Writer	100%																						
Chapter 3	Technical Writer	100%																						
Chapter 4	Programmer	50%																						
Graphical User Interface Design	Programmer	0%																						
Hard coding	Programmer	0%																						

Figure 5. Gantt Chart

The chart shows the period when this project is created, along with the task or activity that was done by the researcher.

4.1.4 Economic Feasibility

Cost and Benefit Analysis

EXPENSES	AMOUNT
INTERNET EXPENSES	
TRANSPORTATION	
PAPER AND PHOTOCOPY EXPENSES	
MISCELLANEOUS EXPENSES	
TOTAL	

Table 1. Cost and Benefits Analysis

This table reflects the list of expenses or cost incurred to sustain the creation of the project.

Cost Recovery Scheme

EXPENSES					
INTERNET EXPENSES					
TRANSPORTATION					
PAPER AND PHOTOCOPY EXPENSES					
MISCELLANEOUS EXPENSES					
TOTAL					

Table 2. Cost Recovery Scheme

This table reflects the division of cost to pay the cost incurred upon the creation of the project

4.1.5 Requirements Modeling

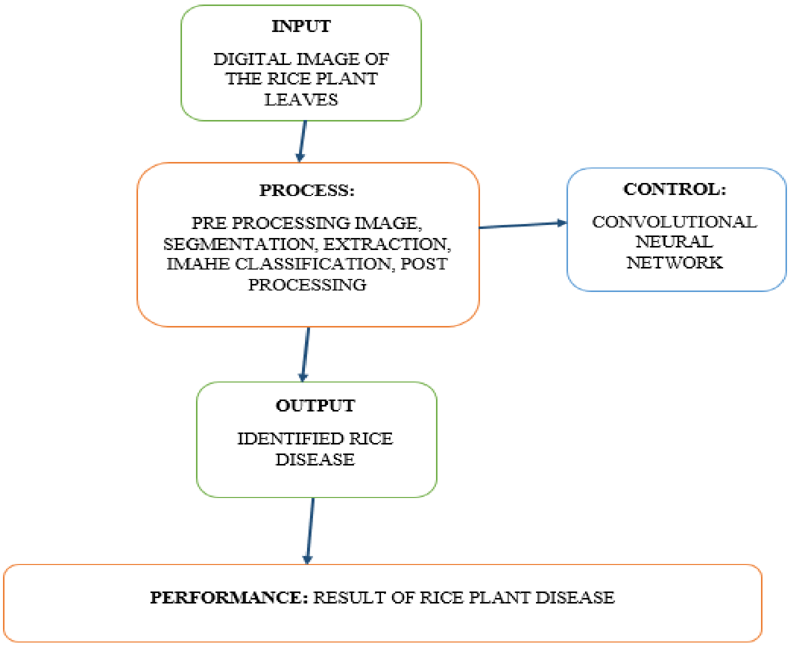

Figure 6. Requirements Modeling for detecting rice disease

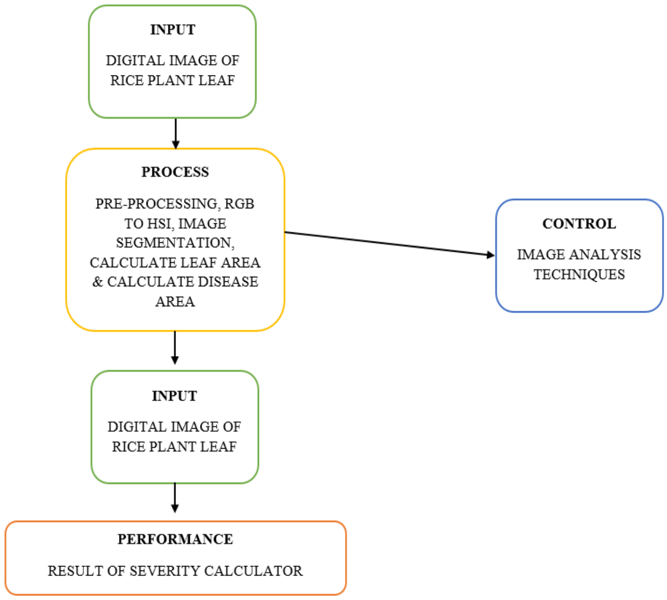

Figure 7. Requirements Modeling for Severity Calculator

Object Modeling

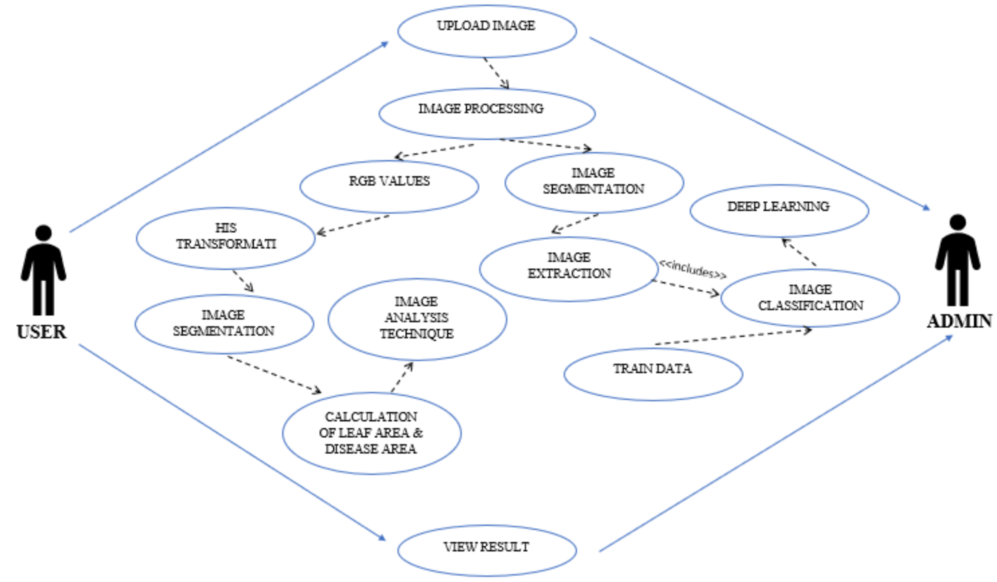

Figure 8. Use case Diagram

Sequence Diagram

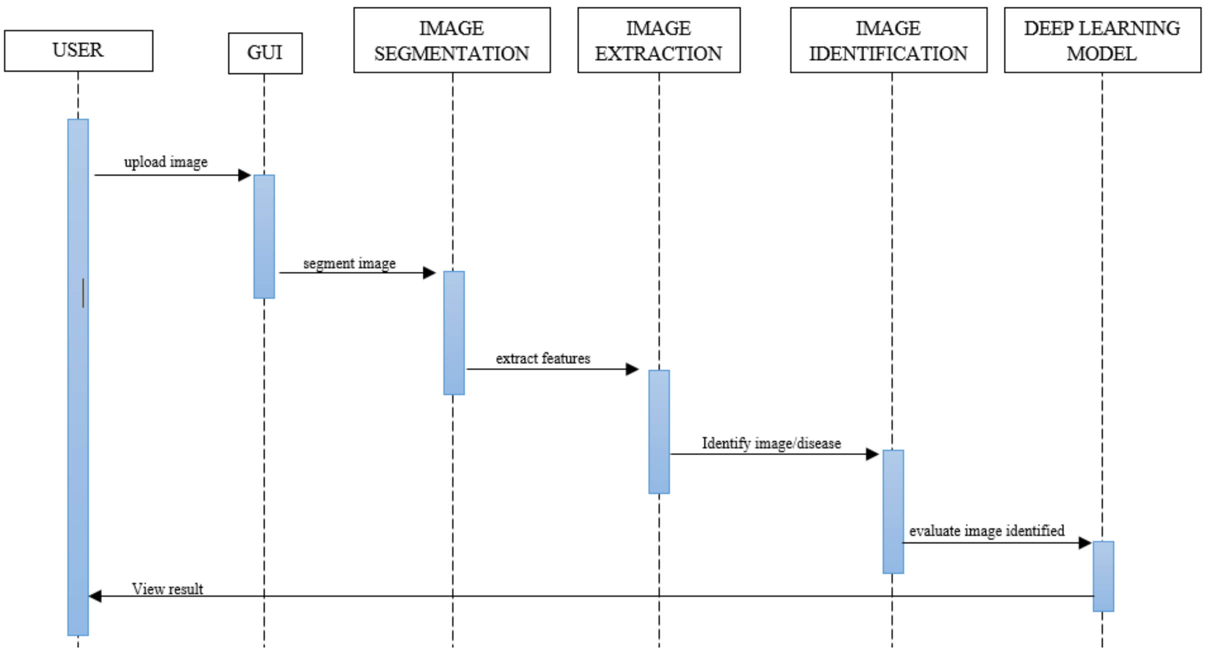

Figure 9. User Disease Rice Plant Detector Sequence Diagram

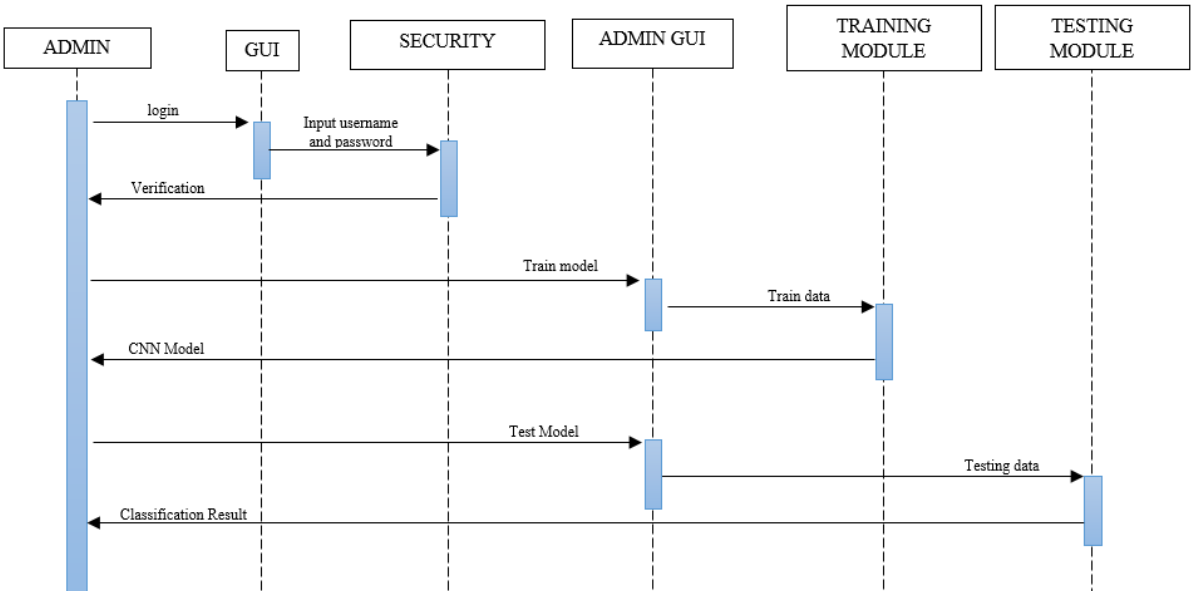

Figure 10. Admin Sequence Diagram

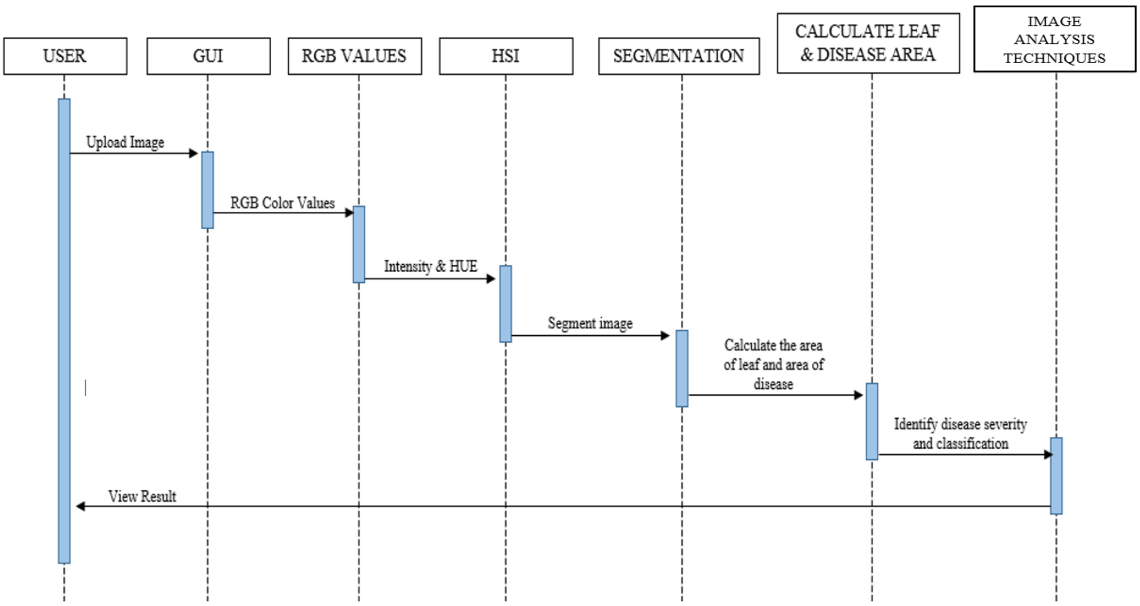

Figure 11. User Severity Calculator Sequence diagram

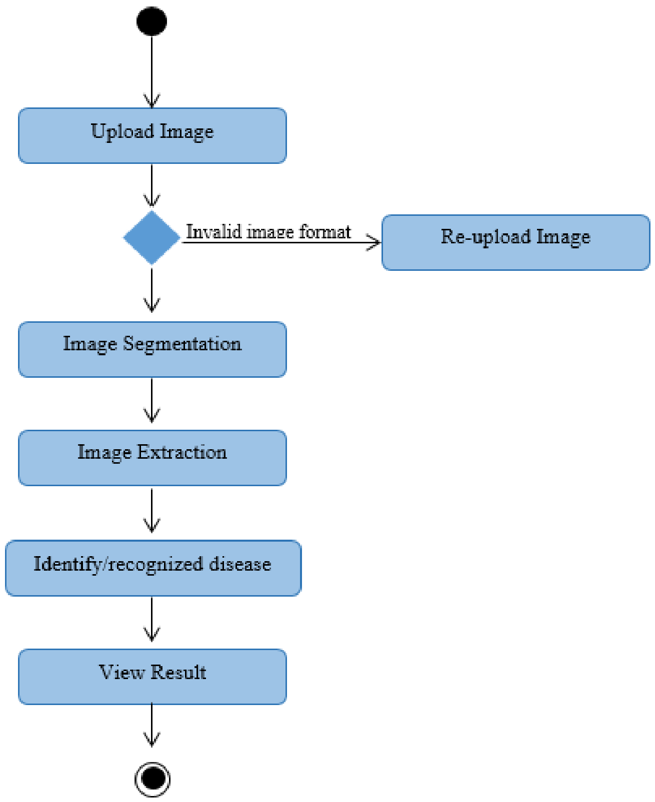

Figure 12. User Activity Diagram

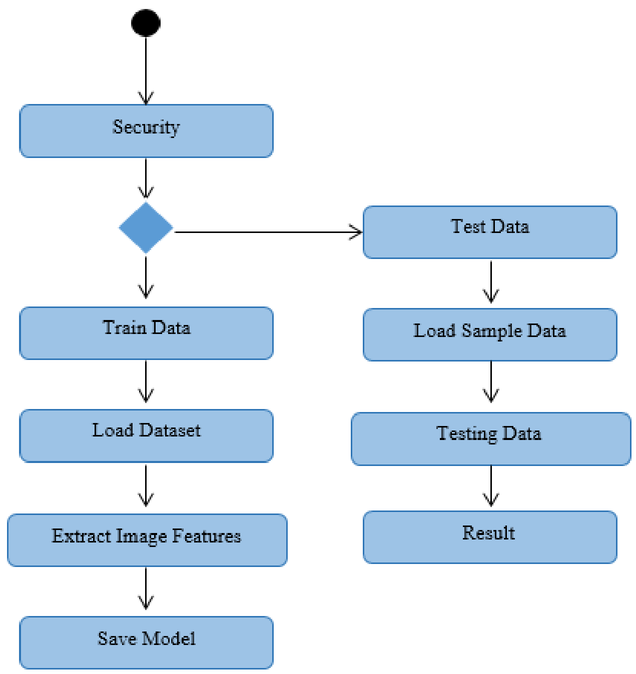

Figure 13. Admin Activity Diagram

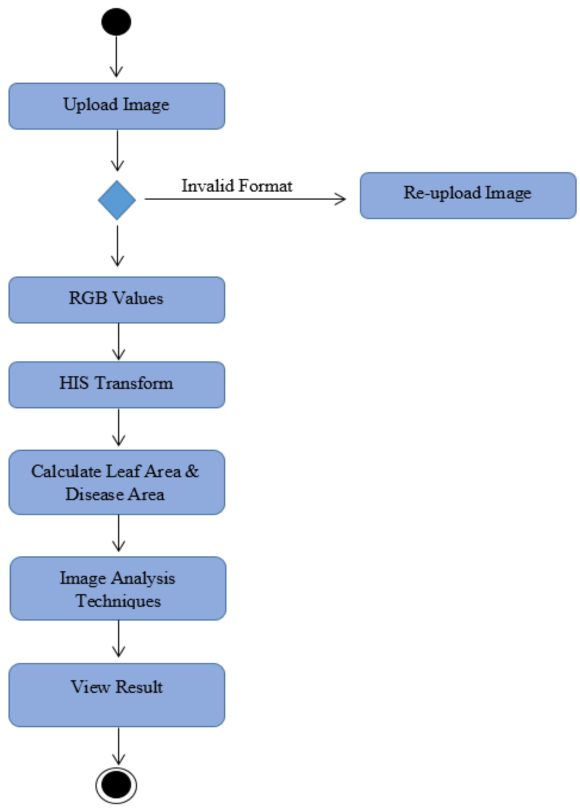

Figure 14. User Severity Calculator Activity Diagrams

4.1.6. Risk Assessment Analysis

Risk Assessment Analysis

The table below is the Risk Assessment Analysis of the project. It represents the risk analysis that the proponents intend to follow in order for the project to function as intended. The table also holds the possible hindrances that the system will encounter upon project implementation and project deployment.

Table. Risk Assessment Analysis

Threat	Vulnerability	Asset	Impact	Likelihood	Risk	Control Recommendation
System Failure High	Sudden internet connection loss Low	Servers Low	All services will be unable Critical	Medium	High Data will not be stored	Choose a will trusted cloud service provider
Power interruption Medium	Server firewall will be breached Low	Servers Low	Data loss Critical	Medium	Low Data will not be stored	No actions.

Accidental Human Interference – Data Deletion	Permissions and prompts is configured properly. Medium	Website, data on share. Critical	Services and functionalities will not be implemented properly.	Medium	Medium	Permissions and confirmations should be properly developed.

Table 3. Risk Assessment Analysis

4.2 Design

4.2.1 Output and User Interface Design

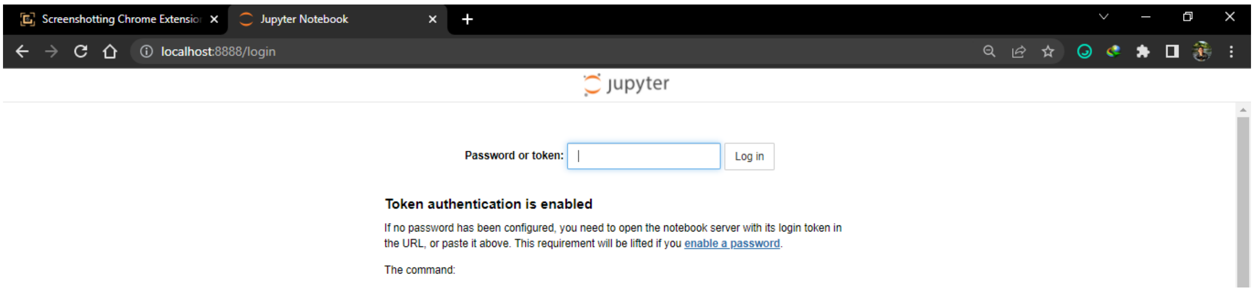

Figure 15. Admin Training Model Login Page

The figure above illustrates the interface for the admin to Log In and train Data Set. This is where the admin trains the data sets necessary for the prediction and accuracy of the application.

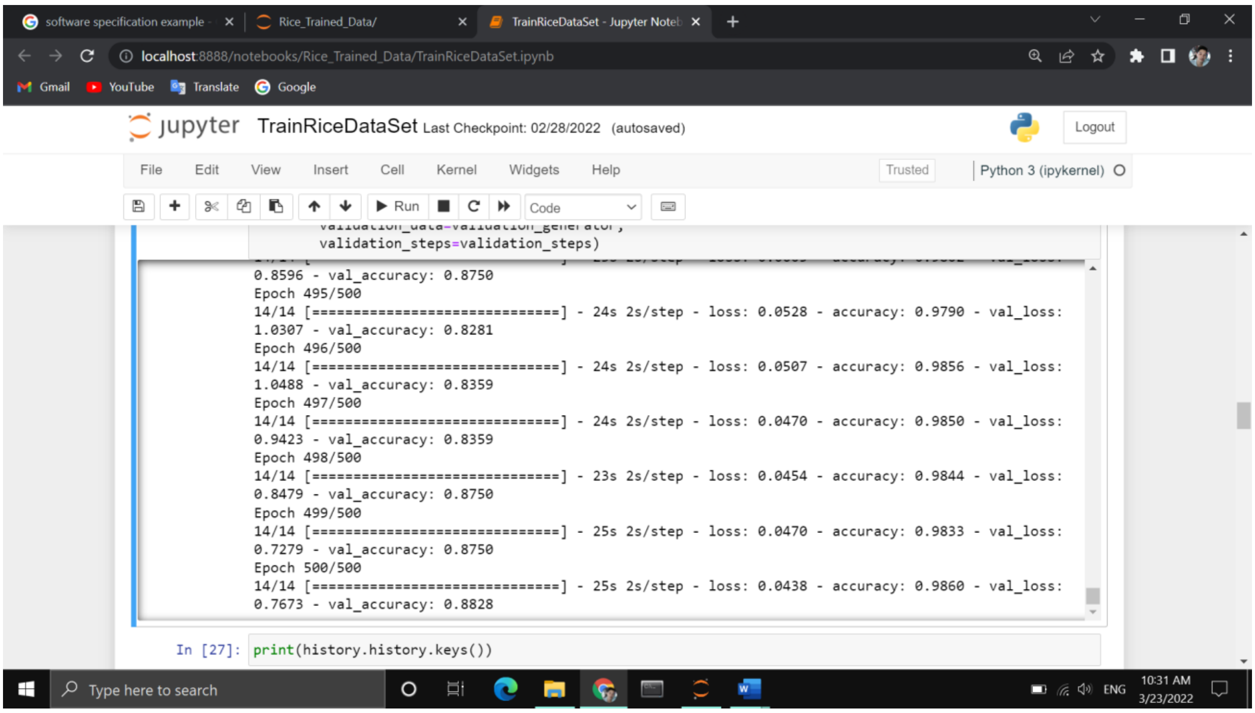

Figure 16. Training Model Page

Figure 16 illustrates the training model, which shows an accuracy of 98.60%. Accuracy in this area determines the outcome of the prediction.

Figure 17. Home Page

Figure 17 shows the Home Page, it has button which has the following functions;

1. Home, in this function it has the information about how important this study/web-application is.
2. Prediction, in this function it is where you can drag and upload an image then predict diseases and calculate its severity.
3. Rice Disease, this function is where you can find the description of each rice diseases that is included in the application and how to manage this kind of diseases.
4. How the project will work, contains the information about how the application will work.
5. About, contains information about the authors, Mission and Vision.

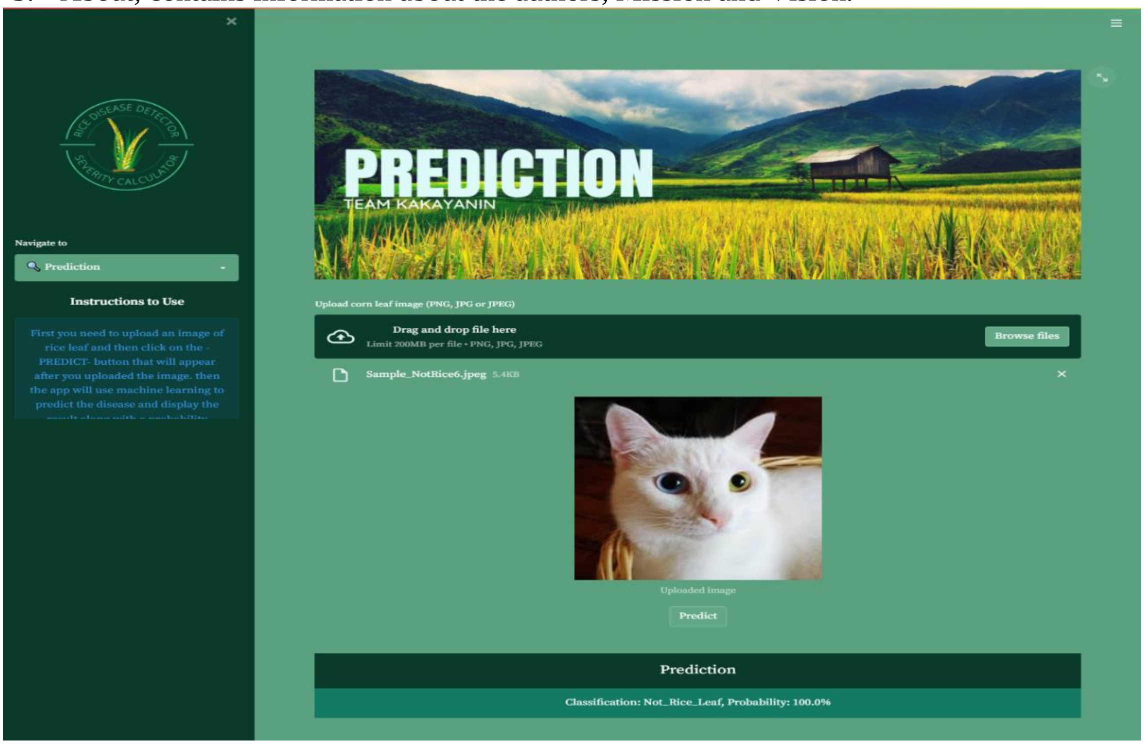

Figure 18. Prediction Page

Figure 18, shows the prediction of the system if the uploaded image does not belong to the type of diseases. The prediction is composed of the classification and accuracy in percentage manner.

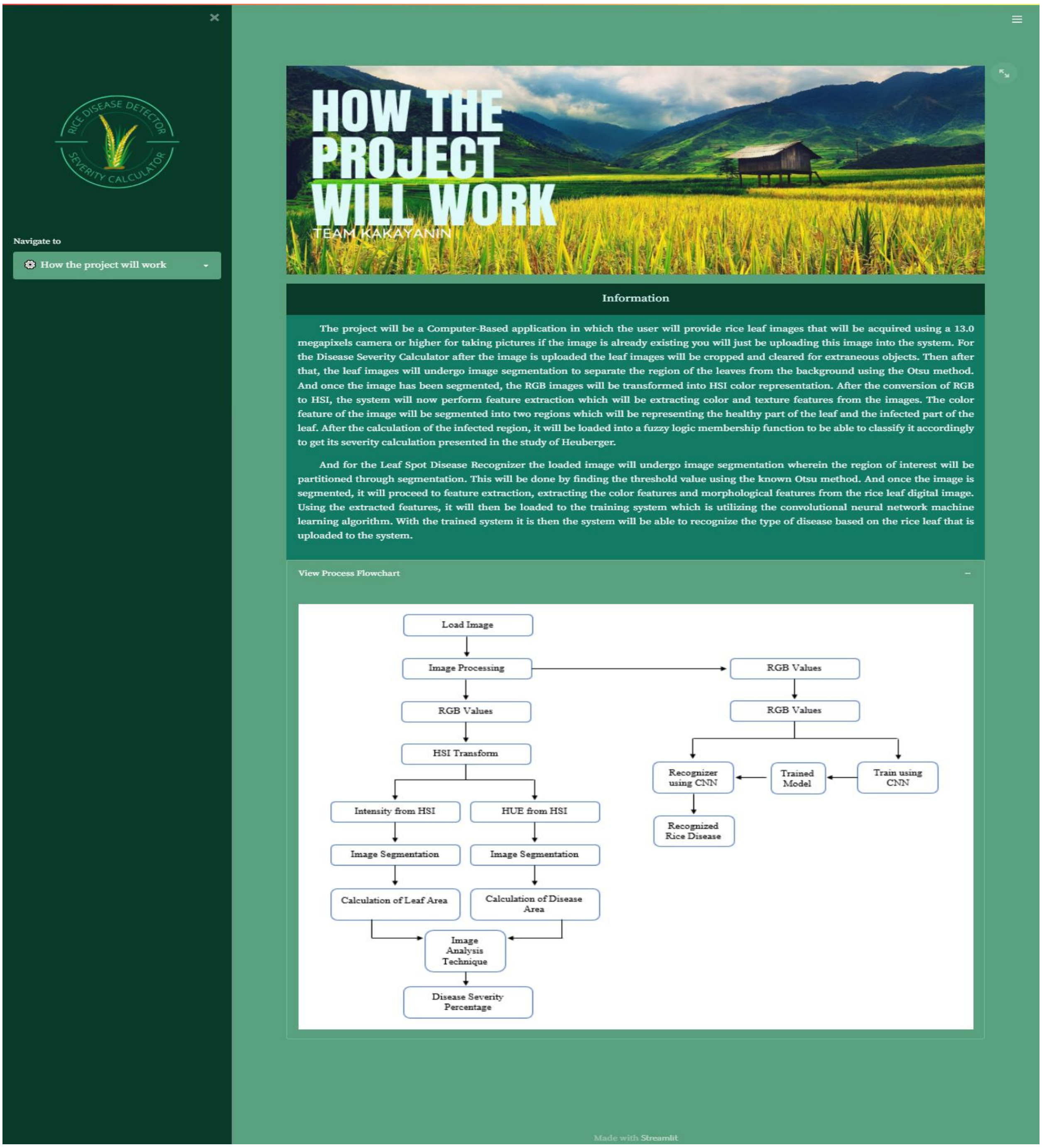

Figure 19. How the project will work Page

Figure 19, it shows the flow of the application and how it is being processed.

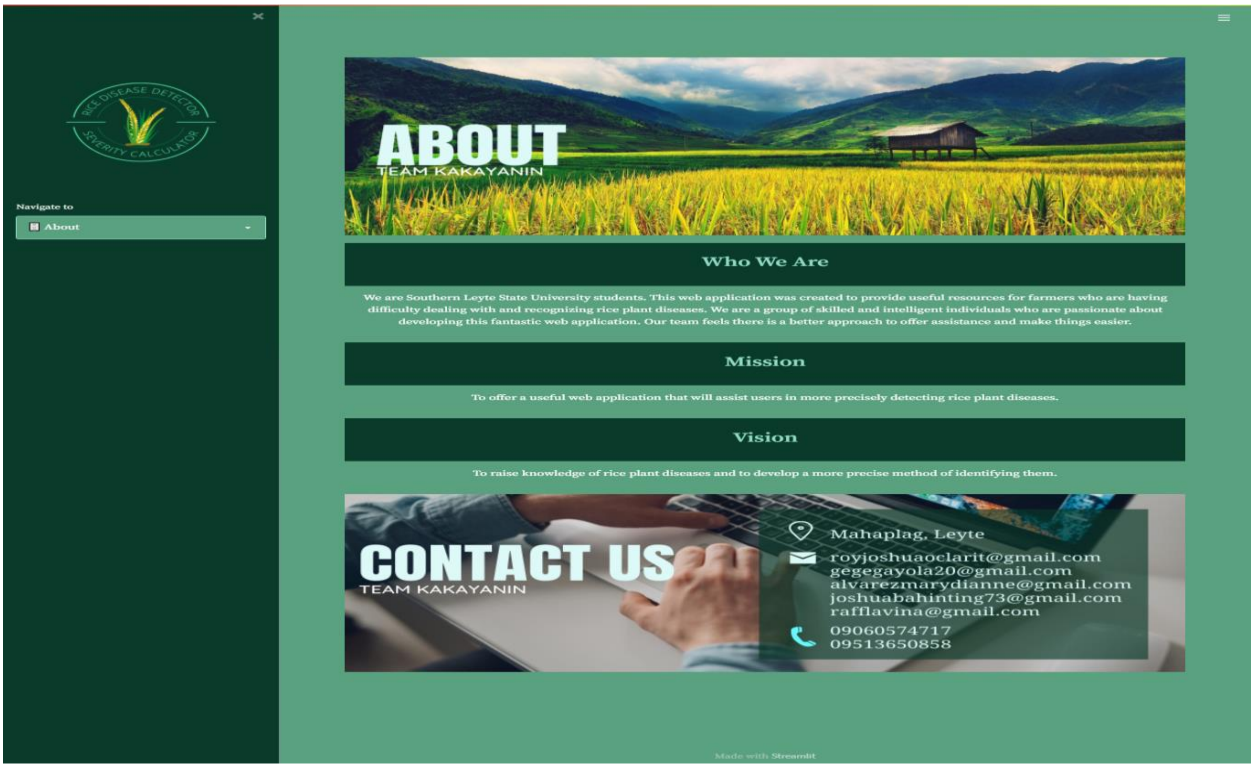

Figure 20. About page

Figure 20, show information about its Vision and Mission. And also shows the contact and location of the team.

Disease Identification Process

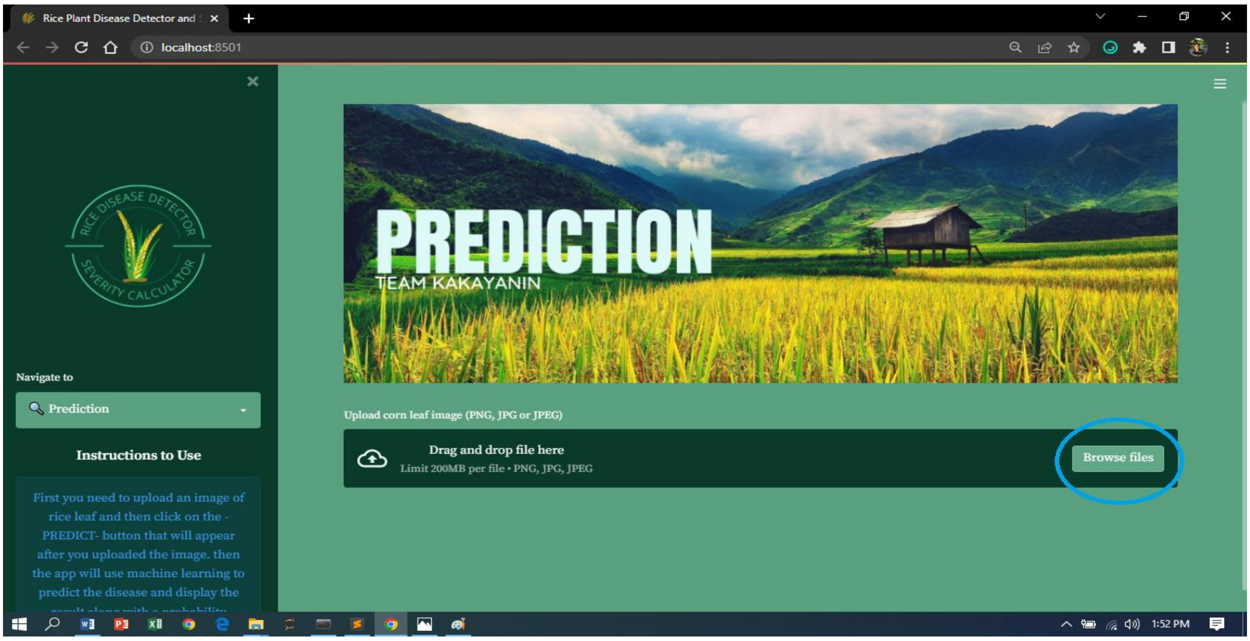

Figure 21. Browse Image

In the prediction page, the user is able to upload an image of rice plant leaf with an extension name of jpg, png or jpeg through clicking the browser file to select the image you want to upload.

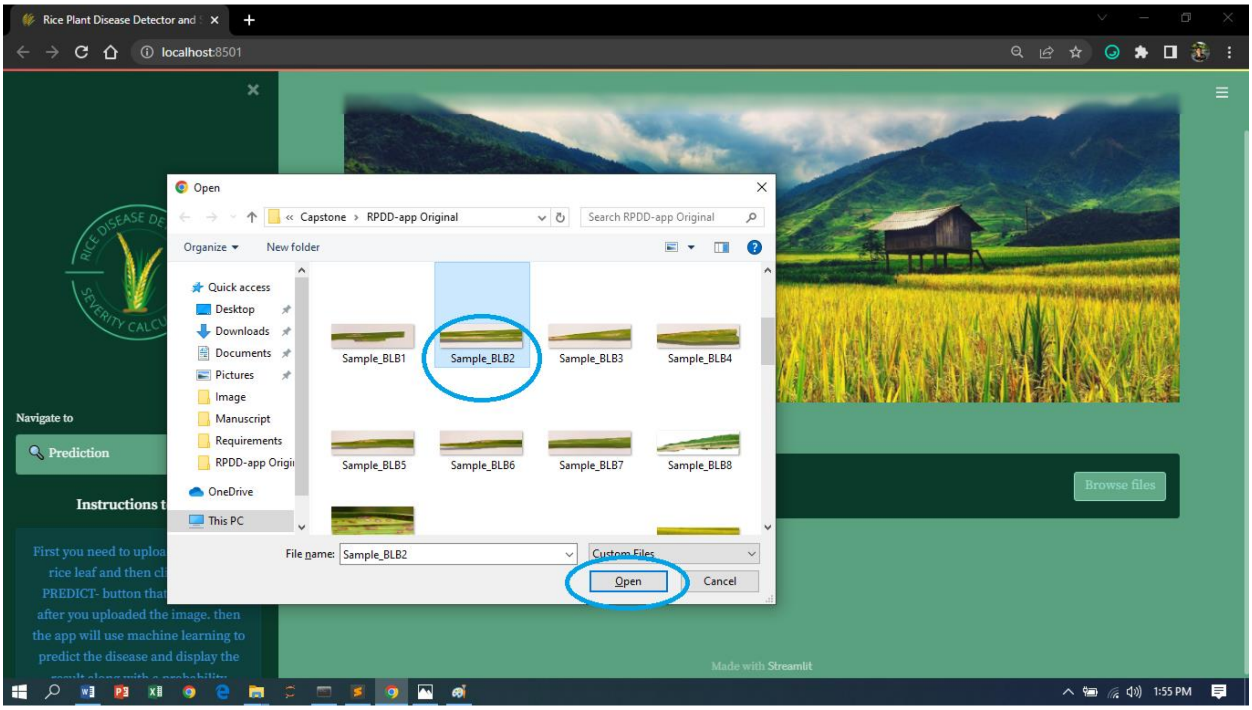

Figure 22. Select Image

Figure 22, shows how to select and upload an image. After you clicking on the browse file button, a window will appear. At the window the user can select the image they want to upload.

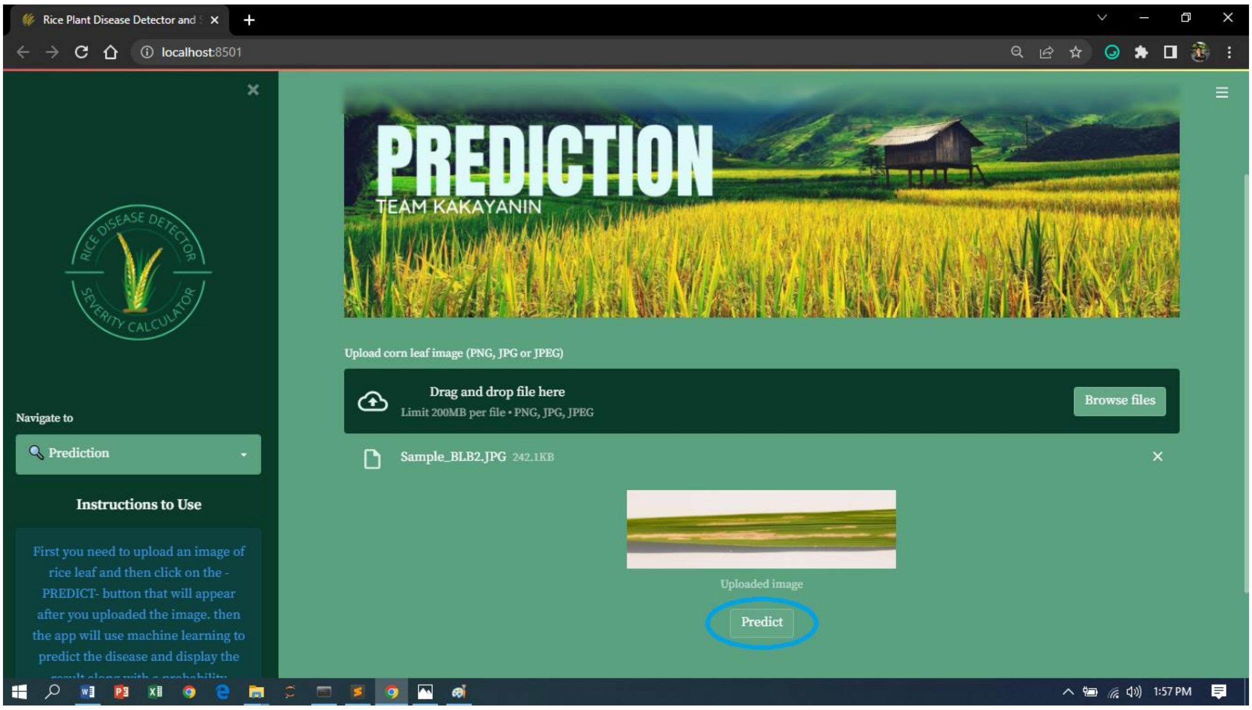

Figure 23. Predict Button

Figure 23, the function of this button is to predict and calculate the severity of an image. After clicking this button, the application will process its identification.

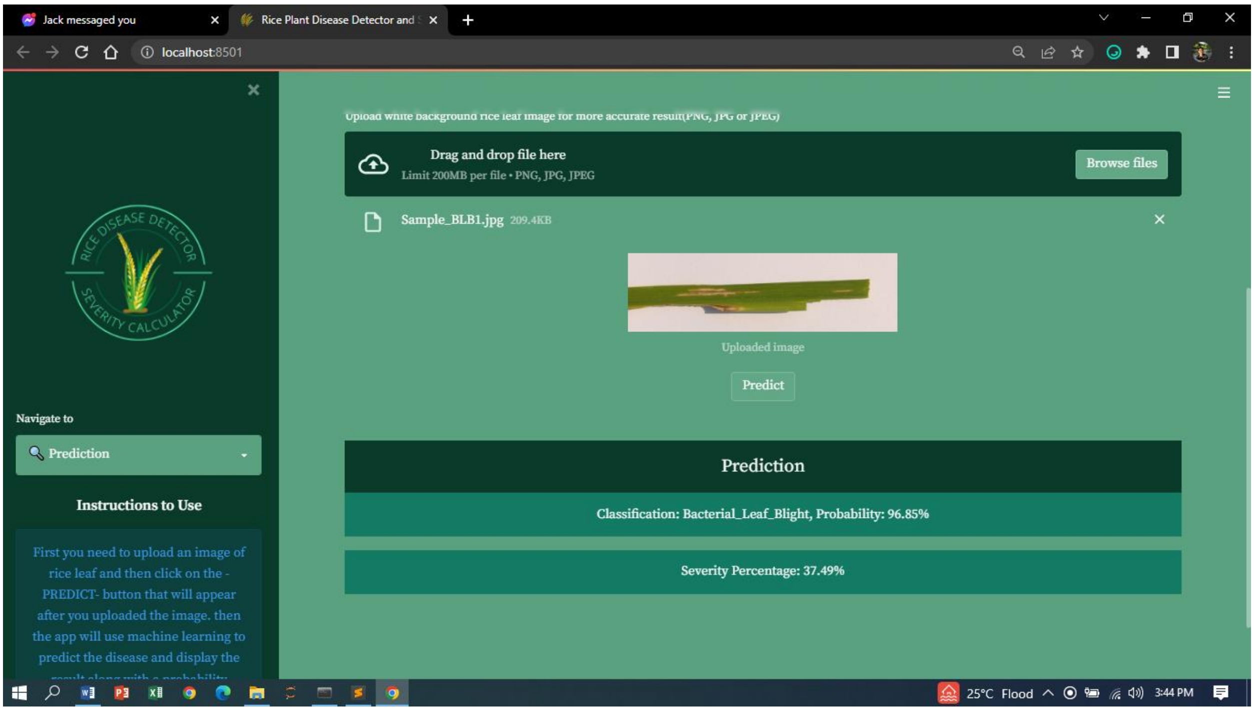

Figure 24. Prediction Output

Figure24 shows the results of the uploaded image. If the uploaded image has been infected with rice disease, the system will classify its type and show how severe the disease is in a percentage manner.

4.2.2 Data Design

Entity Relationship Diagram

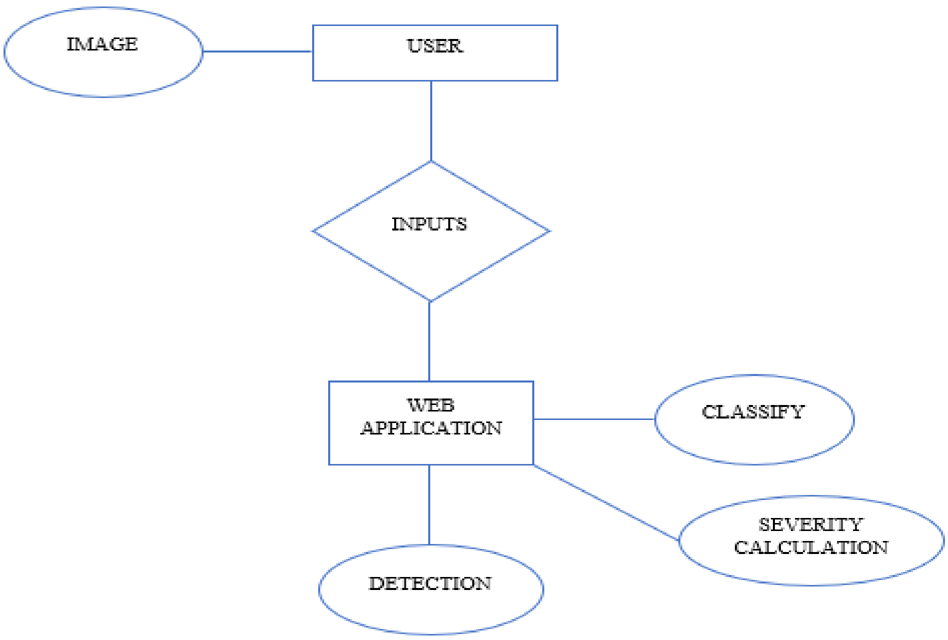

Figure 25. Entity Relationship Diagram

Data Dictionary

The table shows repository of elements, definition, and attributes that provides contextual information about the data that exist in the data store.

Classification	Elements or display name	Definition	Quantity (Training)	Quantity (Validation)	Quantity (Testing)	Acceptable File extension	Required ?
C1	Bacterial Leaf Blight	The initial symptoms of bacterial leaf blight are Water-soaked to yellowish stripes on leaf blades or starting at leaf tips with a wavy margin.	276	34	10	JPG, JPEG, PNG	Y
C2	Brown Spot	The initial symptoms can occur on leaves, leaf collars, nodes and panicles. Leaf spots are typically elliptical (football shaped), with gray-white centers and brown to red-brown margins	186	23	10	JPG, JPEG, PNG	Y
C3	Leaf Blast	Blast symptoms appear on leaves as elliptical spots with light-colored centers and reddish edges. The most	409	50	10	JPG, JPEG, PNG	Y

		serious damage from rice blast occurs when the disease attacks the nodes just below the head, often causing the stem to break.					
C4	Leaf Smut	Typical symptoms of leaf smut break open when wet and releases the black spores. Heavily infected leaves turn yellow, and the leaf tips die and turn gray. The fungus is spread by airborne spores and over-winters on diseased leaf debris in soil.	34	10	10	JPG, JPEG, PNG	Y
C5	Healthy	Young / Mature Healthy Green Leaf	116	12	10	JPG, JPEG, PNG	Y
C6	Not Rice Leaf	Not Rice Leaf	820	97	10	JPG, JPEG, PNG	Y

Table 4. Data Dictionary

4.2.3 System Architecture

Network Model

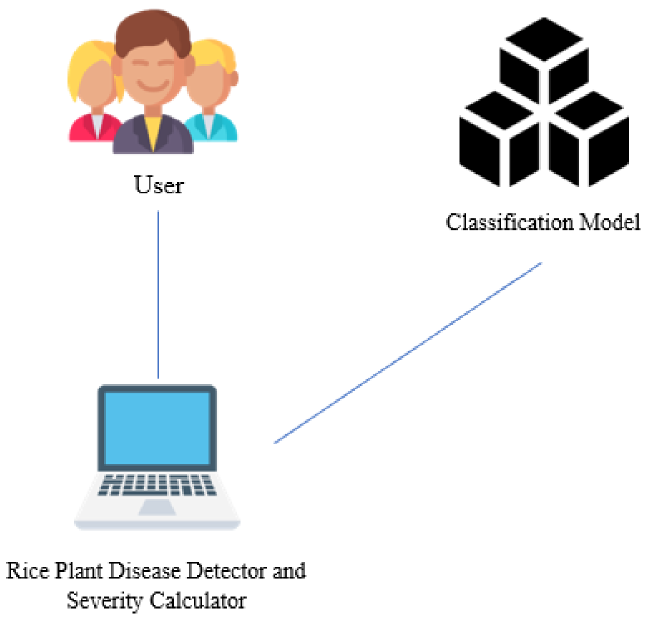

Figure 26. Network Model

Figure 26, represent the relationship of how does the client can access the application, the figure represents on where do the client interacts with as they use the application.

4.3 Development

4.3.1 Software Specification

The Image-Based Rice Plant Disease Detector and Severity Calculator is a Computer-Based software application that can be installed in any computer with Microsoft Operating System with a Windows version 7,8 and 10. It identifies the disease of a rice plant in which aims to identify several types of rice disease. This software is capable of running without the use of internet connection as long as all the needed software dependencies of the program is also installed in the computer. The system will accept an image from the user that will be subjected to object detection, which will identify all rice illnesses seen in the image. It only allows one image to be processed at a time and will not enable two or more photographs to be processed at the same time.

Operating System	Windows 10 Home Single Language(64bit)
Internet Browser	Chrome, Firefox, Edge

4.3.2 Hardware Specification

Computer is the most needed technology we can use in this system because this will be deployed in a computer-based application. Hence, all operations should be mainly done in the computer. This system will need a third-party web cam or camera with a minimum of 720p resolution that will be used for capturing the input data.

Memory	8GB
Processor	Intel ® Core ™ i3-6006U CPU @ 2.00GHz 2.0 GHz
Storage	1TB Windows-HDD

4.3.3 Program Specification

Image-Based Rice Plant Disease Detector is capable of detecting varieties of rice disease. The system is independent and self-contained, an integrated data base ensures the storage and the retrieval of every data available. It able to achieve with the help of CNN model that will be created to train the datasets so that it can be able to classify and identify the rice plant diseases. Using image processing to create an algorithm that will detect all of the rice disease in the provided image and identify it individually. The application use in a software called Streamlit it is used for creating Computer-Based applications using Python Programming language.

4.3.4 Programming Environment

Front-End

HTML

CSS

Back-End

Streamlit Framework

Python 3.9

4.3.5 Deployment Diagram

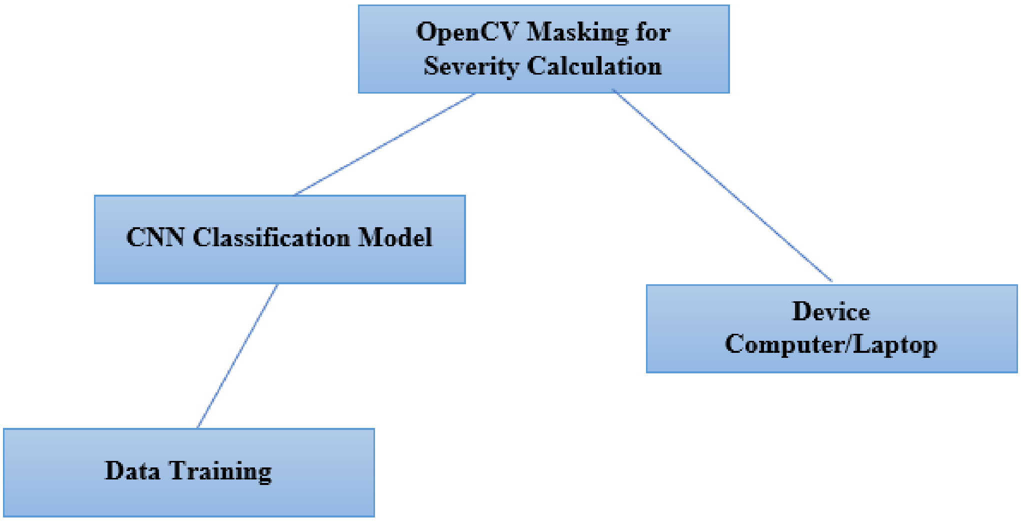

Figure 27. Deployment Diagram

4.3.6 Test Plan

Test Phase	Duration(days)	Tester	Reviewer	Date(s)	Status
Unit Testing	10 days	Roy Joshua Oclarit	Geraldine Cahigus	February 20-March 2 ,2022	Finish
Integration Testing	3 days	Roy Joshua Oclarit	Mary Dianne Alvarez	March 3 - 5 ,2022	Finish
Compatibility Testing	4 days	Geraldine Cahigus	Mary Dianne Alvarez	March 6 – 9, 2022	Finish
Performance Testing	6 days	Roy Joshua Oclarit	Geraldine Cahigus	March 10-15, 2022	Finish
Stress Testing	2 days	Geraldine Cahigus	Mary Dianne Alvarez	March 16-17, 2022	Finish
Load Testing	2 days	Geraldine Cahigus	Roy Joshua Oclarit	March 18-19, 2022	Finish
System Testing	5 days	Roy Joshua Oclarit	Geraldine Cahigus	March 20-24, 2022	Finish

Table 5. Test Plan

4.4 Testing

4.4.1 Unit Testing

Evaluating or testing the classification model is a most important test that is needed in this project because everything in this project depends on the quality of the classification model that will be used for classification. The model was created from a total of 1858 training samples coming from 6 different classes with a 225 validation samples and was trained in a total of 500 epochs. The result of the training gained a total of 0.9860 highest training accuracy. Figure 19 shows a graph of the classification model training plot. It was observed in the graph that the training and validation accuracy plot was maintaining its progress which is close to 1.0.

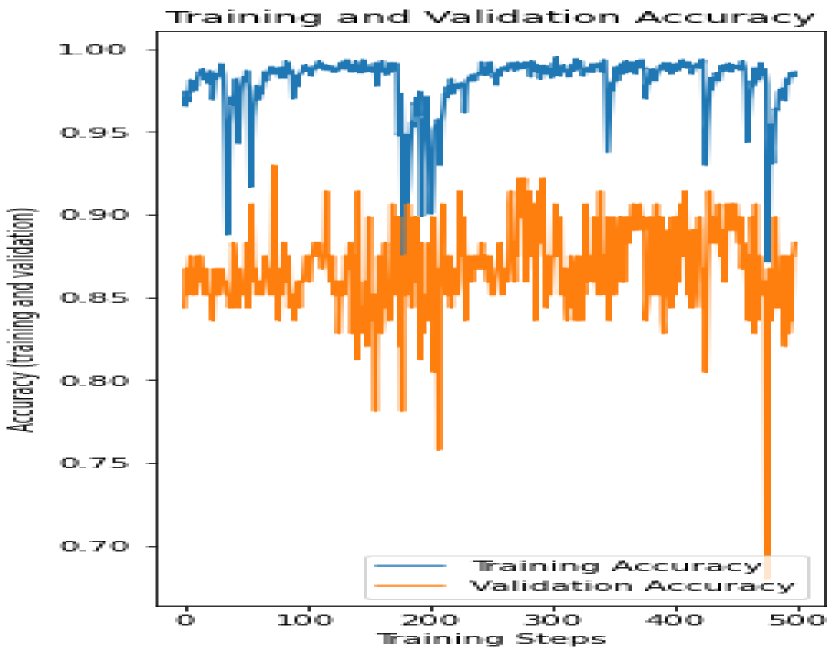

Figure 28. Model Accuracy

4.4.2 Integration Testing

Integrating the classification model to the Graphical User Interfaces was the next phase of developing this project, it is needed to ensure that integration of the model should be successful. The model was tested as it was integrated with its GUI, a set of testing samples was selected from the 250 test samples during the model performance evaluation. The test samples were uploaded to the GUI manually and it was observed that the results are similar to the performance during the model evaluation hence, it was concluded that deploying the model to a computer-based GUI is successful.

4.4.3 Compatibility Testing

The application was tested in different computers to monitor its capability to operate in a different hardware device. The software application was deployed and run in the following devices:

Device Type	Model	Specification
Personal Laptop	Dell Inspiron 15-3567	Windows 10, Intel Core i3
Laptop	Lenovo IdeaPad	Windows 10, Intel Core i5 10th Gen
Laptop	Lenovo i3	Windows 10, Intel Core i3 8th Gen

Table 6. Compatibility Test on Device

Deployment of the application to the device stated on the table above was successful and works in its expected performance. But for the personal laptop that I used it's a bit slow at starting our program due to its low specification and my personal laptop is a bit old. I suggest that if you want this application to run smoothly try on high specs laptop or computers.

4.4.4 Performance Testing

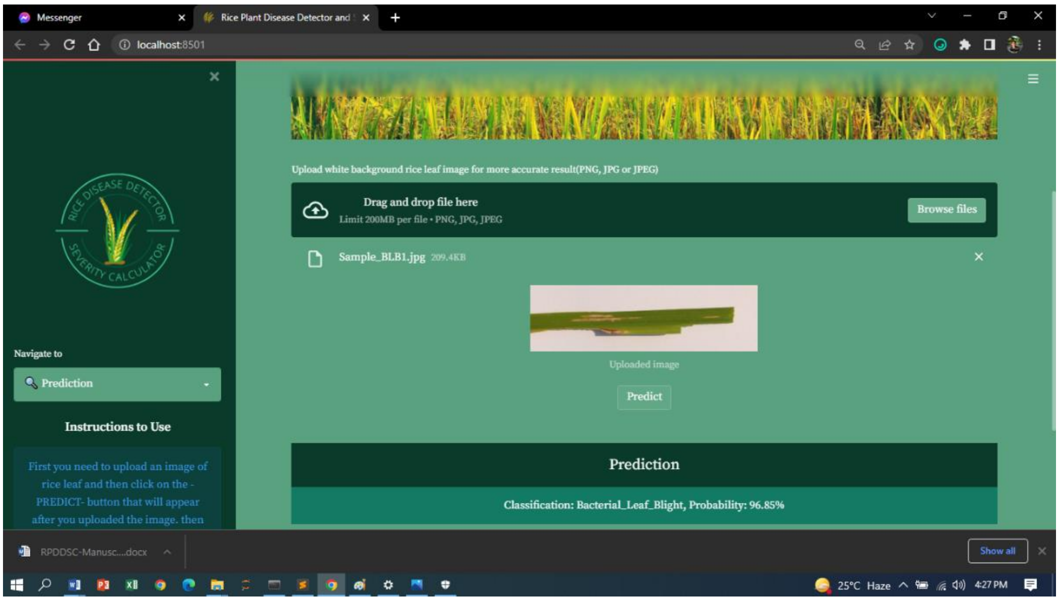

Figure 29. Prediction Output

Figure 29, shows the sample output of a rice plant leaf image taken from the internet with a Bacterial leaf blight disease, the application was able to predict the disease with a 96.85% probability.

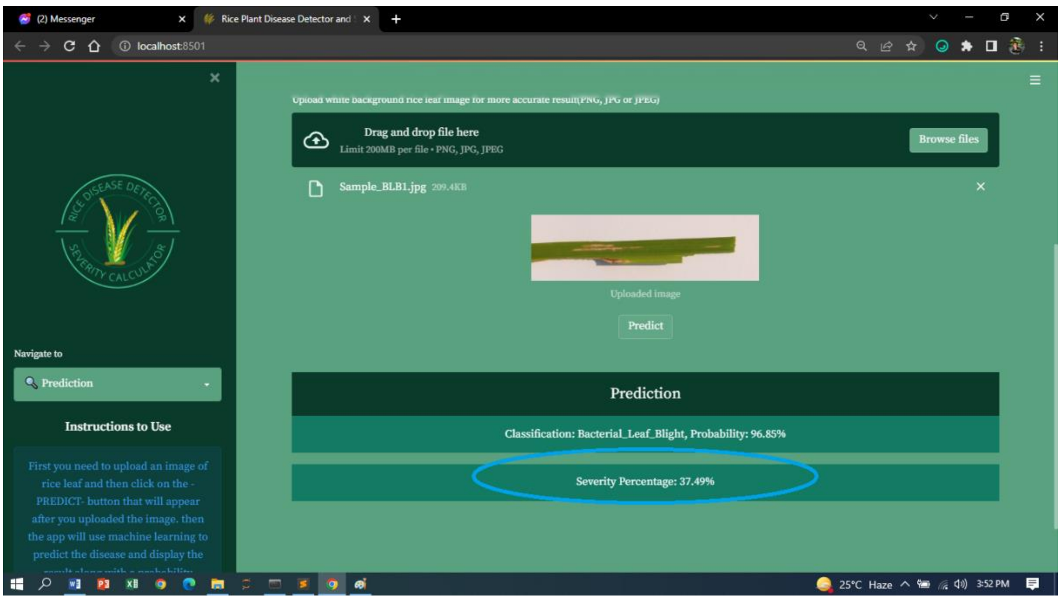

Figure 30. Severity Percentage

Figure 30, shows the result severity of the predicted rice plant disease image, the application was able to calculate the severity of the disease with a severity percentage of 37.49%.

4.4.5 Stress Testing

The test for the web-application overall performance was a success but it also important to test the capability of the system when it was used beyond its expected usage. The web-applica tion only accepts three file formats JPEG, PNG, ang JPG. Hence, the application was tested using different file formats that was consider as an invalid input as well as if the image that y ou input invalid for image reshaping

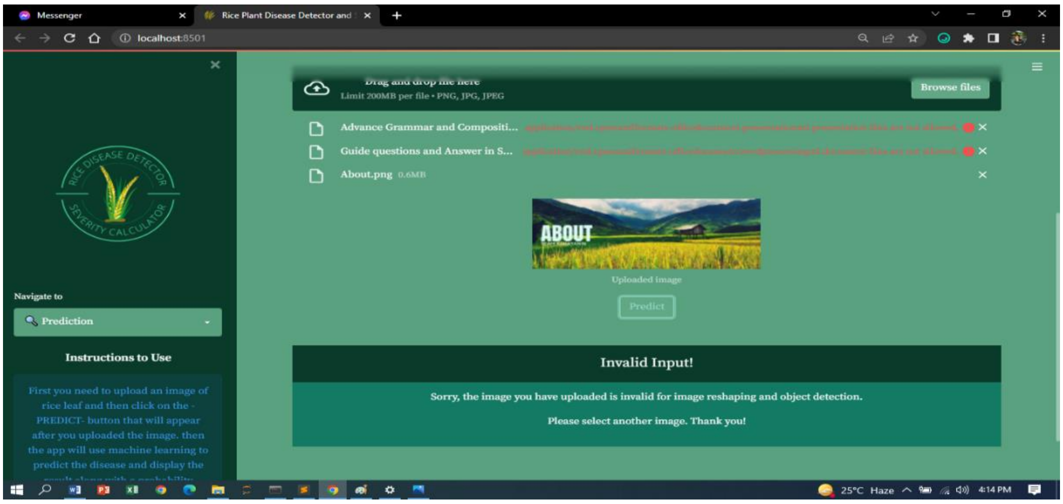

Figure 31. Error Message

4.4.6 Load Testing

Testing the usage of the software program by simulating multiple users that will be accessin g the program concurrently is part of the testing plan. However, this software is deployed inde pendently in every hardware component such as laptop and computers devices, this does not h ave any shared client-server model that will affect its performance. Thus, this software will not have any problems in its loading when accessed by multiple users.

4.4.7 System Testing

This project goes through several stages of testing; there are a total of six testing techniques l isted in this study, which cover all of the system's essential features. With all of the tests passin g, it can be stated that the overall system testing was successful as well. The system was tested as it was being deployed; it was placed on various computers and its categorization and compu tation abilities were tested, and the application was able to produce the required results.

CONCLUSION AND RECOMMENDATIONS

This study was able to meet its main objectives, which included developing a classification model that could classify Rice Leaf Diseases and effectively embedding it into a computer-based web-application, as well as evaluating the software's accuracy in quantifying the severity of leaf spot disease. The technology can detect a rice disease and determine the degree of leaf spot. The model's performance testing revealed that the application is accurate in predicting Rice Leaf Diseases, with a 96.60 percent accuracy.

As a result, there is a lot of opportunity for development in this study. The first step is to improve the classification model's performance, and then explore include other recently found rice diseases. The technology can only recognize four forms of rice diseases and can also tell if the image isn't a rice leaf. The second goal is to increase the accuracy of the rice spot severity calculation. And lastly the third-party python library ‘streamlit’ as of now is not capable of locating the file path of an image while working with OpenCV image processing method, you need to paste the image along with your main application for it to read or not to encounter problems. It is suggested that the method be expanded to cover other rice leaf diseases and the severity percentages for each disease be calculated more precisely and as for the third-party problem with streamlit it is suggest that to improve and locate the files without a problem.

IMPLEMENTATION PLAN

Project Implementation Checklist

Below is listed out task of implementation that the proponents need to accomplish in the cou rse of the project implementation phase.

No.	Task	Status
1.	Project Implementation Session	Finish
2.	System Presentation Planning	Finish
3.	Data Gathering	Finish
4.	Deployment Procedure Planning	Finish
5.	System Testing	Finish
6.	System Credibility Checking	Finish
7.	Project Finalization	Finish

Table 7. Project Implementation Checklist

Implementation contingency

The table below shows the project implementation contingency plan. The following are the l isted task and contingencies that the proponents intended contingency implementation

No.	Task	Contingency
1.	System Presentation Session	The system presentation strategy should have backup during the session/meeting .
2.	Data Gathering	If the image is rejected, collect a clear i mage based on the data.
3.	X'System Testing	During the system's evaluation. To mak e the system source code testable and sa fer for testing, it should contain a backu p.
4.	Data Recovery Strategies	Determine the source of the problem. K eep track of all data sources and look fo r any potential flaws.

Table 8. Implementation Contingency

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APPENDICES

Appendix

RELEVANT SOURCE CODE

Model Training Source Code

```
In [1]: from __future__ import absolute_import, division, print_function, unicode_literals
        import os
        import time
        import json
        import numpy as np
        import matplotlib.pylab as plt

        import tensorflow as tf
        import tensorflow_hub as hub

        from tensorflow.keras.layers import Dense, Flatten, Conv2D
        from tensorflow.keras import Model
        from tensorflow.keras.preprocessing.image import ImageDataGenerator
        from tensorflow.keras.optimizers import Adam
        from tensorflow.keras import layers

        import cv2
        import itertools
        import random
        from collections import Counter
        from glob import iglob

In [2]: start = time.time()

In [3]: zip_file='img3.zip'
        data_dir = os.path.join(os.path.dirname(zip_file), 'Dataset')
        train_dir = os.path.join(data_dir, 'Train')
        validation_dir = os.path.join(data_dir, 'Validation')

In [4]: with open('Dataset/classification.json', 'r') as f:
            category_to_name = json.load(f)
            classes = list(category_to_name.values())

        print (classes)
```

```
In [5]: pixels = 120
        image_size = (pixels, pixels)
        batch_size = 128

In [6]: validation_datagen = tf.keras.preprocessing.image.ImageDataGenerator(rescale=1./255)
        validation_generator = validation_datagen.flow_from_directory(
            validation_dir,
            shuffle=False,
            seed=None,
            color_mode="rgb",
            class_mode="categorical",
            target_size=image_size,
            batch_size=batch_size)

        do_data_augmentation = True


        if do_data_augmentation:
            train_datagen = tf.keras.preprocessing.image.ImageDataGenerator(
                rescale = 1./255,
                rotation_range=40,
                horizontal_flip=True,
                width_shift_range=0.2,
                height_shift_range=0.2,
                shear_range=0.2,
                zoom_range=0.2,
                fill_mode='nearest' )
        else:
            train_datagen = validation_datagen

        train_generator = train_datagen.flow_from_directory(
            train_dir,
            subset="training",
            shuffle=True,
            seed=None,
            color_mode="rgb",
            class_mode="categorical",
            target_size=image_size,
            batch_size=batch_size)
```

```
In [7]: model = tf.keras.Sequential([
            tf.keras.layers.Conv2D(72, (3, 3), activation='relu', input_shape=(120, 120, 3)),
            tf.keras.layers.MaxPooling2D((2, 2)),
            tf.keras.layers.Conv2D(32, (3, 3), activation='relu'),
            tf.keras.layers.Flatten(input_shape=image_size+(3,)),
            tf.keras.layers.Dense(128, activation='relu'),
            tf.keras.layers.Dropout(rate=0.2),
            tf.keras.layers.Dense(64, activation='relu'),
            tf.keras.layers.Dense(train_generator.num_classes, activation='softmax',
                                  kernel_regularizer=tf.keras.regularizers.l2(0.0001))
        ])

In [8]: model.summary()
```

```
In [9]: learning_rate = 0.001
        model.compile(
           optimizer=tf.keras.optimizers.Adam(lr=learning_rate),
           loss='categorical_crossentropy',
           metrics=['accuracy'])
```

```
C:\Users\royjo\anaconda3\lib\site-packages\keras\optimizer_v2\adam.py:105: UserWarning: The `lr` argument is deprecated, use `l
earning_rate` instead.
  super(Adam, self).__init__(name, **kwargs)
```

```
In [12]: epochs = 300
         epochs_steps = train_generator.samples//train_generator.batch_size
         validation_steps = validation_generator.samples//validation_generator.batch_size

         with tf.device('/device:CPU:0'):
             history = model.fit(
                 train_generator,
                 steps_per_epoch=epochs_steps,
                 epochs=epochs,
                 validation_data=validation_generator,
                 validation_steps=validation_steps)
```

```
In [12]: print(history.history.keys())
```

```
dict_keys(['loss', 'accuracy', 'val_loss', 'val_accuracy'])
```

```
In [43]: acc = history.history['accuracy']
         val_acc = history.history['val_accuracy']
         loss = history.history['loss']
         val_loss = history.history['val_loss']
         epochs_range = range(epochs)

         plt.figure(figsize=(8, 8))

         plt.subplot(1, 2, 1)
         plt.plot(epochs_range, acc, label='Training Accuracy')
         plt.plot(epochs_range, val_acc, label='Validation Accuracy')
         plt.legend(loc='lower right')
         plt.title('Training and Validation Accuracy')
         plt.ylabel("Accuracy (training and validation)")
         plt.xlabel("Training Steps")

         plt.subplot(1, 2, 2)
         plt.plot(epochs_range, loss, label='Training Loss')
         plt.plot(epochs_range, val_loss, label='Validation Loss')
         plt.legend(loc='upper right')
         plt.title('Training and Validation Loss')
         plt.ylabel("Loss (training and validation)")
         plt.xlabel("Training Steps")

         plt.show()
```

```
In [44]: def load_image(filename):
             img = cv2.imread(os.path.join(validation_dir, filename))
             img = cv2.resize(img, (image_size[0], image_size[1]) )
             img = img /255

             return img

         def predict_image(image):
             probabilities = model.predict(np.asarray([img]))[0]
             class_idx = np.argmax(probabilities)

             return {classes[class_idx]: probabilities[class_idx]}
```

```
In [45]: n = 5
         for idx, filename in enumerate(random.sample(validation_generator.filenames, n)):
             print("SOURCE: class: %s, file: %s" % (os.path.split(filename)[0], filename))

             img = load_image(filename)
             prediction = predict_image(img)
             print("PREDICTED: class: %s, confidence: %f" % (list(prediction.keys())[0], list(prediction.values())[0]))
             plt.imshow(img)
             plt.figure(idx)
             plt.show()
```

```
In [46]: end = time.time()
```

```
In [47]: print("Execution Time: ", end-start, "s")
```

```
Execution Time:  1368.0643649101257 s
```

```
In [48]: model.save('Rice_TrainData')
```

```
INFO:tensorflow:Assets written to: Rice_TrainData\assets
```

Web Application Main File Codes

```
import streamlit as st
from model import predict
import pandas as pd
from PIL import Image
from Page import about, RiceDiseases, HowTheProject, home, prediction

st.set_page_config(
  page_title="Rice Plant Disease Detector and Severity Calculator",
  page_icon="Image/icon.png",
  layout="wide",
  initial_sidebar_state="expanded",
)

st.markdown('<style>body{text-align: center;}</style>', unsafe_allow_html=True)

PAGES = {
        "🏠 Home": home,
        "🔍 Prediction": prediction,
        "🦠 Rice Diseases": RiceDiseases,
        "⚙️ How the project will work": HowTheProject,
        "🗄️ About": about
}
#logo
with st.sidebar.container():
        image = Image.open('Image/logo.png')
        st.image(image, use_column_width=True)

#Selectionbox
selection = st.sidebar.selectbox("Navigate to",list(PAGES.keys()))
page = PAGES[selection]
```

```
page.app()
```

Model File Codes

```
import numpy as np
from PIL import Image
from keras.preprocessing.image import load_img, img_to_array
from keras.models import load_model

def predict(img):
    IMAGE_SIZE = 120
    classes = [
    'Bacterial_Leaf_Blight',
    'Brown_Spot',
    'Healthy',
    'Leaf_Blast',
    'Leaf_Smut',
    'Not_Rice_Leaf']
    model_path = r'Rice_TrainedModel'
    model = load_model(model_path)
    img = Image.open(img)
    img = img.resize((IMAGE_SIZE, IMAGE_SIZE))
    img = img_to_array(img)
    img = img.reshape((1, IMAGE_SIZE, IMAGE_SIZE, 3))
    img = img/255.
    class_probabilities = model.predict(x=img)
    class_probabilities = np.squeeze(class_probabilities)
    prediction_index = int(np.argmax(class_probabilities))
    prediction_class = classes[prediction_index]
    prediction_probability = class_probabilities[prediction_index] * 100
    prediction_probability = round(prediction_probability, 2)
    return prediction_class, prediction_probability
```

Home Page Codes

```
import streamlit as st
import streamlit.components.v1 as components
from PIL import Image

def app():
    image = Image.open('Image/home.png')

    st.image(image, use_column_width=True)
    #What is Rice Leaf
    con=st.container()
    with con :
        st.markdown("""
        <style>
            .topnav {
                background-color: #0a3a2a;
                overflow: hidden;
            }
            .topnav a {
                display: block;
                color: #137a63;
                text-align: Center;
                padding: 14px 16px;
                text-decoration: none;
                font-size: 18px;
            }
            .Paragraph {
                background-color: #137a63;
                overflow: hidden;
            }
```

```
.Paragraph a {
    display: block;
    color: Black;
    text-align: Justify;
    padding: 14px 16px;
    font-size: 18px;
}
</style>
<body>
<div class="topnav">
    <a><Font Color="#ddfaf8">We are here to raise knowledge about rice plant diseases and to develop a more precise way to identify rice diseases.</Font Color></a>
    <a style= "background-color: #5AA17F"><Font Color="White">Information</Font color></a>
</div>
<div class="Paragraph">
    <a><p>      Detection of rice plant disease and its severity has always been challenging considering the similarities of symptoms. Locally, the only available technique in diagnosing the rice disease and determining the severity of leaf spot disease was naked eye observation or visual analysis. As the visual analysis requires constant human observations and manual measurements, the process tends to be very costly, tiresome, and time-consuming and can lead to errors especially when dealing with large areas of plants. This also requires continuous monitoring of experts which might be expensive.
    <p>      It is important to detect the plants disease at early stage and accurate diagnosis the infectious disease is critically important because diagnosis can improve the effectiveness of treatments and avoid long-term complications for the infected patient plant. Undiagnosed patients' plant can unknowingly transmit the disease to others. Furthermore, estimating or measuring the severity of disease on plants is fundamental to many studies in plant pathology and has practical applications where disease control is needed, including crop disease surveys, decision making, comparing crop management approaches, understanding and estimating yield loss, and rating germplasm for crop breeding purposes. With this, the use of emerging technologies like computer vision and machine learning would be promising so that early and accurate identification and detection of plant diseases for early and timely implementation and application of corresponding remedial measures.
    <p>      Image processing techniques and machine learning are proved accurate and economic practices for measuring the parameters related to various plant diseases to avoid losses in the number of agricultural products and yields (Ramesh et.al. 2020). Recent advances in computer vision particularly machine learning techniques have been applied in agriculture to extract information from the images and to represent this information effectively and efficiently.
```

```
    <p>      Hence, in this study, the authors employed one of the most popular learning algorithms at present and most applied to analyze visual imagery - the convolutional neural network and visual computing. A computer-based rice disease detector and severity calculator will be implemented to facilitate the experts and the farmers in diagnosing rice diseases.

    </p></a>

  </div>

</body>

""",unsafe_allow_html=True)
```

Prediction Page Codes

```
import streamlit as st

from model import predict

from PIL import Image

import cv2

import numpy as np


def app():

    image1 = Image.open('Image/Prediction.png')


    st.image(image1, use_column_width=True)

    st.text("")

    img = st.file_uploader(label='Upload white background rice leaf image for more accurate
result(PNG, JPG or JPEG)', type=['png', 'jpg', 'jpeg'])

    if img is not None:

        col1, col2,col3 = st.columns(3)

        col1.text("")

        with col2:

            st.image(image=img.read(), caption='Uploaded image', use_column_width = True)

        col3.text("")

        predict_button = st.button(label='Predict')


        if predict_button:
```

```
st.text('')
st.text('')
try:
    prediction_class, prediction_probability = predict(img)
    c=st.container()
    with c:
        st.markdown("""
            <style>
                .topnav {
                    background-color: #0a3a2a;
                    overflow: hidden;
                }
                .topnav a {
                    display: block;
                    color: #f2f2f2;
                    text-align: center;
                    padding: 14px 16px;
                    text-decoration: none;
                    font-size: 22px;
                }
            </style>
            <body>
                <div class="topnav">
                    <a>Prediction</a>
                </div>
            </body>
            """,unsafe_allow_html=True)
    a = f'Classification: {prediction_class}, Probability: {prediction_probability}%'
    html_pre = f"""
        <style>
        p.a{{
            padding: 14px 5px;
```

```
        background-color: #137a63;
      }}
      </style>
      <p class="a">{a}</p>
      """
    st.markdown(html_pre,unsafe_allow_html=True)

    if prediction_class == 'Bacterial_Leaf_Blight':

      text = str(img.name)
      img = cv2.imread(text)

      img = cv2.resize(img ,((int)(img.shape[1]/5),(int)(img.shape[0]/5)))
      original = img.copy()
      neworiginal = img.copy()
      #col1, col2,col3 = st.columns(3)
      #col1.text("")
      #with col2:
      #    st.text("Original Image")
      #    st.image(img)
      #col3.text("")
```

#Calculating number of pixels with shade of white(p) to check if exclusion of these pixels is required or not (if more than a fixed %) in order to differentiate the white background or white patches in image caused by flash, if present.

```
      p = 0
      for i in range(img.shape[0]):
        for j in range(img.shape[1]):
          B = img[i][j][0]
          G = img[i][j][1]
          R = img[i][j][2]
          if (B > 110 and G > 110 and R > 110):
            p += 1
```

```
#finding the % of pixels in shade of white
totalpixels = img.shape[0]*img.shape[1]
per_white = 100 * p/totalpixels
'''
print 'percantage of white: ' + str(per_white) + '\n'
print 'total: ' + str(totalpixels) + '\n'
print 'white: ' + str(p) + '\n'
'''
#excluding all the pixels with colour close to white if they are more than 10% in the
image
if per_white > 10:
    img[i][j] = [200,200,200]
    #st.text('color change')
    #st.image(img)

#Guassian blur
blur1 = cv2.GaussianBlur(img,(3,3),1)

#mean-shift algo
newimg = np.zeros((img.shape[0], img.shape[1],3),np.uint8)
criteria = (cv2.TERM_CRITERIA_EPS + cv2.TERM_CRITERIA_MAX_ITER , 10 ,1.0)

img = cv2.pyrMeanShiftFiltering(blur1, 20, 30, newimg, 0, criteria)
#st.text('means shift image')
#st.image(img)

#Guassian blur
blur = cv2.GaussianBlur(img,(11,11),1)

#Canny-edge detection
canny = cv2.Canny(blur, 160, 290)

canny = cv2.cvtColor(canny,cv2.COLOR_GRAY2BGR)
```

```
#contour to find leafs
bordered = cv2.cvtColor(canny,cv2.COLOR_BGR2GRAY)
contours,hierarchy = cv2.findContours(bordered, cv2.RETR_TREE,
cv2.CHAIN_APPROX_NONE)
maxC = 0
for x in range(len(contours)):
                #if take max or one less than max then will not work in images
  if len(contours[x]) > maxC:                 # pictures with zoomed leaf
    maxC = len(contours[x])
    maxid = x

perimeter = cv2.arcLength(contours[maxid],True)
#print perimeter
Tarea = cv2.contourArea(contours[maxid])
cv2.drawContours(neworiginal,contours[maxid],-1,(0,0,255))
#st.text('Contour')
#st.image(neworiginal)

#Creating rectangular roi around contour
height, width, _ = canny.shape
min_x, min_y = width, height
max_x = max_y = 0
frame = canny.copy()

# computes the bounding box for the contour, and draws it on the frame,
for contour, hier in zip(contours, hierarchy):
  (x,y,w,h) = cv2.boundingRect(contours[maxid])
  min_x, max_x = min(x, min_x), max(x+w, max_x)
  min_y, max_y = min(y, min_y), max(y+h, max_y)
  if w > 80 and h > 80:
    roi = img[y:y+h , x:x+w]
    originalroi = original[y:y+h , x:x+w]
```

```
if (max_x - min_x > 0 and max_y - min_y > 0):
    roi = img[min_y:max_y , min_x:max_x]
    originalroi = original[min_y:max_y , min_x:max_x]

#st.text('ROI')
#st.image(frame)
#st.text('rectangle ROI')
#st.image(roi)
img = roi

#Changing colour-space
imghls = cv2.cvtColor(roi, cv2.COLOR_BGR2HLS)
#st.text('HILS')
#st.image(imghls)
imghls[np.where((imghls==[30,200,2]).all(axis=2))] = [0,200,0]
#st.text('new HILS')
#st.image(imghls)

#Only hue channel
huehls = imghls[:,:,0]
#st.text('img_hue hls')
#st.image(huehls)

huehls[np.where(huehls==[0])] = [35]
#st.text('image_hue with mask')
#st.image(huehls)

#Thresholding on hue image
ret, thresh = cv2.threshold(huehls,28,255,cv2.THRESH_BINARY_INV)

#col1, col2,col3 = st.columns(3)
```

```
#col1.text("")
#with col2:
#    st.text('thresh')
#    st.image(thresh)
#col3.text("")


#Masking thresholded image from original image
mask = cv2.bitwise_and(originalroi,originalroi,mask = thresh)
#col1, col2,col3 = st.columns(3)
#col1.text("")
#with col2:
 #   st.text('masked out image')
 #   st.image(mask)
#col3.text("")


#Finding contours for all infected regions
contours,heirarchy = cv2.findContours(thresh, cv2.RETR_TREE,
cv2.CHAIN_APPROX_NONE)

Infarea = 0
for x in range(len(contours)):
    cv2.drawContours(originalroi,contours[x],-1,(0,0,255))

    #Calculating area of infected region
    Infarea += cv2.contourArea(contours[x])

if Infarea > Tarea:
    Tarea = img.shape[0]*img.shape[1]

try:
    per = 100 * Infarea/Tarea
```

```
            round_decimal = "{:.2f}".format(per)

        except ZeroDivisionError:
            per = 0

        html_pre = f"""
            <style>
            p.a{{
            padding: 14px 5px;
            background-color: #137a63;
            }}
            </style>
            <p class="a">Severity Percentage: {round_decimal}%</p>
            """
        st.markdown(html_pre,unsafe_allow_html=True)
    else:
        st.text("")

except ValueError:
    st.markdown("""
            <style>
                .topnav {
                    background-color: #0a3a2a;
                    overflow: hidden;
                }
                .topnav a {
                    display: block;
                    color: #f2f2f2;
                    text-align: center;
                    padding: 14px 16px;
                    text-decoration: none;
```

```
                font-size: 22px;
            }
            .Paragraph {
                overflow: hidden;
                background-color: #137a63;
            }
            .Paragraph a {
                display: block;
                color: Black;
                text-align: Center;
                padding: 14px 16px;
                font-size: 17px;
            }
        </style>
        <body>
            <div class="topnav">
                <a>Invalid Input!</a>
            </div>
            <div class="Paragraph">
                <a><p>Sorry, the image you have uploaded is invalid for image reshaping and object detection.
                <p>Please select another image. Thank you!</p></a>
             </div>
        </body>
        """,unsafe_allow_html=True)


    # Instructions section (sidebar)
    st.sidebar.subheader('Instructions to Use')
    st.sidebar.info("First you need to upload an image of rice leaf and then click on the -PREDICT- button that will appear after you uploaded the image. \
    then the app will use machine learning to predict the disease and display the result along with a probability percentage and how severe the disease are.")
```

```
    # Information section (sidebar)
    st.sidebar.subheader('Important Information')
    st.sidebar.write('The web application can detect only the following Rice Diseases:')
    st.sidebar.info('Bacterial Leaf Blight, Brown Spot, Leaf Smut, and Leaf Blast')
```

Rice Disease Page Codes

```
import streamlit as st
import streamlit.components.v1 as components
from PIL import Image

def app():
    image = Image.open('Image/RiceDiseases.png')

    st.image(image, use_column_width=True)
    #What is Rice Leaf
    con=st.container()
    with con :
        st.markdown("""
        <style>
            .topnav {
                background-color: #0a3a2a;
                overflow: hidden;
            }
            .topnav a {
                display: block;
                color: #137a63;
                text-align: Justify;
                padding: 14px 16px;
                text-decoration: none;
                font-size: 22px;
            }
```

```
.Paragraph {
    background-color: #137a63;
    overflow: hidden;
}
.Paragraph a {
    display: block;
    color: Black;
    text-align: Justify;
    padding: 14px 16px;
    font-size: 17px;
}
</style>
<body>
<div class="topnav">
    <a><Font Color="#ddfaf8">Rice Plant</Font Color></a>
</div>
<div class="Paragraph">
    <a><p>      Rice is the seed of the grass species Oryza sativa (Asian rice) or less commonly Oryza glaberrima (African rice). The name wild rice is usually used for species of the genera Zizania and Porteresia, both wild and domesticated, although the term may also be used for primitive or uncultivated varieties of Oryza.

    <p>      As a cereal grain, domesticated rice is the most widely consumed staple food for over half of the world's human population, especially in Asia and Africa. It is the agricultural commodity with the third-highest worldwide production, after sugarcane and maize. Since sizable portions of sugarcane and maize crops are used for purposes other than human consumption, rice is the most important food crop with regard to human nutrition and caloric intake, providing more than one-fifth of the calories consumed worldwide by humans. There are many varieties of rice and culinary preferences tend to vary regionally.

    </p></a>
    <a style= "background-color: #92ddc8"><Font Color="#0a3a2a">Rice Disease</Font color></a>
<div class="Paragraph">
    <a><p>      In a growing population, rice demand in the country is expected to grow faster than production. In this kind situation, damage to rice crops by any means is unacceptable. Rice diseases have a devastating effect on rice production.
```

```
            <p>      There are many diseases that hamper the growth and productivity in rice which lead to great ecological and economical losses. Some of the types of rice plant diseases that are included in our web-application are:
        </p></a>
      </div>
    </body>
    """,unsafe_allow_html=True)

  #Brown Spot
    st.write('')
    st.markdown("""
    <style>
      .topnav {
        background-color: #0a3a2a;
        overflow: hidden;
      }
      .topnav a {
        display: block;
        color: #137a63;
        text-align: Justify;
        padding: 14px 16px;
        text-decoration: none;
        font-size: 22px;
      }
      .Paragraph {
        background-color: #137a63;
        overflow: hidden;
      }
      .Paragraph a {
        display: block;
        color: Black;
        text-align: Justify;
        padding: 14px 16px;
```

```
            font-size: 17px;
        }
    </style>
    <body>
    <div id="site_content">
        <div class="topnav">
            <a>1. Brown Spot</a>
        </div>
        <div class="Paragraph">
            <a><p>Brown spot has been historically largely ignored as one of the most common and most damaging rice diseases.</p></a>
            <a style= "background-color: #92ddc8"><Font Color="#0a3a2a">What it does</Font color></a>
        </div>
        <div class="Paragraph">
            <a><p>      Brown spot is a fungal disease that infects the coleoptile, leaves, leaf sheath, panicle branches,
            glumes, and spikelets.Its most observable damage is the numerous big spots on the leaves which can kill
            the whole leaf. When infection occurs in the seed, unfilled grains or spotted or discolored seeds are formed.</p></a>
        </div>
        <div class="Paragraph">
            <a style= "background-color: #92ddc8"><Font Color="#0a3a2a">Why and where it occurs</Font color></a>
        </div>
        <div class="Paragraph">
            <a><p>      The disease can develop in areas with high relative humidity (86−100%) and temperature between 16 and 36°C. It is common in unflooded and nutrient-deficient soil, or in soils that accumulate toxic substances.
                For infection to occur, the leaves must be wet for 8−24 hours.
                The fungus can survive in the seed for more than four years and can spread from plant to plant through air. Major sources of brown spot in the field include:
               <p style ="padding: 0px 0px 0px 35px">• infected seed, which give rise to infected seedlings
               <p style ="padding: 0px 0px 0px 35px">• volunteer rice
```

<p style ="padding: 0px 0px 0px 35px">• infected rice debris

<p style ="padding: 0px 0px 0px 35px">• weeds

<p>   Brown spot can occur at all crop stages, but the infection is most critical during maximum tillering up to the ripening stages of the crop.</p>

</p>

</div>

<div class="Paragraph">

<Font Color="#0a3a2a">How to identify

</div>

<div class="Paragraph">

<a><p>Check for lesions:

<p style ="padding: 0px 0px 0px 35px">• infected seed, which give rise to infected seedlings•Infected seedlings have small, circular, yellow brown or brown lesions that may girdle the coleoptile and distort primary and secondary leaves.

<p style ="padding: 0px 0px 0px 35px">• infected seed, which give rise to infected seedlings•Starting at tillering stage, lesions can be observed on the leaves. They are initially small, circular, and dark brown to purple-brown.

<p style ="padding: 0px 0px 0px 35px">• infected seed, which give rise to infected seedlings•Fully developed lesions are circular to oval with a light brown to gray center, surrounded by a reddish brown margin caused by the toxin produced by the fungi.

<p>   On susceptible varieties, lesions are 5−14 mm long which can cause leaves to wilt. On resistant varieties, the lesions are brown and pinhead-sized.

<p>   Lesions on leaf sheaths are similar to those on the leaves. Infected glumes and panicle branches have dark brown to black oval spots or discoloration on the entire surface.

Spikelets can also be infected. Infection of florets leads to incomplete or disrupted grain filling and a reduction in grain quality. The disease-causing fungi can also penetrate grains, causing 'pecky rice', a term used to describe spotting and discoloration of grains.

In certain rice varieties, brown spot lesions can be mistaken for blast lesions. To confirm, check if spots are circular, brownish, and have a gray center surrounded by a reddish margin.

</p>

</div>

<div class="Paragraph">

<Font Color="#0a3a2a">Why is it important

</div>

<div class="Paragraph">

```
<a><p>      Brown spot causes both quantity and quality losses.

On average, the disease causes 5% yield loss across all lowland rice production in South and Southeast Asia. Severely infected field can have as high as 45% yield loss.

Heavily infected seeds cause seedling blight and lead to 10−58% seedling mortality. It also affects the quality and the number of grains per panicle, and reduces the kernel weight.

In terms of history, Brown spot was considered to be the major factor contributing to the Great Bengal Famine in 1943.

    </p></a>

  </div>

  <div class="Paragraph">

    <a style= "background-color: #92ddc8"><Font Color="#0a3a2a">How to manage</font color></a>

  </div>

  <div class="Paragraph">

    <a><p>Improving soil fertility is the first step in managing brown spot. To do this:

      <p style ="padding: 0px 0px 0px 35px">• monitor soil nutrients regularly

      <p style ="padding: 0px 0px 0px 35px">• apply required fertilizers

     <p style ="padding: 0px 0px 0px 35px">• for soils that are low in silicon, apply calcium silicate slag before planting

    <p>      Fertilizers, however, can be costly and may take many cropping seasons before becoming effective. More economical management options include:

      <p style ="padding: 0px 0px 0px 35px">• Use resistant varieties.

    <p style ="padding: 0px 0px 0px 50px">Contact your local agriculture office for up-to-date lists of varieties available.

      <p style ="padding: 0px 0px 0px 35px">• Use fungicides (e.g., iprodione, propiconazole, azoxystrobin, trifloxystrobin, and carbendazim) as seed treatments.

      <p style ="padding: 0px 0px 0px 35px">• Treat seeds with hot water (53−54°C) for 10−12 minutes before planting, to control primary infection at the seedling stage. To increase effectiveness of treatment, pre-soak seeds in cold water for eight hours.

    </p></a>

  </div>

  </div>

</div>

</body>

""", unsafe_allow_html=True)
```

```
    with st.expander("View Brown Spot Images"):
        st.text('')
        st.text('')
        image = Image.open('Image/brownspot1.jpg')
        st.image(image, use_column_width=True)
        image1 = Image.open('Image/brownspot2.jpg')
        st.image(image1, use_column_width=True)
#Bacterial Leaf Blight
    st.write('')
    st.markdown("""
    <style>
        .topnav {
            background-color: #0a3a2a;
            overflow: hidden;
        }
        .topnav a {
            display: block;
            color: #137a63;
            text-align: Justify;
            padding: 14px 16px;
            text-decoration: none;
            font-size: 22px;
        }
        .Paragraph {
            background-color: #137a63;
            overflow: hidden;
        }
        .Paragraph a {
            display: block;
            color: Black;
            text-align: Justify;
            padding: 14px 16px;
```

```
        font-size: 17px;
    }
</style>
<body>
<div id="site_content">
    <div class="topnav">
        <a>2. Bacterial Leaf Blight</a>
    </div>
    <div class="Paragraph">
        <a><p>rice bacterial blight, also called bacterial blight of rice, deadly bacterial disease that is among the most destructive afflictions of cultivated rice(Oryza sativa and O. glaberrima).</p></a>
        <a style= "background-color: #92ddc8"><Font Color="#0a3a2a">What it does</font color></a>
    </div>
    <div class="Paragraph">
        <a><p>      Bacterial blight is caused by Xanthomonas oryzae pv. oryzae.
            It causes wilting of seedlings and yellowing and drying of leaves.
    </p></a>
    </div>
    <div class="Paragraph">
        <a style= "background-color: #92ddc8"><Font Color="#0a3a2a">Why and where it occurs</font color></a>
    </div>
    <div class="Paragraph">
            <a><p>      The disease is most likely to develop in areas that have weeds and stubbles of infected plants. It can occur in both tropical and temperate environments, particularly in irrigated and rainfed lowland areas. In general, the disease favors temperatures at 25−34°C, with relative humidity above 70%.
            It is commonly observed when strong winds and continuous heavy rains occur, allowing the disease-causing bacteria to easily spread through ooze droplets on lesions of infected plants.
            Bacterial blight can be severe in susceptible rice varieties under high nitrogen fertilization.
        </p></a>
    </div>
```

<div class="Paragraph">

<Font Color="#0a3a2a">How to identify

</div>

<div class="Paragraph">

<a><p>   Check for wilting and yellowing of leaves, or wilting of seedlings (also called kresek).

On seedlings, infected leaves turn grayish green and roll up. As the disease progresses, the leaves turn yellow to straw-colored and wilt, leading whole seedlings to dry up and die.

Kresek on seedlings may sometimes be confused with early rice stem borer damage.

To distinguish kresek symptoms from stem borer damage, squeeze the lower end of infected seedlings between the fingers. Kresek symptoms should show yellowish bacterial ooze coming out of the cut ends. Unlike plants infested with stem borer, rice plants with kresek are not easily pulled out from soil.

<p>Check for lesions:

<p style ="padding: 0px 0px 0px 35px">• On older plants, lesions usually develop as water-soaked to yellow-orange stripes on leaf blades or leaf tips or on mechanically injured parts of leaves. Lesions have a wavy margin and progress toward the leaf base.

<p style ="padding: 0px 0px 0px 35px">• On young lesions, bacterial ooze resembling a milky dew drop can be observed early in the morning. The bacterial ooze later on dries up and becomes small yellowish beads underneath the leaf.

<p style ="padding: 0px 0px 0px 35px">• Old lesions turn yellow to grayish white with black dots due to the growth of various saprophytic fungi. On severely infected leaves, lesions may extend to the leaf sheath.

<p>To quickly diagnose bacterial blight on leaf:

<p style ="padding: 0px 0px 0px 35px">• cut a young lesion across and place in a transparent glass container with clear water.

<p style ="padding: 0px 0px 0px 35px">• after a few minutes, hold the container against light and observe for thick or turbid liquid coming from the cut end of the leaf.

</p>

</div>

<div class="Paragraph">

<Font Color="#0a3a2a">Why is it important</Font Color>

</div>

<div class="Paragraph">

<a><p>   Bacterial blight is one of the most serious diseases of rice. The earlier the disease occurs, the higher the yield loss.

```
        Yield loss due to bacterial blight can be as much as 70% when susceptible varieties are grown, in environments favorable to the disease.

        When plants are infected at booting stage, bacterial blight does not affect yield but results in poor quality grains and a high proportion of broken kernels.

        </p></a>

    </div>

    <div class="Paragraph">

        <a style= "background-color: #92ddc8"><Font Color="#0a3a2a">How to manage</font color></a>

    </div>

    <div class="Paragraph">

        <a><p>      Planting resistant varieties has been proven to be the most efficient, most reliable, and cheapest way to control bacterial blight.

        <p>Other disease control options include:

        <p style ="padding: 0px 0px 0px 35px">• Use balanced amounts of plant nutrients, especially nitrogen.

        <p style ="padding: 0px 0px 0px 35px">• Ensure good drainage of fields (in conventionally flooded crops) and nurseries.

        <p style ="padding: 0px 0px 0px 35px">• Keep fields clean. Remove weed hosts and plow under rice stubble, straw, rice ratoons and volunteer seedlings, which can serve as hosts of bacteria.

        <p>      Fertilizers, however, can be costly and may take many cropping seasons before becoming effective. More economical management options include:

        <p style ="padding: 0px 0px 0px 35px">• Allow fallow fields to dry in order to suppress disease agents in the soil and plant residues.

        </p></a>

    </div>

    </div>

</div>

</body>

""", unsafe_allow_html=True)

with st.expander("View Bacterial Leaf Blight Images"):

    col1, col2, col3= st.columns(3)

    with col1:

        st.text('')
```

```
        with col2:
            st.text('')
            st.text('')
            image = Image.open('Image/BLB1.jpeg')
            st.image(image, width = 224)
            image1 = Image.open('Image/BLB2.jpeg')
            st.image(image1, width = 224)
        with col3:
            st.text('')
#Leaf Blast
    st.write('')
    st.markdown("""
    <style>
        .topnav {
            background-color: #0a3a2a;
            overflow: hidden;
        }
        .topnav a {
            display: block;
            color: #137a63;
            text-align: Justify;
            padding: 14px 16px;
            text-decoration: none;
            font-size: 22px;
        }
        .Paragraph {
            background-color: #137a63;
            overflow: hidden;
        }
        .Paragraph a {
            display: block;
            color: Black;
```

```
        text-align: Justify;

        padding: 14px 16px;

        font-size: 17px;

    }

</style>

<body>

<div id="site_content">

    <div class="topnav">

        <a>3. Leaf Blast(Leaf and Collar)</a>

    </div>

    <div class="Paragraph">

            <a><p>Magnaporthe grisea, also known as rice blast fungus, rice rotten neck, rice seedling
      blight, blast of rice, oval leaf spot of graminea, pitting disease, ryegrass blast, Johnson spot,
      neck blast, and Imochi is a plant-pathogenic fungus and model organism that causes a serious
      disease affecting rice.</p></a>

        <a style= "background-color: #92ddc8"><Font Color="#0a3a2a">What it does</font
      color></a>

    </div>

    <div class="Paragraph">

          <a><p>       Blast is caused by the fungus
      Magnaporthe oryzae. It can affect all above ground parts of a rice plant: leaf, collar, node, neck,
      parts of panicle, and sometimes leaf sheath.

    </p></a>

    </div>

    <div class="Paragraph">

        <a style= "background-color: #92ddc8"><Font Color="#0a3a2a">Why and where it
      occurs</font></a>

    </div>

    <div class="Paragraph">

          <a><p>      Blast can occur wherever blast spores
      are present.

            It occurs in areas with low soil moisture, frequent and prolonged periods of rain shower,
      and cool temperature in the daytime. In upland rice, large day-night temperature differences that
      cause dew formation on leaves and overall cooler temperatures favor the development of the
      disease.

            Rice can have blast in all growth stages. However, leaf blast incidence tends to lessen as
      plants mature and develop adult plant resistance to the disease.
```

</p>

</div>

<div class="Paragraph">

<Font Color="#0a3a2a">How to identify

</div>

<div class="Paragraph">

<a><p>Check the leaf and collar for lesions:

<p style ="padding: 0px 0px 0px 35px">• Initial symptoms appear as white to gray-green lesions or spots, with dark green borders.

<p style ="padding: 0px 0px 0px 35px">• Older lesions on the leaves are elliptical or spindle-shaped and whitish to gray centers with red to brownish or necrotic border.

<p>Check for other symptoms:

<p style ="padding: 0px 0px 0px 35px">• Some resemble diamond shape, wide in the center and pointed toward either ends.

<p style ="padding: 0px 0px 0px 35px">• Lesions can enlarge and coalesce, growing together, to kill the entire leaves.

<p>   Blast lesions can commonly be confused with Brown Spot lesions.

Leaf blast lesions are usually elongated and pointed at each end, while brown spot lesions tend to be more round, brown in color and have a yellow halo surrounding the lesion.

</p>

</div>

<div class="Paragraph">

<Font Color="#0a3a2a">Why is it important

</div>

<div class="Paragraph">

<a><p>   Rice blast is one of the most destructive diseases of rice. A leaf blast infection can kill seedlings or plants up to the tillering stage. At later growth stages, a severe leaf blast infection reduces leaf area for grain fill, reducing grain yield.

Leaf blast can kill rice plants at seedling stage and cause yield losses in cases of severe infection.

</p>

</div>

<div class="Paragraph">

```
<a style= "background-color: #92ddc8"><Font Color="#0a3a2a">How to manage</font color></a>

</div>

<div class="Paragraph">

<a><p>      The primary control option for blast is to plant resistant varieties. Contact your local agriculture office for up-to-date lists of varieties available.

<p>Other crop management measures can also be done, such as:

<p style ="padding: 0px 0px 0px 35px">• Adjust planting time. Sow seeds early, when possible, after the onset of the rainy season

<p style ="padding: 0px 0px 0px 35px">• Split nitrogen fertilizer application in two or more treatments. Excessive use of fertilizer can increase blast intensity.

<p style ="padding: 0px 0px 0px 35px">• Flood the field as often as possible.

<p>      Silicon fertilizers (e.g., calcium silicate) can be applied to soils that are silicon deficient to reduce blast. However, because of its high cost, silicon should be applied efficiently. Cheap sources of silicon, such as straws of rice genotypes with high silicon content, can be an alternative. Care should be taken to ensure that the straw is free from blast as the fungus can survive on rice straw and the use of infected straw as a silicon source can spread the disease further.

Systemic fungicides like triazoles and strobilurins can be used judiciously for control to control blast. A fungicide application at heading can be effective in controlling the disease.

</p></a>

</div>

</div>

</div>

</body>

""", unsafe_allow_html=True)

with st.expander("View Leaf Blast Images"):

    col1, col2, col3= st.columns(3)

    with col1:

        st.text('')

    with col2:

        st.text('')

        image = Image.open('Image/LF1.jpg')

        st.image(image, width = 300)

        image1 = Image.open('Image/LF2.png')
```

```
        st.image(image1, width = 300)
    with col3:
        st.text('')

#Leaf Smut
    st.write('')
    st.markdown("""
    <style>
        .topnav {
            background-color: #0a3a2a;
            overflow: hidden;
        }
        .topnav a {
            display: block;
            color: #137a63;
            text-align: Justify;
            padding: 14px 16px;
            text-decoration: none;
            font-size: 22px;
        }
        .Paragraph {
            background-color: #137a63;
            overflow: hidden;
        }
        .Paragraph a {
            display: block;
            color: Black;
            text-align: Justify;
            padding: 14px 16px;
            font-size: 17px;
        }
    </style>
```

```
<body>
<div id="site_content">
<div class="topnav">
<a>5. Leaf Smut</a>
</div>
<div class="Paragraph">
<a><p> Leaf smut ,caused by fungus Entyloma oryzae is a widely distributed ,but somewhat minor,disease of rice.</p></a>
<a style= "background-color: #92ddc8"><Font Color="#0a3a2a">What it does</font color></a>
</div>
<div class="Paragraph">
<a><p>The fungus produces slightly raised,angular ,black spots(sori)on both sides of leaves.
</p></a>
</div>
<div class="Paragraph">
<a style= "background-color: #92ddc8"><Font Color="#0a3a2a">Why and where it occurs</font color></a>
</div>
<div class="Paragraph">
<a><p>      The fungus is spread by airborne spores and over - winters on diseased leaf debris in soil.leaf smut occurs late in the growing season and causes little loss.The disease is favoured by high nitrogen rates.
</p></a>
</div>
<div class="Paragraph">
<a style= "background-color: #92ddc8"><Font Color="#0a3a2a">How to identify</font color></a>
</div>
<div class="Paragraph">
<a><p>       The characteristic sign of rice with leaf smut is the presence of small black spots on the leaves. They are slightly raised and angular and give the leaves the appearance of having been sprinkled with ground pepper. Coverage by these spots is most complete on the oldest leaves.
</p></a>
```

```
    </div>

    <div class="Paragraph">

      <a style= "background-color: #92ddc8"><Font Color="#0a3a2a">Why is it important</font color></a>

    </div>

    <div class="Paragraph">

        <a><p>       In most situations, there is no major loss caused by rice leaf smut, so treatment isn't usually given. However, it can be a good idea to use good general management practices to prevent the infection or keep it in check, and to keep plants healthy overall.

      </p></a>

    </div>

    <div class="Paragraph">

      <a style= "background-color: #92ddc8"><Font Color="#0a3a2a">How to manage</font color></a>

    </div>

    <div class="Paragraph">

        <a><p>       As with many other fungal infections, this one is spread by infected plant material in the soil. When healthy leaves contact the water or ground with old diseased leaves, they can become infected. Cleaning up debris at the end of each growing season can prevent spread of leaf smut. Keeping a good nutrient balance is also important, as high nitrogen levels increases the incidence of the disease. Finally, if leaf smut has been a problem in your growing area, consider using rice varieties with some resistance.

      </p></a>

    </div>

    </div>

  </div>

  </body>

  """, unsafe_allow_html=True)

  with st.expander("View Leaf Smut Images"):

    st.text('')

    image = Image.open('Image/LS.jpg')

    st.image(image, use_column_width=True)

    image1 = Image.open('Image/LS2.jpg')

    st.image(image1, use_column_width=True)
```

How the Project Will Work Page Codes

```
import streamlit as st
import streamlit.components.v1 as components
from PIL import Image

def app():
    image = Image.open('Image/how.png')

    st.image(image, use_column_width=True)
    #What is Rice Leaf
    con=st.container()
    with con :
        st.markdown("""
        <style>
            .topnav {
                background-color: #0a3a2a;
                overflow: hidden;
            }
            .topnav a {
                display: block;
                color: #137a63;
                text-align: Center;
                padding: 14px 16px;
                text-decoration: none;
                font-size: 18px;
            }
            .Paragraph {
                background-color: #137a63;
                overflow: hidden;
            }
```

```
    .Paragraph a {
        display: block;
        color: Black;
        text-align: Justify;
        padding: 14px 16px;
        font-size: 18px;
    }
</style>
<body>
    <div class="topnav">
        <a><Font Color="#ddfaf8">Information</Font Color></a>
    </div>
    <div class="Paragraph">
     <a><p>      The project will be a Computer-Based application in which the user will provide rice leaf images that will be acquired using a 13.0 megapixels camera or higher for taking pictures if the image is already existing you will just be uploading this image into the system. For the Disease Severity Calculator after the image is uploaded the leaf images will be cropped and cleared for extraneous objects. Then after that, the leaf images will undergo image segmentation to separate the region of the leaves from the background using the Otsu method. And once the image has been segmented, the RGB images will be transformed into HSI color representation. After the conversion of RGB to HSI, the system will now perform feature extraction which will be extracting color and texture features from the images. The color feature of the image will be segmented into two regions which will be representing the healthy part of the leaf and the infected part of the leaf. After the calculation of the infected region, it will be loaded into a fuzzy logic membership function to be able to classify it accordingly to get its severity calculation presented in the study of Heuberger.

     <p>      And for the Leaf Spot Disease Recognizer the loaded image will undergo image segmentation wherein the region of interest will be partitioned through segmentation. This will be done by finding the threshold value using the known Otsu method. And once the image is segmented, it will proceed to feature extraction, extracting the color features and morphological features from the rice leaf digital image. Using the extracted features, it will then be loaded to the training system which is utilizing the convolutional neural network machine learning algorithm. With the trained system it is then the system will be able to recognize the type of disease based on the rice leaf that is uploaded to the system.
        </p></a>
    </div>
</body>
""",unsafe_allow_html=True)
```

```
    with st.expander("View Process Flowchart"):
        st.text('')
        st.text('')
        image = Image.open('Image/how2.png')
        st.image(image, use_column_width=True)
```

About Page Codes

```
import streamlit as st
import streamlit.components.v1 as components
from PIL import Image

def app():
    image = Image.open('C:/Users/royjo/OneDrive/Desktop/RPDD-app/Image/About.png')

    st.image(image, use_column_width=True)
    #About
    con=st.container()
    with con :
        st.markdown("""
        <style>
            .topnav {
                background-color: #0a3a2a;
                overflow: hidden;
            }
            .topnav a {
                display: block;
                color: #0a3a2a;
                text-align: Center;
                padding: 14px 16px;
                text-decoration: none;
                font-size: 22px;
```

```
        }
        .Paragraph {
          background-color: #5AA17F;
          overflow: hidden;
        }
        .Paragraph a {
          display: block;
          color: Black;
          text-align: Center;
          padding: 14px 16px;
          font-size: 17px;
        }
    </style>
    <body>
        <div class="topnav">
          <a style= "background-color: #0a3a2a"><Font Color="#92ddc8"><h3>Who We Are</Font
color></h3></a>
        </div>
        <div class="Paragraph">
          <a><p><Font Color="white">We are Southern Leyte State University students. This web
application was created to provide useful resources for farmers who are having difficulty dealing with
and recognizing rice plant diseases. We are a group of skilled and intelligent individuals who are
passionate about developing this fantastic web application. Our team feels there is a better approach to
offer assistance and make things easier.
        </Font color></p></a>
        </div>
        <div class="topnav">
          <a style= "background-color: #0a3a2a"><Font Color="#92ddc8"><h3>Mission</Font
color></h3></a>
        </div>
        <div class="Paragraph">
          <a><p><Font Color="white">To offer a useful web application that will assist users in more
precisely detecting rice plant diseases.
        </Font color></p></a>
        </div>
```

```
<div class="topnav">
<a style= "background-color: #0a3a2a"><Font Color="#92ddc8"><h3>Vision</Font color></h3></a>
</div>
<div class="Paragraph">
<a><p><Font Color="white">To raise knowledge of rice plant diseases and to develop a more precise method of identifying them.
</Font color></p></a>
</div>
</body>
""",unsafe_allow_html=True)
image = Image.open('Image/contact.png')
st.image(image, use_column_width=True)
```

Training Plot in Jupiter Note Book

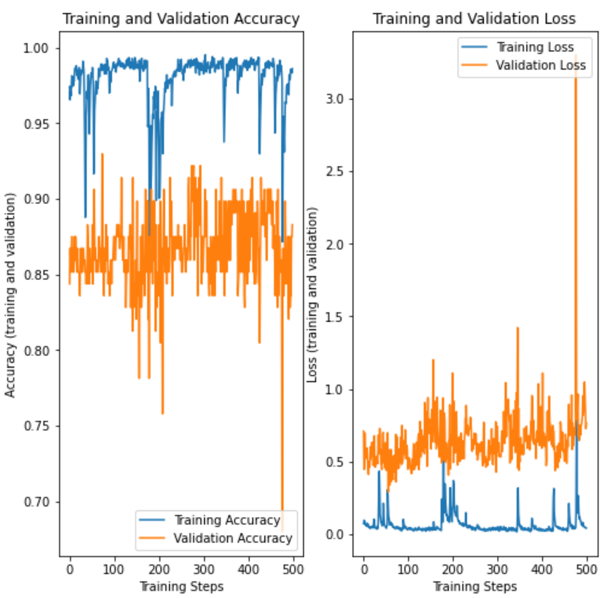

Figure 32. Training Plot in Jupyter Notebook

CURRICULUM VITAE

GERALDENE G. CAHIGUS

Poblacion, Mahaplag Leyte

09161976494 / 09216011305

gegegayola20@gmail.com

OBJECTIVES

To have a secure job and enable to enhance my learning and skills as well as to contribute my knowledge to the success of the team.

PERSONAL INFORMATION

Age: 27
Birthdate: March 20, 1995
Birth Place: Himamara, Mahaplag Leyte
Civil Status: Single
Citizenship: Filipino
Religion: Roman Catholic
Father: Joel Cahigus
Mother: Erlinda Cahigus

EDUCATIONAL BACKGROUND

TERTIARY :
Southern Leyte State University
Sogod, Southern Leyte
Bachelor of Science in Information Technology
Major in Networking
Ongoing

SECONDARY:
Mahaplag National High Scholl Upper
Upper, Mahaplag Leyte
AY 2011-2012

PRIMARY:
Mahaplag Central School
Poblacion, Mahaplag Leyte
AY 2007-2008

I HEREBY CERTIFY that the above information is true and correct to the best of my knowledge and belief.

MARY DIANNE B. ALVAREZ

Otikon, Libagon, Southern Leyte

09675646685

alvarezmarydianne@gmail.com

OBJECTIVES

To have a secure job and enable to enhance my learning and skills as well as to contribute my knowledge to the success of the team.

PERSONAL INFORMATION

Age: 22
Birthdate: September 6, 1999
Birth Place: Ormoc City, Leyte
Civil Status: Single
Citizenship: Filipino
Religion: Roman Catholic
Father: Aldrino Alvarez
Mother: Charita Alvarez

EDUCATIONAL BACKGROUND

TERTIARY :
Southern Leyte State University
Sogod, Southern Leyte
Bachelor of Science in Information Technology
Major in Networking
Ongoing

SECONDARY:
Southern Leyte State University - Main Campus
Sogod, Southern Leyte
TVL – Computer System Servicing
AY 2017-2018

PRIMARY:
Ormoc City Central School
Ormoc City, Leyte
AY 2011-2012

I HEREBY CERTIFY that the above information is true and correct to the best of my knowledge and belief.

ROY JOSHUA S. OCLARIT

Mahayag, Mahaplag Leyte

09060574717 / 09513650858

royjoshuaoclarit@gmail.com

OCLARIT, ROY JOSHUA S.

OBJECTIVES

To have a secure job and enable to enhance my learning and skills as well as to contribute my knowledge to the success of the team.

PERSONAL INFORMATION

Age: 22
Birthdate: November 19, 1999
Birth Place: Plaridel, Baybay City Leyte
Civil Status: Single
Citizenship: Filipino
Religion: Roman Catholic
Father: Joselito A. Oclarit
Mother: Rosalia S. Oclarit

EDUCATIONAL BACKGROUND

TERTIARY :
Southern Leyte State University
Sogod, Southern Leyte
Bachelor of Science in Information Technology
Major in Networking
Ongoing

SECONDARY:
Mahaplag National High School San Isidro
San Isidro, Mahaplag Leyte
TVL - Computer Hardware Servicing
AY 2017-2018

PRIMARY:
San Isidro Elementary School
San Isidro, Mahaplag Leyte
AY 2011-2012

I HEREBY CERTIFY that the above information is true and correct to the best of my knowledge and belief.

JOSHUA A. BAHINTING

Poblacion, Mahaplag Leyte

09078853069

joshuabahinting73@gmail.com

BAHINTING, JOSHUA A.

OBJECTIVES

To have a secure job and enable to enhance my learning and skills as well as to contribute my knowledge to the success of the team.

PERSONAL INFORMATION

Age: 22
Birthdate: March 30, 2000
Birth Place: Baybay City Leyte
Civil Status: Single
Citizenship: Filipino
Religion: Roman Catholic
Father: Danilo L. Bahinting
Mother: Arnila A. Bahinting

EDUCATIONAL BACKGROUND

TERTIARY :
Southern Leyte State University
Sogod, Southern Leyte
Bachelor of Science in Information Technology
Major in Networking
Ongoing

SECONDARY:
Mahaplag National High School San Isidro
San Isidro, Mahaplag Leyte
TVL - Computer Hardware Servicing
AY 2017-2018

PRIMARY:
Mahaplag Central School
Poblacion, Mahaplag Leyte
AY 2011-2012

I HEREBY CERTIFY that the above information is true and correct to the best of my knowledge and belief.

RAFFY V. LAVIÑA

Cahagnaan, Matalom Leyte

09975279040

rafflavina@gmail.com

Laviña, Raffy V.

OBJECTIVES

To have a secure job and enable to enhance my learning and skills as well as to contribute my knowledge to the success of the team.

PERSONAL INFORMATION

Age: 23
Birthdate: February 14, 1999
Birth Place: Cahagnaan, Matalom Leyte
Civil Status: Single
Citizenship: Filipino
Religion: Roman Catholic
Father: Bernabe L. Laviña Jr
Mother: Ma. Elvie V. Laviña

EDUCATIONAL BACKGROUND

TERTIARY :
Southern Leyte State University
Sogod, Southern Leyte
Bachelor of Science in Information Technology
Major in Networking
Ongoing

SECONDARY:
Cahagnaan National High School
Cahagnaan, Matalom Leyte
General Academic Strand
2017-2018

PRIMARY:
Cahagnaan Central School
Cahagnaan, Matalom Leyte
AY 2011-2012

I HEREBY CERTIFY that the above information is true and correct to the best of my knowledge and belief.

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CAPSTONE PROJECT HEARING NOTICE

Date Filled: [/] Proposal
Ref. Code: [ ] Oral Defense
Date: Time: Venue:

DEPARTMENT: CCSIT
Research Title: RICE PLAND DISEASE DETECTOR AND SEVERITY CALCULATOR USING MACHINE LEARNING AND VISUAL COMPUTING.
Proponents:
Roy Joshua S. Oclarit
Joshua A. Bahinting
Raffy V. Laviña
Geraldine G. Cahigus
Mary Dianne B. Alvarez

C E R T I F I C A T I O N

To undersigned members comprising the panel for oral examination hereby agree to the schedule of hearing for the above research. [Please **PRINT NAME** and **SIGN**]

JANNIE FLEUR V. ORAÑO
Research Adviser

ITSO Office / Research

JANNIE FLEUR V. ORAÑO
Panel Chairman

GERALDING MANGMANG
Panel 1

JAMES BRIAN FLORES
Panel 2

APPROVE BY:
ALEX BACALLA
Dean CCSIT