IMAGE-BASED CORN DISEASE IDENTIFIER

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

BY
Angele Rose Dejesica
Mark RJ Marte
Mark Vincent Casilac
Jay Manguilimotan
Roque Pajuyo

Ms. Jannie Fleur V. Oraño
Adviser

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Republic of the Philippines
SOUTHERN LEYTE STATE UNVERSITY
Sogod, Southern Leyte
Website: www.slsuonline.edu.ph
Email: slsumaincampus@gmail.com
op@slsuonline.edu.ph
Telefax No. (053) 382-3294

College of Computer Studies and Information Technology

APPROVAL SHEET

The Capstone Project Study entitled "**IMAGE-BASED CORN DISEASE IDENTIFIER**" prepared and submitted by Angele Rose Dejesica, Mark RJ Marte, Roque Pajuyo, Mark Vincent Casilac, and Jay Manguilimotan. has been examined and is recommended for approval and acceptance.

RECOMMENDED:

JANNIE FLEUR V. ORAÑO	**RHODERICK MALANGSA**
Adviser	Research Facilitator

APPROVED by the Committee on Oral Examination with a grade of PASSED on

____

ALEX BACALLA
Chairman

GERALDINE MANGMANG	**JAMES BRIAN FLORES**
Member	Member

ACCEPTED and APPROVED in partial fulfillment of the requirements in Bachelor of Science in Information Technology.

ALEX BACALLA
Dean, CCSIT

Date: ___________

DEDICATION

This study is wholeheartedly dedicated to our beloved parents, who have been our source of inspiration and gave us strength when we thought of giving up, who continually provide their moral, spiritual, emotional, and financial support.

To the Instructors, who guided us throughout this journey.

To our Capstone Adviser, Jannie Fleur V. Oraño, who shared her words of advice, knowledge of expertise and encouragement to continue this study.

To the members of this team, for the determination throughout this study.

And lastly, we dedicated this to our Almighty of God, thank you for the guidance, strength, power of mind, protection and skills and for giving us a healthy life. All of these, we offer you.

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This study could not have been possible without the kind support and help of many individuals. We would like to extend our sincere thanks to all of them.

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And to the friends and classmates, who have willingly helped us out with their abilities.

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Chapter I

INTRODUCTION

1.1 Project Context

Corn is a tall annual cereal grass (*Zea mays*) that is widely grown for its large elongated ears of starchy seeds. The seeds, which are also known as corn, are used as food for humans and livestock, and as a source of biofuel and can be processed into a wide range of useful chemicals (Britannica, 2019). Corn was developed over years through a selective breeding process. As of today, corn is one of the most important food crops in the world where it provides more food, energy, and carbohydrates than any other food crops. Corn was cultivated on more land area than any other commercial food crops on the planet, (Gardening Channel, 2021).

According to Statista Research Department in the Philippines, corn production was based on the landscape and topography of an area. In 2020, maize production of the Philippines was 8,368 tons. Maize production in the Philippines increased from 2,013 tons in 1971 to 8,368 tons in 2020 growing at an average annual rate of 3.41% (Knoema, 2021). The Agriculture Sector is barring any major natural calamities. It is expected to grow 2.5% this year, on the back of stronger production in major agricultural commodities, such as corn, and high-value crops. These commodities comprise more than 70% of the country's agricultural GVA. Production and exportation help to stimulate the economy of the country where most of it, including other countries' economy are dependent on agriculture – either in a small or big way, and that, corn contributes to the economic growth of the Philippines.

In addition, the Agriculture Sector faced major challenges last year in corn crop, high diseases incidence has been reported in many parts of the country. Philippines was considered as the most virulent of the downy mildew pathogen affecting maize, causing substantial losses to crop production (Murray 2009). Local and systemic infections by fungi, bacteria, viruses, and mycoplasma-like organisms, storage mold, nematode diseases, and parasitism by which weeds (Striga spp.) were included.

There are many corn diseases and some of the common known types of corn diseases are:

1. Common rust is caused by the fungus *Puccinia sorghi* and occurs every growing season. It is seldom a concern in hybrid corn. Early symptoms of common rust are

chlorotic flecks on the leaf surface. These soon develop into powdery, brick-red pustules as the spores break through the leaf surface. As the pustules age, the red spores turn black, so the pustules appear black, and continue to erupt through the leaf surface. Husks, leaf sheaths, and stalks also may be infected.

2. Southern rust is caused by the fungus *Puccinia polysora*. Symptoms are similar to common rust, but pustules are smaller and occur almost exclusively on the upper leaf surface. Pustules are usually circular or oval, very numerous, and densely scattered over the leaf surface. Spores are orange when they erupt from the pustule. As pustules age, they become chocolate brown to black, often forming dark circles around the original pustule.
3. Eyespot is caused by the fungus *Aureobasidium zeae*. The initial symptoms of eyespot are small, water-soaked or chlorotic circular spots. The tissue at the center of the spot later dies and turns tan-colored with a brown ring at the margin. The spot is surrounded by a yellow "halo" that can be seen clearly when the leaf is lighted from behind. Spots may join together into large necrotic areas and the entire leaf may die. The spots remain visible even after the leaf dies.
4. Gray leaf spot, caused by the fungus *Cercospora zeae-maydis*, occurs virtually every growing season. If conditions favor disease development, economic losses can occur. Symptoms first appear on lower leaves about two to three weeks before tasseling. The leaf lesions are long (up to 2 inches), narrow, rectangular, and light tan colored. Later, the lesions can turn gray. They are usually delimited by leaf veins but can join together and kill entire leaves.
5. Tar spot is caused by the fungus *Phyllachora maydis*, and can cause severe yield loss on susceptible hybrids when conditions are favorable for disease. Tar spot appears as small, raised, black spots scattered across the upper and lower leaf surfaces.
6. Northern corn leaf blight (NCLB) is caused by the fungus *Setosphaeria turcica*. Symptoms usually appear first on the lower leaves. Leaf lesions are long (1 to 6 inches) and elliptical, gray-green at first but then turn pale gray or tan. Under moist conditions, dark gray spores are produced, usually on the lower leaf surface, which give lesions a "dirty" gray appearance. Entire leaves on severely blighted plants can die, so individual lesions are not visible. Lesions may occur on the outer husk of ears, but the kernels are not infected.

The Department of Agriculture (DA) is crafting a strategic and robust corn industry development roadmap to address the sector’s challenges. The existing techniques that the farmer does is identifying a gray leaf spot, northern corn leaf blight, tar spot, common and southern rust. The usual process done by a farmer is to submit a photo of the possible disease of corn and wait for the Bureau of Plant Industry to confirm and explain what kind of disease the corn has. This usually takes time and possible disease may worsen before their feedback would be done. Without using technology, manual disease control can be a waste of time and money, and can lead to further corn losses. Moreover, knowing and detecting corn diseases as early as possible is essential for keeping your corn crop healthy and protect your yields as well. Detecting what these diseases looks like is the first step to prevent, protect and avoid losses in the quantity of corn (Bayer, 2020).

With the development of technology, the use of deep learning and image recognition technology for plant disease detection has become an important research direction. In this study, implementing a suitable and fast identification system with machine learning can solve the gap in identifying and classifying the wide variety of corn diseases from images of plant leaves. The identification model focused on using class labels for training images, and built a fine-grained image classification system- a recognition method for corn disease images. Hence, this proposed system is using a novel method for identifying the diseases of corn plants using their images. This research is mainly focused on identifying the variety of corn diseases.

1.2 Purpose and Description of the Project

Image-based corn disease identifier is an innovative technology used in agriculture to solve the issues associated with all existing corn disease detection approaches. The image-based corn disease identifier delivers a more accurate and faster result, which aids in disease control. As a result, this study aids farmers in preventing, managing, and distinguishing a range of maize illnesses in a short amount of time. The project's proponents are tasked with gathering existing data sets of corn disease photos, which will be used to train the system so that it can recognize a range of maize diseases. The system will accept an image from the user that will be subjected to object detection, which will identify all corn illnesses seen in the image. This initiative aims to identify several types of corn disease. We will use image processing to create an algorithm that will detect all of the corn disease in the provided image and identify it individually.

1.3 Objective of the Project

The proponents of this project aimed to develop a system that is capable of identifying a corn disease from an image. Specifically, this project intends to attain the following purposes:

1. To implement Deep Learning algorithm for training the classification model,

2. To design and develop a user-friendly Graphical User Interface for Image-Based Corn Disease

3. To evaluate the accuracy of the system in identifying a variety of corn disease.

1.4 Scope and Limitation of the Project

This project is solely focused on identifying a corn disease. As a result, the system can only identify diseases that affect corn crops. The system in this study can only recognize corn diseases that were included during the classification model's training. Furthermore, the system will only allow one image to be processed at a time and will not enable two or more photographs to be processed at the same time. The system's design and development will take place during the first semester of the school year 2021-2022.

Chapter II

REVIEW OF RELATED LITERATURE

2.1 Related Literature/ Theoretical Background

Machine learning techniques have been successful in identification and classification of wide variety of maize diseases from images of plant leaves (P. Rajendrakumar, 2016). Improvements in deep learning techniques in recent years have made them the state of the art among various computer vision approaches for image classification. Traditional computer vision approach for plant disease detection requires manual selection of features in making classification decisions (Shrinivas D. Desai, 2019), (Pooja Khanna, 2017).

Meanwhile, Deep convolutional neural networks automatically learn most important features by multilayer processing of visual input. Significant prior work in the relevant area includes field imagery based deep neural network by De Chant et al for northern leaf blight detection. Authors have trained several CNNs to classify small region of images into infected and healthy classes and then these small regions are fed into final CNN that classifies the whole image as diseased or healthy (DeChant, 2017).

Furthermore, significant prior work in the relevant area includes field imagery based deep neural network by (De Chant et al (2017)) for northern leaf blight detection. Authors have trained several CNNs to classify small region of images into infected and healthy classes and then these small regions are fed into final CNN that classifies the whole image as diseased or healthy, proposed system achieved an accuracy of 96.7% on test data.

According to some researchers (Garcia et.al., 2019), applied transfer learning on preexisting models trained on different data to improve the classification accuracy of plant diseases. These studies have obtained noteworthy results, but to obtain a feasible solution for precision corn crop monitoring it is highly desirable to design plant disease identification methods that can provide reasonable accuracy on standalone mobile device without the requirement of Internet access. It will enable farmers to make quick and accurate decisions about crop disease.

In Addition, technological methods such as image processing and machine learning contribute a significant impact on plant diseases detection and identification. Several researches have been made wherein features such as color, texture, and shape combined with different classification algorithms were applied. One of the classifiers is fuzzy logic which was found to be effective in the studies. Further studies can be carried out by extracting more feature variables and applying machine learning algorithms to improve its classification accuracy. This can be implemented as well to work in a mobile platform that would increase its level of accessibility and usability (Oraño, et al., 2018).

Lastly, the capability of the computer program to recognize a corn leaf disease is made possible through the use of an artificial neural network called the multilayer perceptron (MLP). The computer program has to undergo supervised learning. Supervised learning is the machine learning task of inferring functions from labeled data (Motri et al, 2012).

2.2 Related Studies

Deep Convolutional Neural Network-based Detection System for Real-time Corn Plant Disease Recognition (Mishraa, 2020) presents a real-time method based on a deep convolutional neural network for corn leaf disease recognition. Deep neural network performance is improved by tuning the hyper-parameters and adjusting to pooling combinations on a system with GPU. During the recognition of corn leaf disease, the deep learning model achieves an accuracy of 88.46% demonstrating the feasibility of this method. The presented corn plant disease recognition model is capable of running on standalone smart devices like raspberry-pi or smartphones and drones.

Similarly, corn classification using Deep Learning with UAV imagery (Trujillano, et al., 2018) proposes as a proof of concept to use Deep learning techniques for the classification of near infrared images, acquired by an Unmanned Aerial Vehicle (UAV), in order to estimate areas of corn, for food security purpose. The results show that using a well-balanced (altitudes, seasons, regions) database during the acquisition process improves the performance of a trained system, therefore facing crop classification from a variable and difficult-to-access geography.

According to (Zhang, et al., 2015) Image Recognition of Maize Leaf Disease Based on GA-SVM, proposed an improved SVM called genetic algorithm support vector machine (GA-SVM). The author collected and classified six types of corn leaf diseases. The following steps were carried out to classify the diseases: For image processing, the JPEG images were transformed into BMP format. Furthermore, the images were converted from RGB template to HSI, to extract various features (average and standard deviations of R, G, B and shape features such as area, circumference, circularity, height, and width, etc). Then segmentation was implemented to get binary images. Finally, the technique of Orthogonal rotation was used to obtain appropriate parameters for the genetic algorithm. Twenty feature parameters were fed to the model. For classification comparisons between SVM and GA-SVM, four kernels were selected: linear, polynomial, RBF and sigmoid. The author concluded after comparison that GA-SVM has a higher classification rate (between 69.63% - 90.09% for SVM and between 88.72% -92.59% for GA-SVM).

In some cases, Maize Leaf Disease Recognition and Classification Based on Imaging and Machine Learning Techniques (Enquhone Alehegn, 2017), a classified three types of corn leaf diseases (common rust, leaf blight, leaf spot) using KNN (K-nearest neighbour) and ANN (artificial neural network) classification algorithms. Images of healthy and corn leaf diseases were taken from Ethiopia farming areas. For training and testing, a minimum of 800 images were considered. Texture, morphology and color features were obtained from the images. Total 22 features were fed to the classification model of KNN and ANN. Lastly, the author concluded that ANN had a higher performance rate with an accuracy of 94.4% whereas KNN reached an accuracy of 82.5%.

In Addition, Plant Disease Identification Using SVM and ANN Algorithms (Kanaka Durga Anuradha, 2019), used SVM and ANN algorithm for leaf disease classification in tomato and corn plants. Image dataset included 200 pictures with a collection of healthy leaves and diseased leaves like northern leaf blight, common rust, bacterial spot, tomato mosaic virus, etc. They used the following steps to identify the diseases: the RGB picture was converted to the grayscale picture and the image was then segmented by calculating the intensity gradient at each pixel. For feature extraction, HOG (histogram of oriented gradients) procedure was used. The extracted features were fed to the SVM and ANN classifier models. For corn crops, SVM gave an accuracy of 70-75% and ANN gave an accuracy of 55-65%.

Lastly, Identification of Disease of Corn Leaves using Convolutional Neural Networks and Boosting (Prakuti Bhatt, et.al., 2019), a developed a system for the identification of corn leaf diseases using CNN architectures (VGG16, inception-v2, ResNet50, mobileNet-v1) and applied a combination of adaptive boosting with decision tree-based classifier to distinguish between diseases that appeared to be similar. Four categories of image data included healthy leaves, common rust, leaf blight, and leaf spot. Pictures of each class were taken from Plant Village dataset. The pictures were resized for image preprocessing according to the necessity of the CNN model used. Features derived from the CNN models were fed to the classifiers (softmax, support vector machine and random forest). It was observed that inception-v2 gave the highest precision with random forest. From the confusion matrix of each classifier, the author noted that leaf blight and leaf spot classes were difficult to differentiate. Therefore, to increase the classification accuracy between them, the Adaptive boosting technique was applied to the best performing model (based on Inception-v2 and RF). Finally, the model reached an accuracy of ~98%.

Chapter III

TECHNICAL BACKGROUND

3.1 Technicality of the Project

The Image-Based Corn Disease Identifier is a Computer-Based software application that identifies the disease of a corn plant. The user can upload an image of a corn plant leaves so that the system can process it and the system can identify corn plant disease. The proponents aimed for this software to be capable of running with or without the use of internet connection. This goal will be 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 corn plant diseases. And the proponents will design the application in a software called PyQt5 it is used for creating Computer-Based applications using Python Programming language.

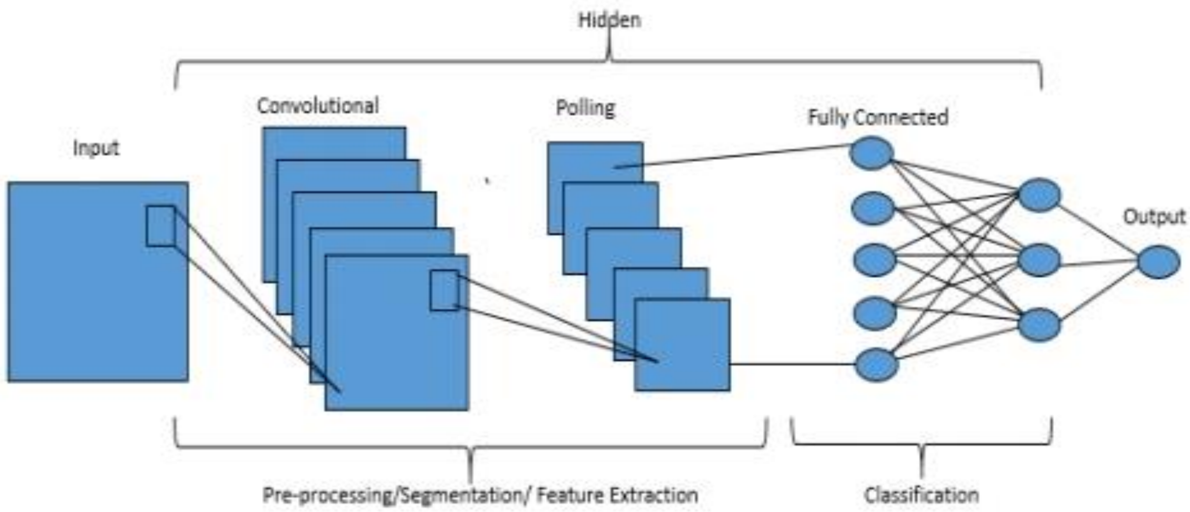

Figure 1. Schematic diagram of Convolutional Neural Network (CNN).

Figure 1 shows that convolutional neural network (CNN) has one or more convolutional layers and are used mainly for image processing, segmentation, features extraction and classification and also for other auto correlated data. The CNN uses a system much like a multilayer perception that has been designed for reduced processing requirements. The layer of CNN consists of an input layer, an output layer and hidden layer that includes multiple convolutional layers and normalization layers. The effective way in removal of limitations and increase in efficiency for image processing results in a system.

3.2 Details of the Technologies to be Used

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

• Python version 3.9

• Tensorflow – a backend framework for running Keras

• Keras – a Python library for developing and evaluating deep learning models

• Streamlit – a Python library for developing custom 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

• Jupyter – for editing and running documents that contains codes

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.

3.3 How the Project will Work

The project will be a Computer-Based application in which the user will provide and upload an image in a jpeg. / Jpg. / png. format that has a clear image of corn plant leaves on it. The pictures from leaf samples of corn are subjected to undergo image processing in which it's enhancing image data so that undesired distortions are suppressed and image features that are relevant for the further processing are emphasized. Next, the corn leaf image will undergo image segmentation where the region of interest will be partitioning into different parts according to their features and properties. Once the image is segmented, it will proceed to features extraction. The features such as color and texture which have to be analyzed were extracted from the image. This may be done to extract the region of interest from the corn leaf image. Using the extracted features, it will be then loaded to that training system which is utilizing Convolutional Neutral Network (CNN) machine learning algorithm. With the trained system it is then the system will be able to identify the type of disease based on the corn leaf image that is uploaded to the system.

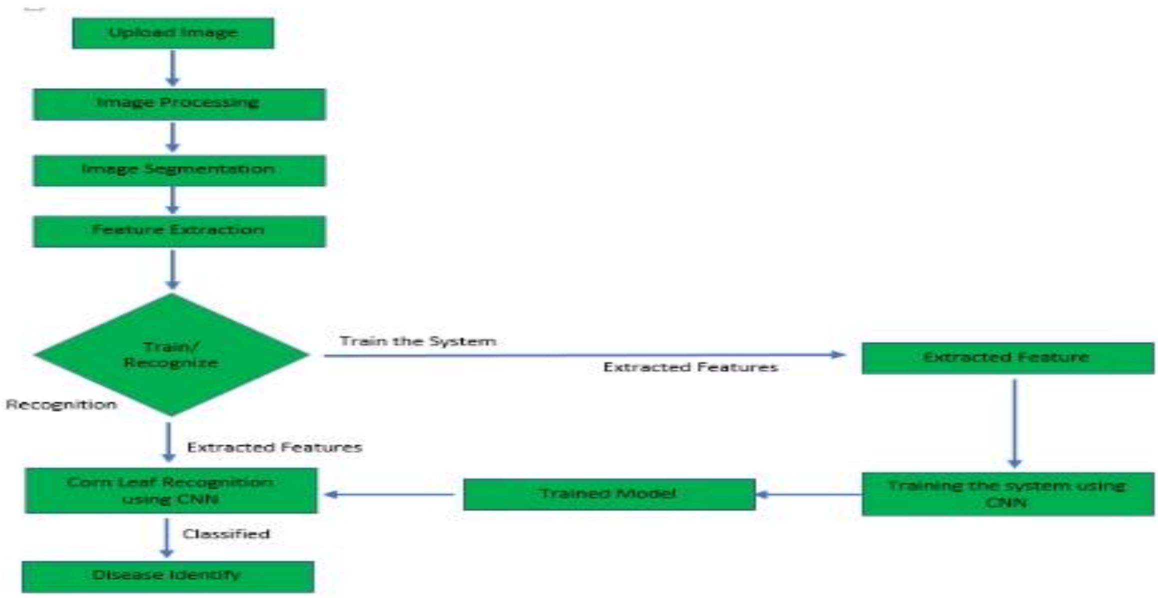

Figure 2. System architecture design of image-base corn disease identifier

Chapter IV

METHODOLOGY

4.1 Requirements Specifications

4.1.1 Operational Feasibility

Fishbone Diagram .

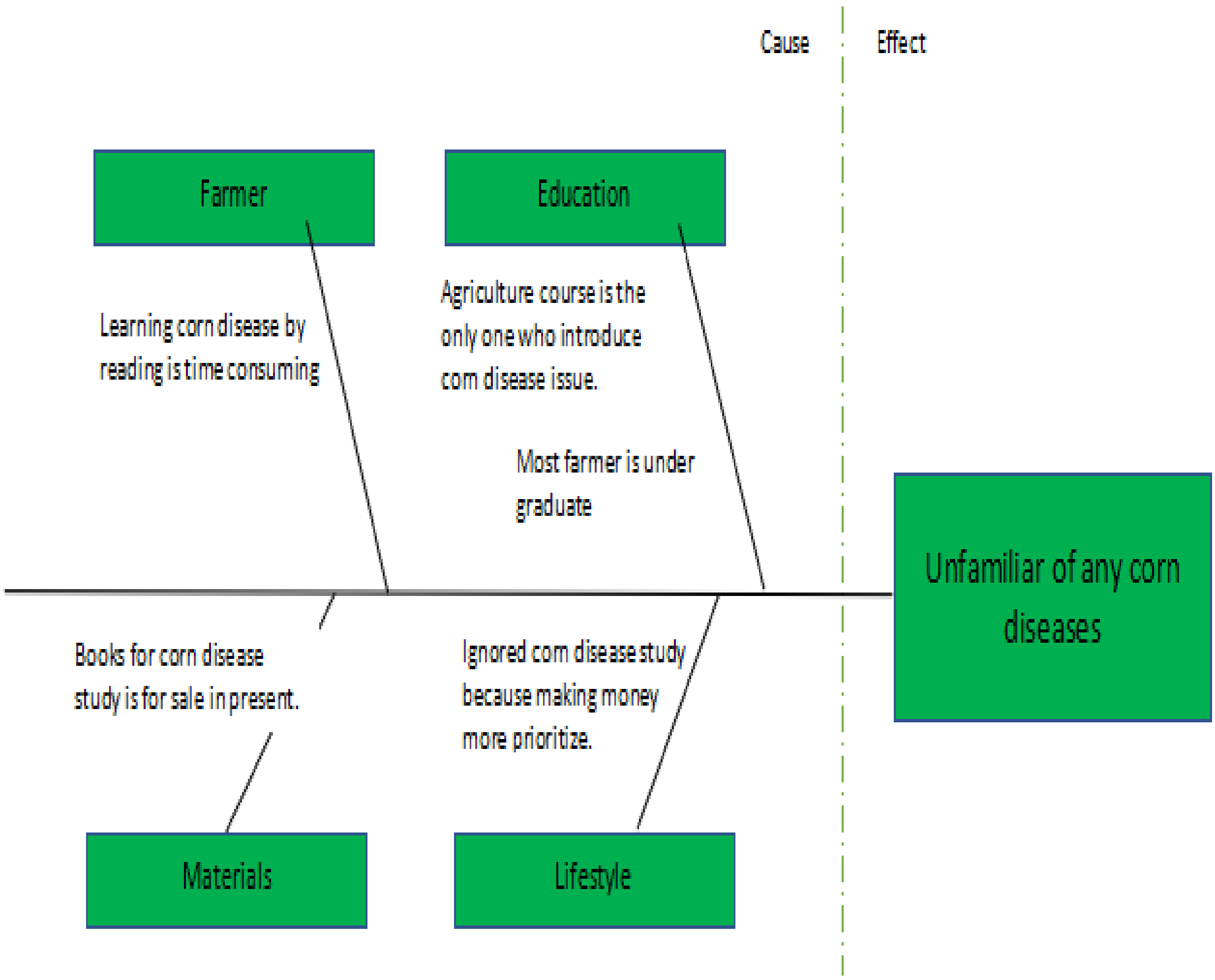

Figure 3. Fishbone Diagram

The diagram shows the causes on why Farmer are unfamiliar with corn diseases. These following factors affects the performance of farmer nowadays in identifying corn diseases.

Functional Decomposition Diagram

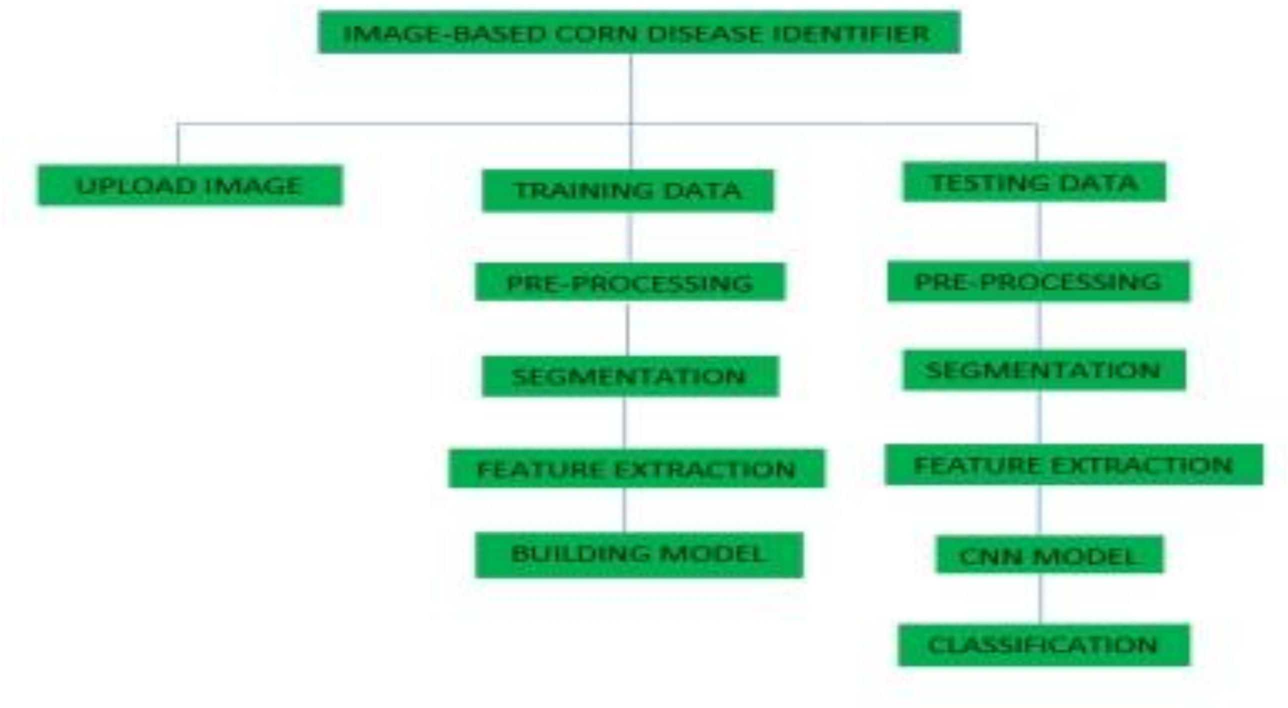

Figure 4. Function Decomposition Diagram

Figure 2 shows the functional decomposition of the system. The functional decomposition consists into three major functions in which includes the Upload Image, Training Data and Testing. First, User can upload image. Then, in Training Data Function it involves sub functionalities such as pre-processing, segmentation, feature extraction and building model. Under Testing it involves pre-processing, segmentation, feature extraction, CNN Model and classification.

Image Acquisition

In this function the image of corn leaf will be uploaded. The user will provide corn leaf images that will be acquired using digital camera or web.

Training Data

Used to help the program understand how to apply technologies to learn and produce a better and accurate results.

Testing Data

To measure the performance, such as its accuracy and efficiency of the algorithm used to train.

Pre-processing

The aim of image pre-processing is enhancing image data so that undesired distortions are suppressed and image features that are relevant for the further processing are emphasized. The Pre-processing sub-process receives an image as input and generates a modified image as output. Pre-processing typically includes operation like image de-noising and image content enhancement. This may be performed several times until the quality of the image is satisfactory.

Segmentation

Image segmentation is the task of clustering parts of an image together that belong to the same object class. This focusses on partitioning an image into different parts according to their features and properties. The primary goal of image segmentation is to simplify the image for analysis. And image segmentation divides and image into various parts that have similar attributes.

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 which have to be analyzed were extracted from the image. This may be done to extract the region of interest which in this case, the infected area or not.

Building Model

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. The model building process involves setting up ways of collecting data, understanding, finding a statistical, or a simulation model to gain understanding and make predictions.

CNN Model

Convolutional Neural Network are used mainly for image processing, classification, segmentation, and cluster them by similarities, and then, perform object recognition. Finding certain features where it can have a better and accurate predictions of its outcome. The depth layers in the three layers of colors (RGB) interpreted by CNNs are referred to as channels.

The first layer in a CNN network is the CONVOLUTIONAL LAYER, which is the core building block and does most of the computational heavy lifting.

Second is the ACTIVATION LAYER which applies the ReLu (Rectified Linear Unit), in this step we apply the rectifier function to increase non-linearity in the CNN. Images are made of different objects that are not linear to each other.

Third, is the POOLING LAYER, which involves downs sampling of features. It is applied through every layer in the 3d volume. Typically, there are hyper parameters within this layer.

Classification

The objective of image classification is to identify and portray, as a unique level. Image classification is the process of categorizing and labeling groups of pixels or vectors within and image base on specific rules. In this part the uploaded corn leave image will be classified if this image have/has disease or none and identify the corn disease.

4.1.2 Technical Feasibility

Capability Checking (Hardware and Software)

The software in this study is a computer-based application that can be installed in any computer with Microsoft Operating System with a Windows version 7,8 and 10. The software can be runnable even without internet connection as long as all the needed software dependencies of the program is also installed 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.

Relevance of Technology

A 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. Third party cameras or web cams can be used to capture high-definition images that we can use as our input data to the system so that we can generate a more accurate result.

4.1.3 Schedule Feasibility

PROJECT TITLE :	IMAGE-BASE CORN DISEASE IDENTIFIER																							
TEAM NAME :	PADAYON																							
PROJECT LEADER:	Casilac, et al.																							
					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	PROGRES	START	END																				
Project Title Brainstorming	Whole team	100%																						
Creating Fromal Proposal	Project Manager	100%																						
Chapter 1	Technical Writter	100%																						
Chapter 2	Technical Writter	100%																						
Chpater 3	Technical Writter	100%																						
Chapter 4	Programmer	100%																						
Graphical User Interface Desining	Programmer	0%																						
Hard Coding	Programmer	0%																						

Figure 5. Gantt Chart

The chart shows the period of time when this project is created, along with the tasks or activity that was done by the researchers.

4.1.4 Economic Feasibility

Cost and Benefit Analysis

EXPENSES	AMOUNT
Internet Expenses	
Paper and Photocopy Expenses	
Transportation	
Miscellaneous Expenses	
Total	

Table1. Cost and Benefit Analysis

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

Cost Recover Scheme

EXPENSES			
Internet Expenses			
Paper and Photocopy Expenses			
Transportation			
Miscellaneous Expenses			
Total			

Table2. Cost Recovery Scheme

This table reflects the division of expenses in order to gradually pay the cost incurred upon the creation of the project.

4.1.5 Requirements Modeling

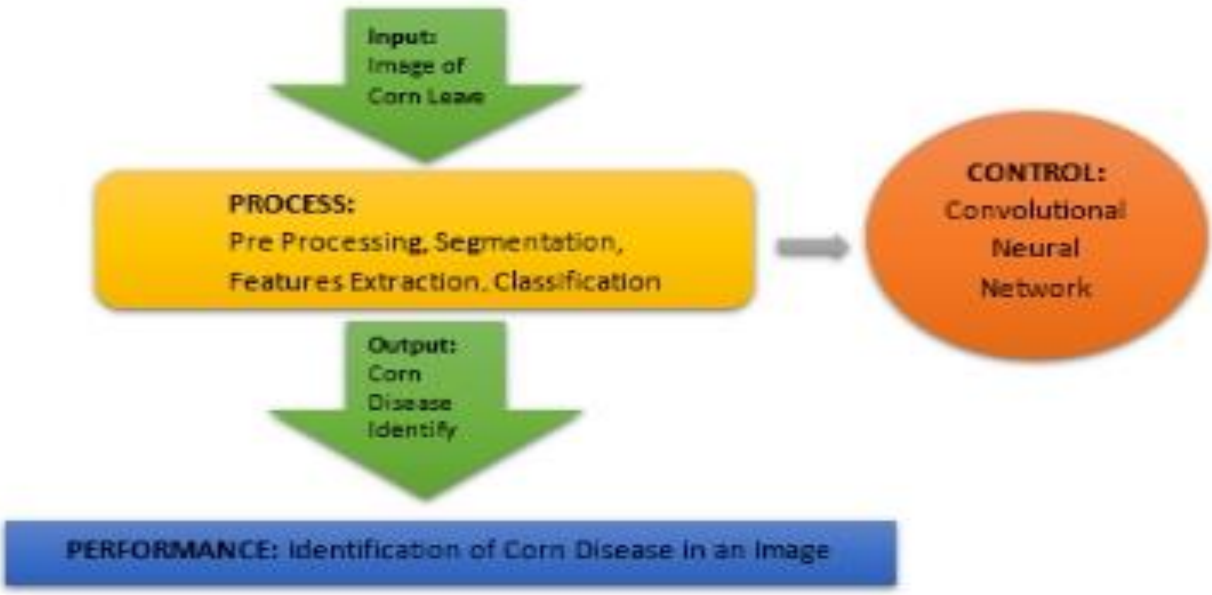

Figure 6. Requirements Modeling

Object Modeling

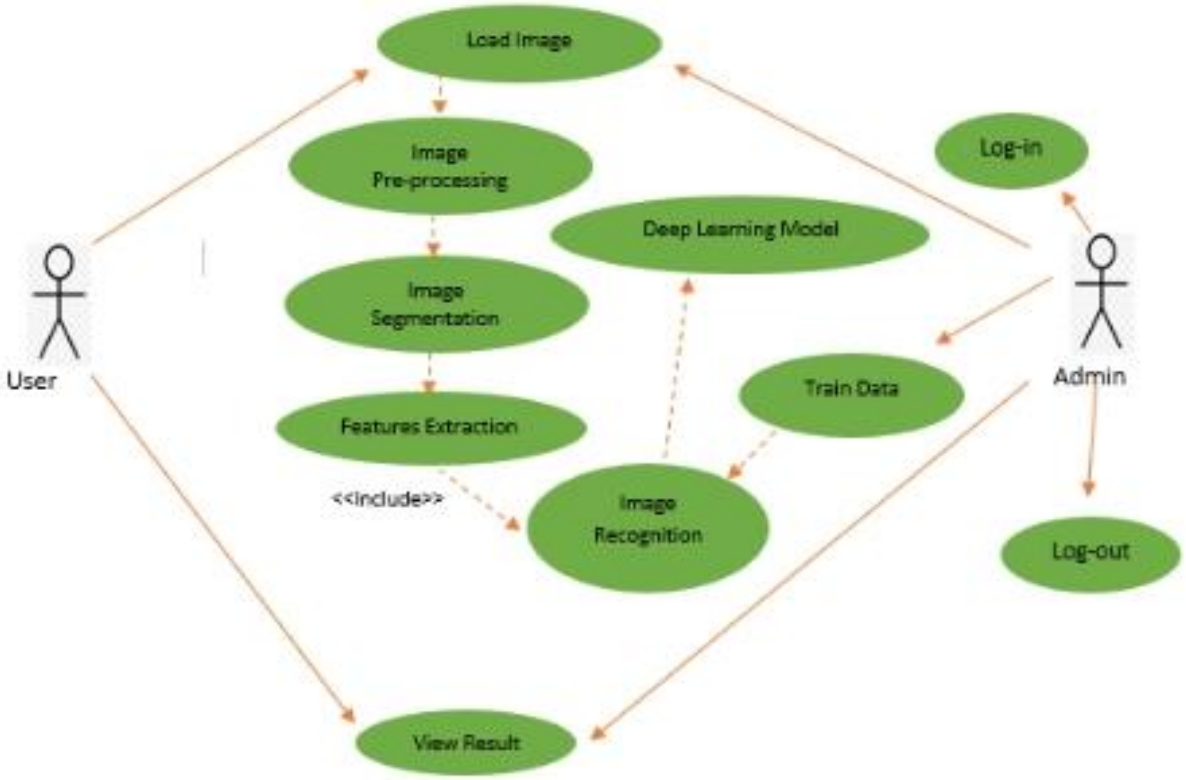

Figure 7. Use Case Diagram

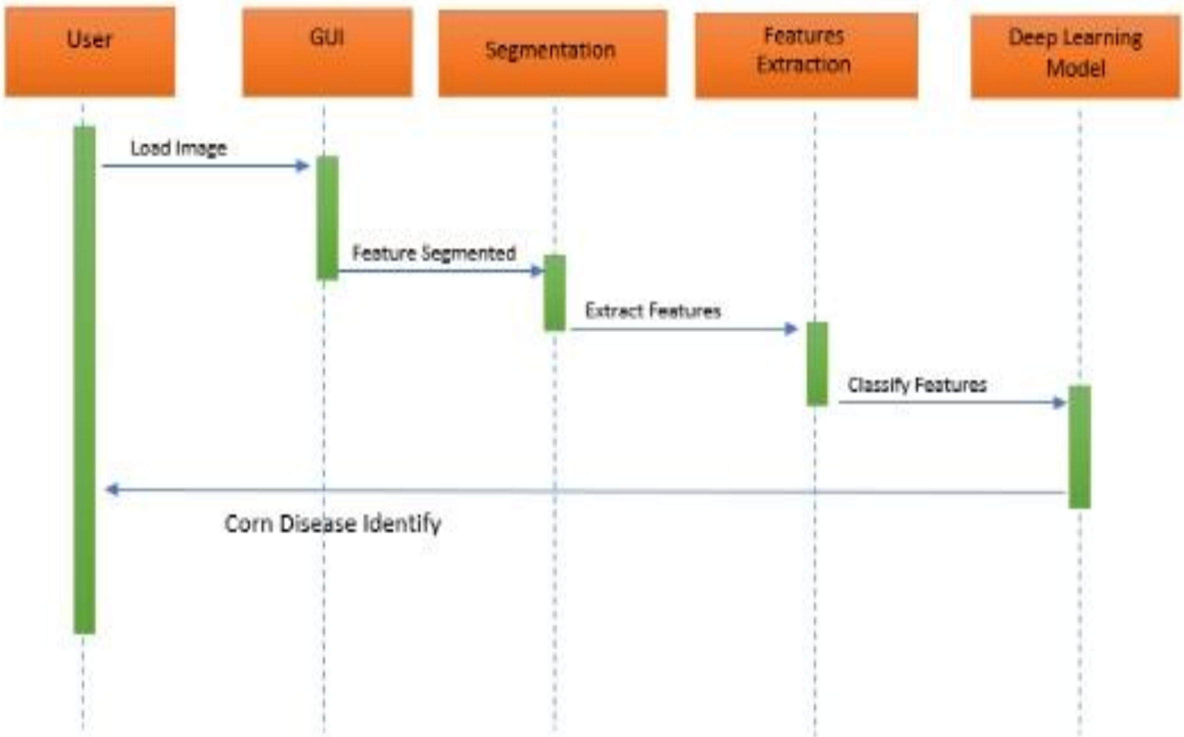

Figure 8. User Sequence Diagram

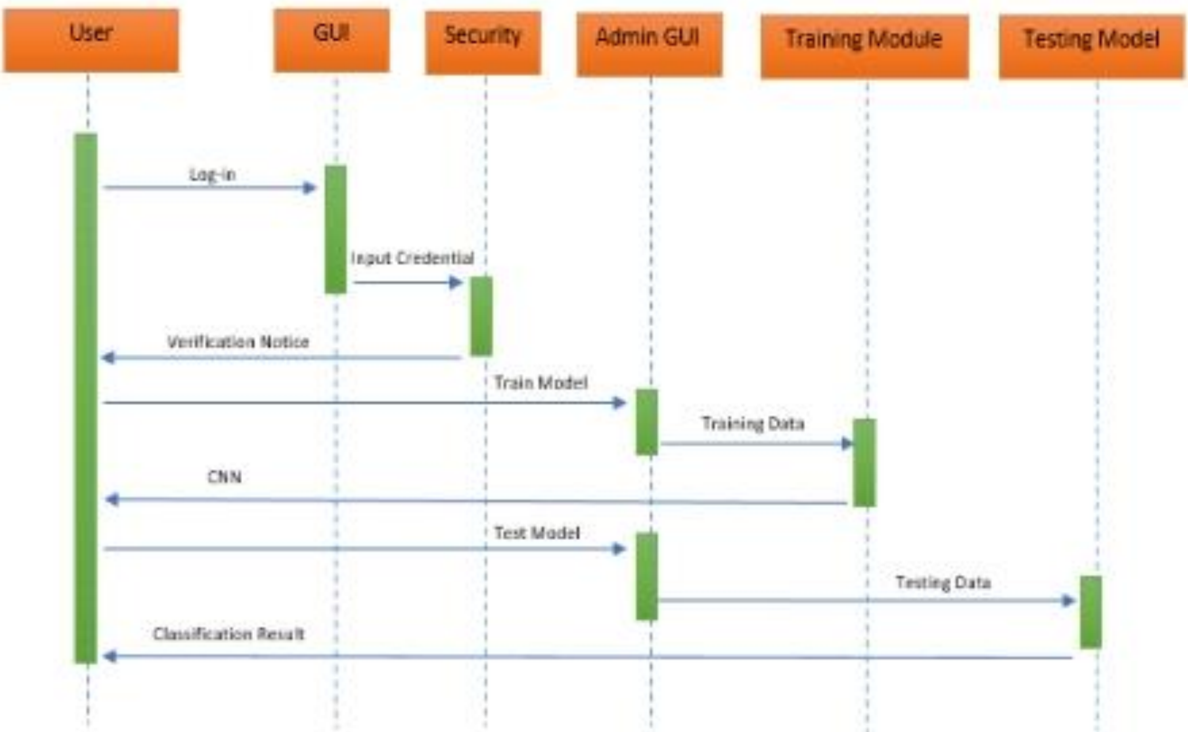

Figure 9. Admin Sequence Diagram

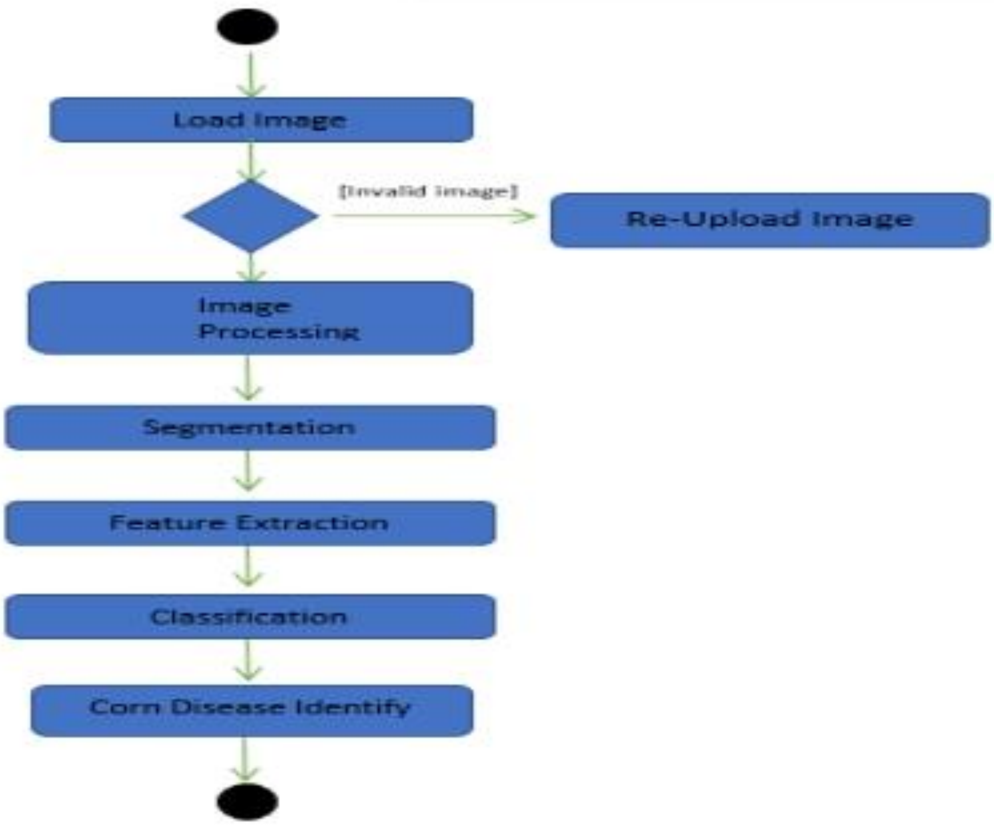

Figure 10. User Activity Diagram

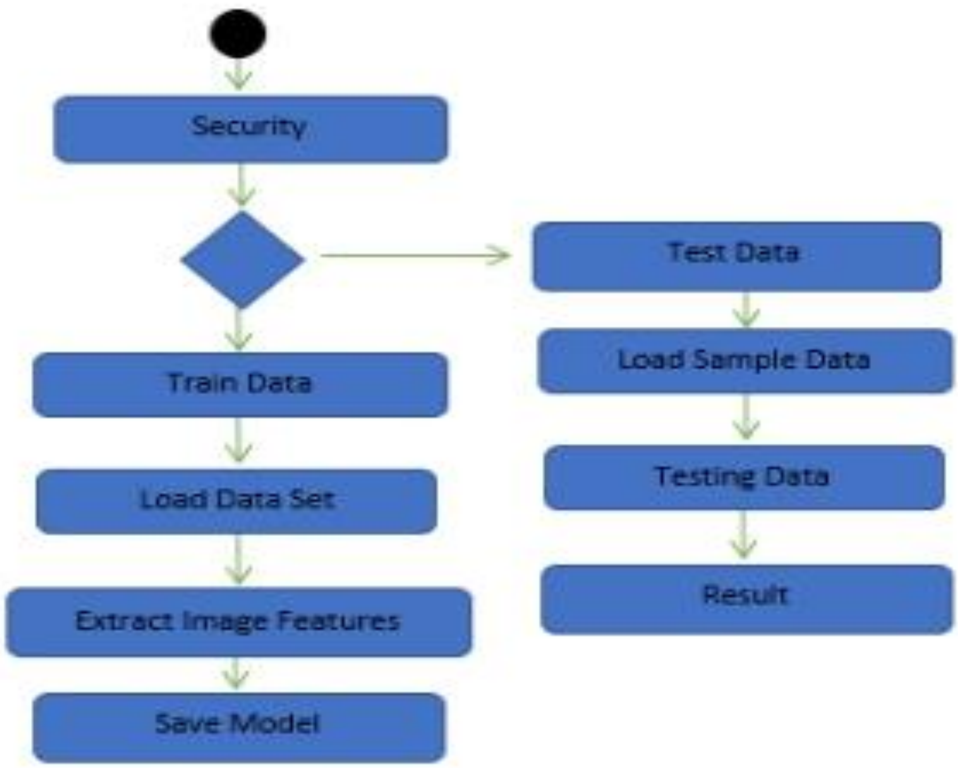

Figure 11. Admin Activity Diagram

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 12. 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 13. Training Model Page

Figure 13 illustrates the Training Model in which shows the results of its accuracy, 98.54%. the accuracy in this area determines the quality of being correct or precise of the prediction.

Figure 14. Home Page

Figure 14 shows the Home Page, it has button which has the following functions;

1. Home, this function has the information, Authors and its Vision and Mission.
2. Instruction, this button provides the steps on how to use the Application.
3. Predict Image, this function is where you can drag and upload an image, and predict.
4. App Description, contains the Technology Development, Purpose of the Application, and How the application will work.
5. Corn Diseases, this button provides information about Corn and its diseases.

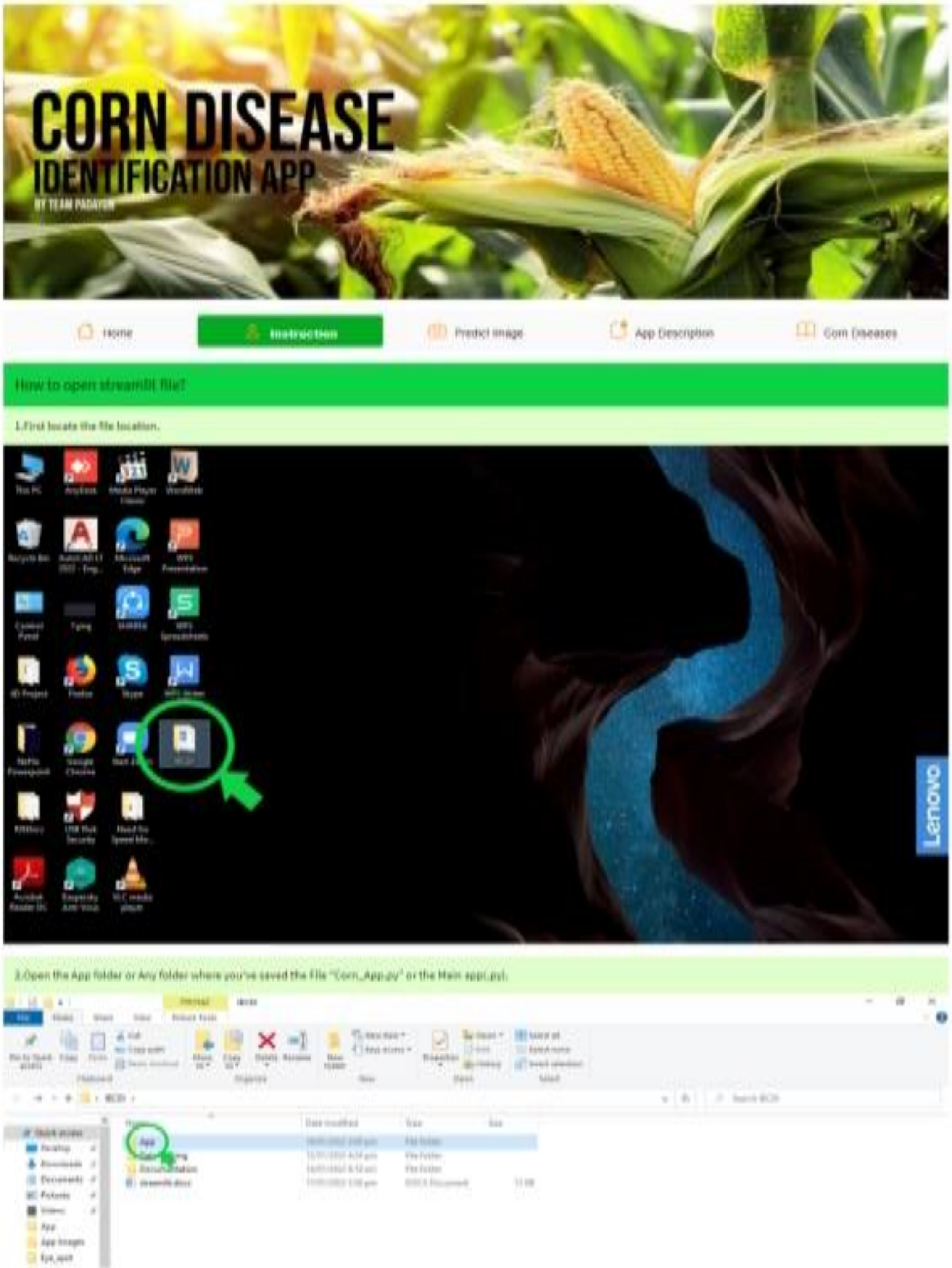

Figure 15. Instruction Page

Figure 15, display the instruction page in which this page contains the instructions on how to use the application sequentially.

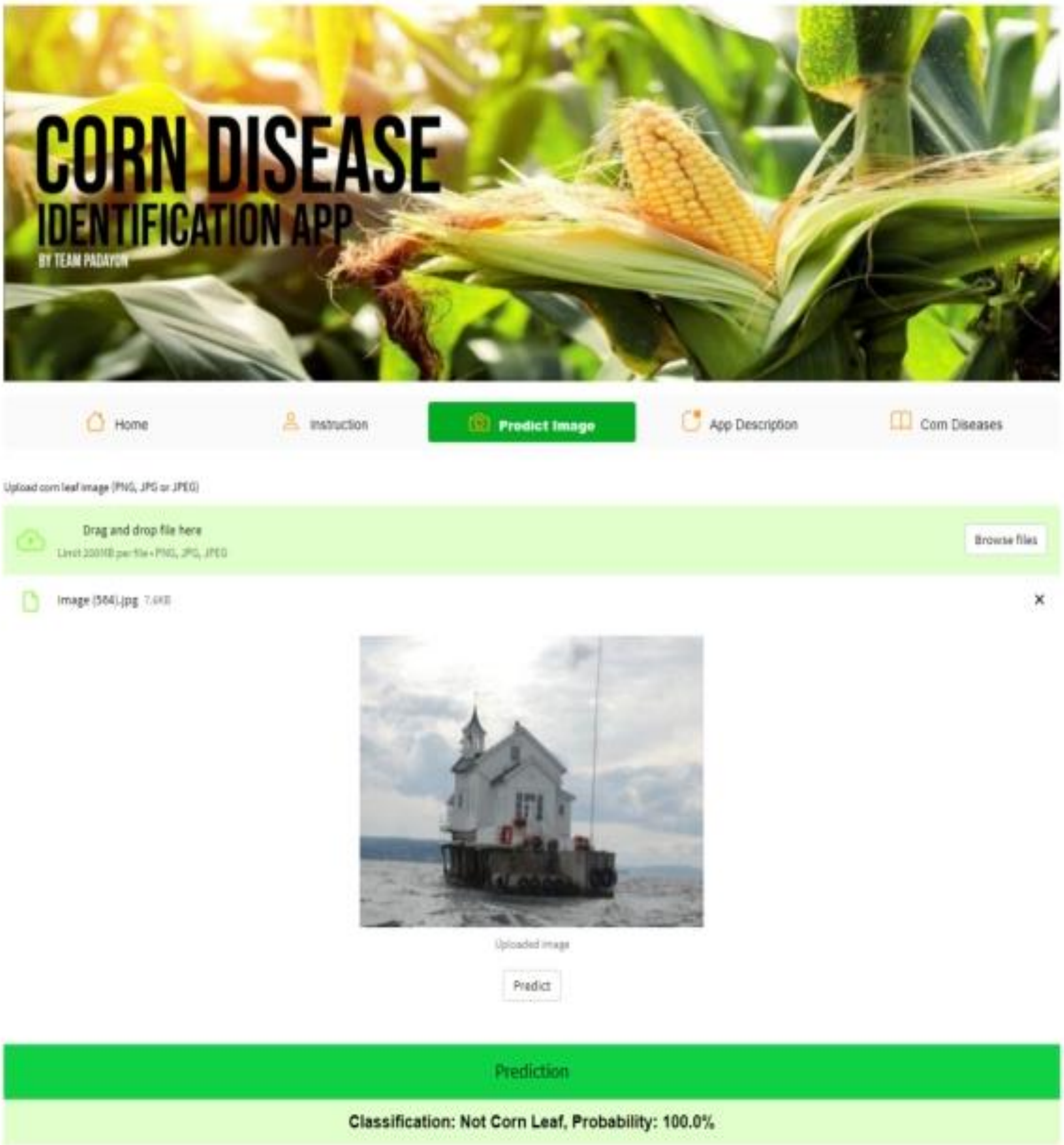

Figure 16. Prediction Page

Figure 16, shows the prediction of the system if the uploaded image does not belong the to type of corn diseases. The prediction is composed of the classification and accuracy in percentage manner.

Figure 17. App Description Page

Figure 17, the app description page it shows the details concerning to the characterization of the system in terms of its development, purpose, technicality, schematic diagram of convolutional neural network, work of the app, and relevance of the technology.

Figure 18. Corn Diseases Page

Figure 18, differentiate the kind of corn diseases such as foliar fungal, southern rust, eyespot, gray leaf spot, tar spot, northern corn leaf blight, and common rust.

Disease Identification Process

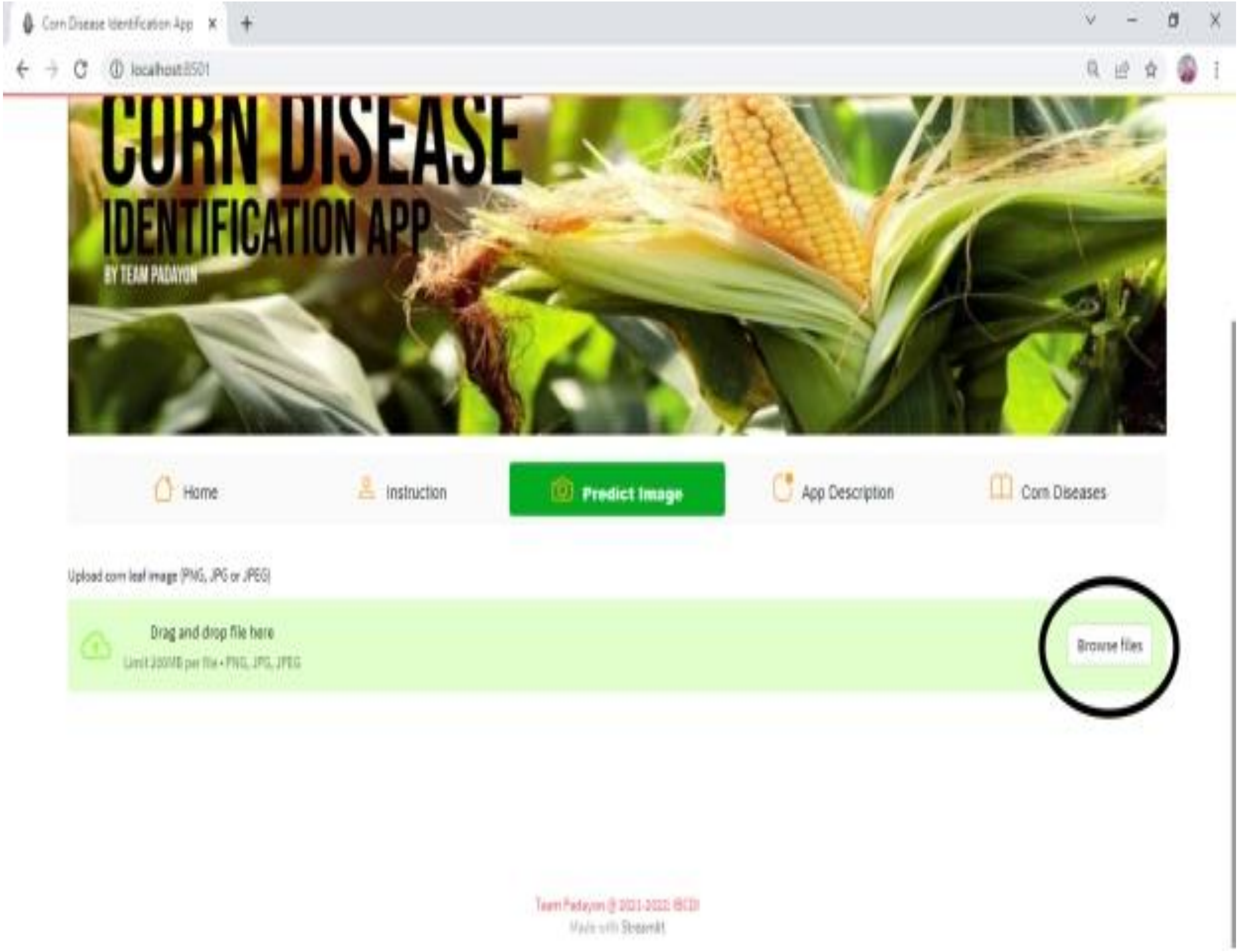

Figure 19. Browse image to identify.

In the prediction page, the user can able to upload corn leaf image in the form of png, jpg, or jpeg through clicking the browse files button.

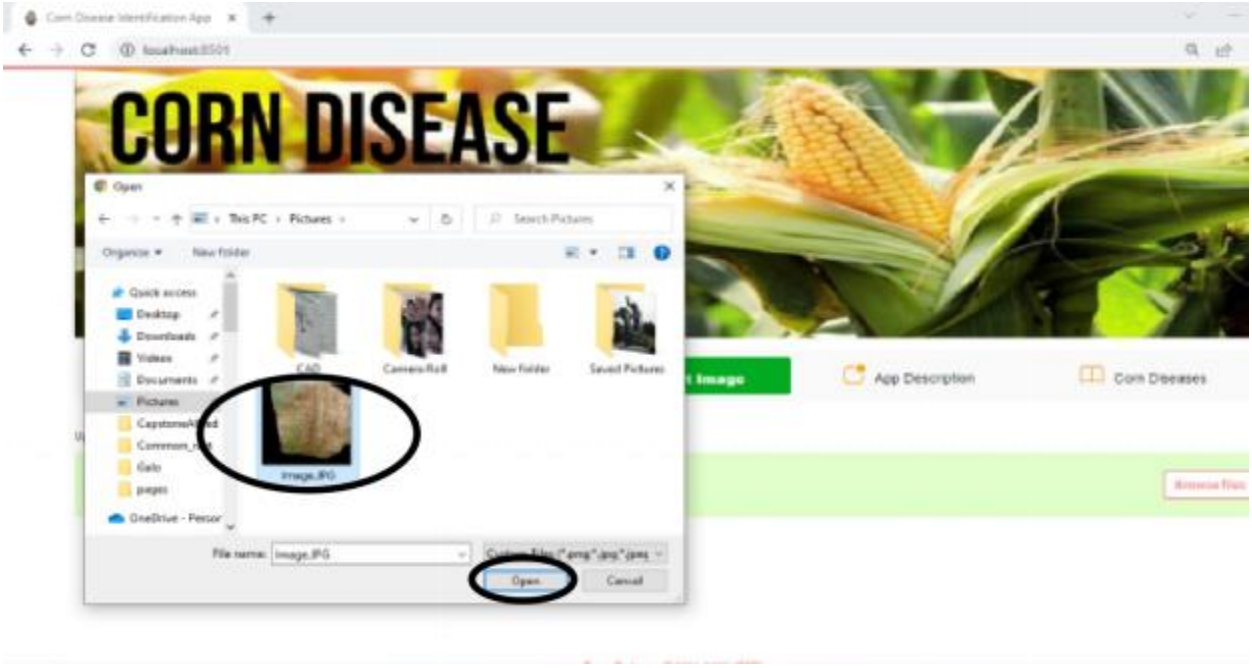

Figure 20. Select an image

Figure 20, illustrates on how to browse files, select and upload an image. After clicking the browse file button, a window will appear comprising the picture files where the user able to choose his/her desired picture to upload.

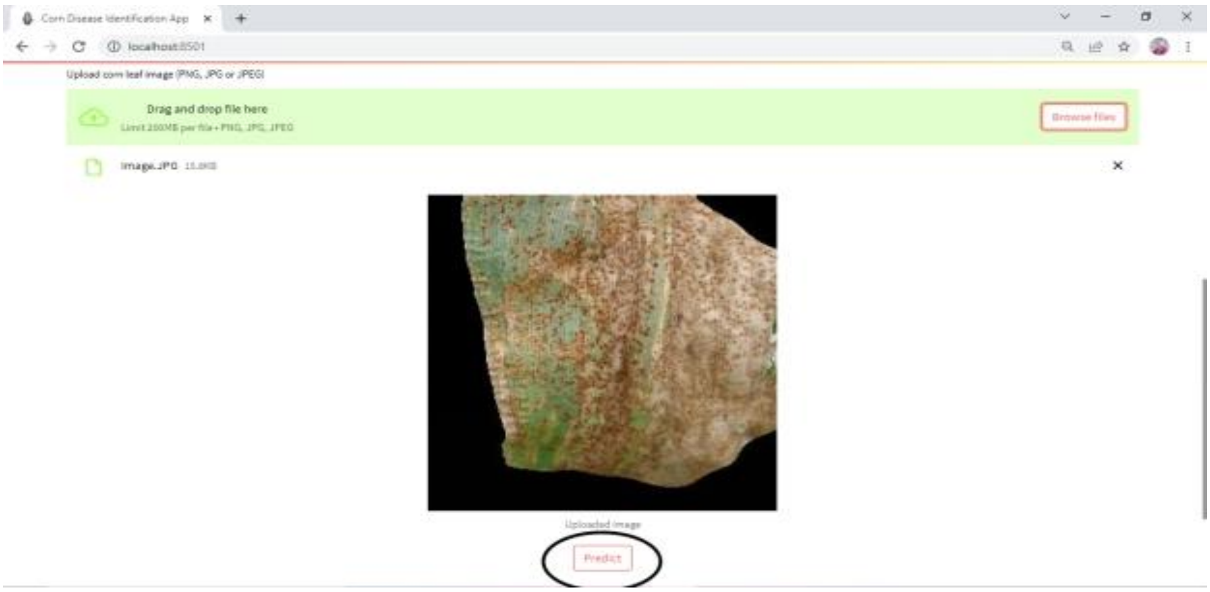

Figure 21. Predict button

Figure 21, This button functions to Predict an image. After clicking the button, the system will process its identification.

Figure 22. Prediction output

Figure 22, this shows the results of the uploaded image. If the uploaded image is a corn leaf disease, the system will classify its type and show its accuracy.

4.2.2 Data Design

Entity Relationship Diagram

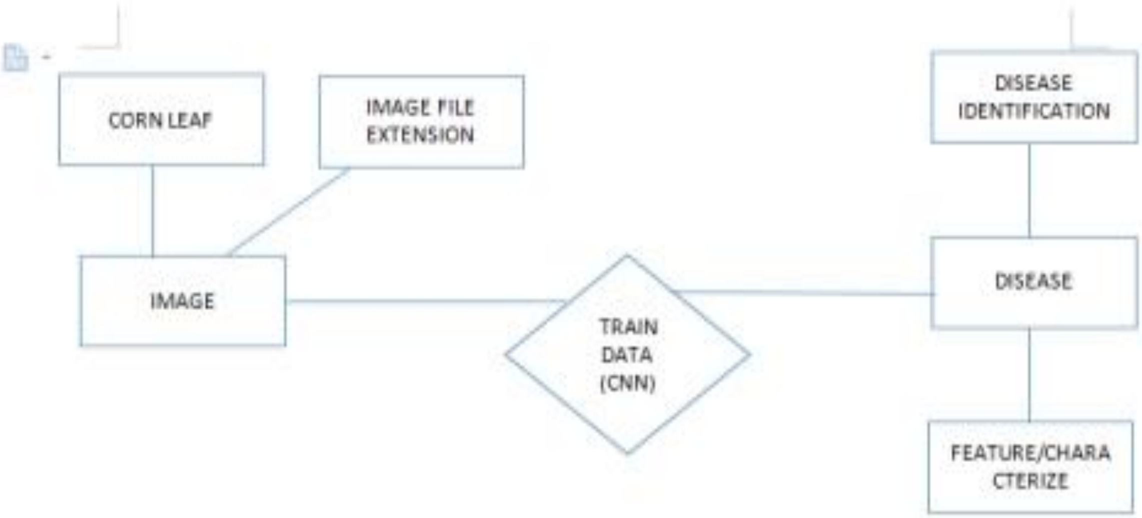

Figure 23. Entity Relationship Diagram

Data Dictionary

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

Classification	**Elements or display name**	**Definition**	**Quantity (Training)**	**Quantity (Validation)**	**Quantity (Testing)**	**Acceptable File extension**	**Required?**
C1	Common Rust	Symptoms of common rust are chlorotic flecks on the leaf surface.	952	119	10	JPG, JPEG, PNG	Y
C2	Eye Spot	The initial symptoms of eyespot are small, water-soaked or chlorotic circular spots.	47	10	10	JPG, JPEG, PNG	Y

C3	Gray Leaf Spot	Symptoms first appear on lower leaves about two to three weeks before tasseling.	460	57	10	JPG, JPEG, PNG	Y
C4	Northern Leaf Blight	Symptoms usually appear first on the lower leaves. Symptoms usually appear first on the lower leaves.	916	114	10	JPG, JPEG, PNG	Y
C5	Southern Rust	Symptoms are similar to common rust. Symptoms are similar to common rust, but pustules are smaller and occur almost exclusively on the upper leaf surface.	116	12	10	JPG, JPEG, PNG	Y
C6	Tar Spot	Tar spot appears as small, raised, black spots scattered across the upper and lower leaf surfaces.	66	10	10	JPG, JPEG, PNG	Y
C7	Healthy	Young / Mature Healthy Green Leaf	930	116	10	JPG, JPEG, PNG	Y
C8	Not A Corn Leaf	Not a Corn Leaf	733	91	10	JPG, JPEG, PNG	Y

Table 4. Data Dictionary

4.2.3 System Architecture

Network Model

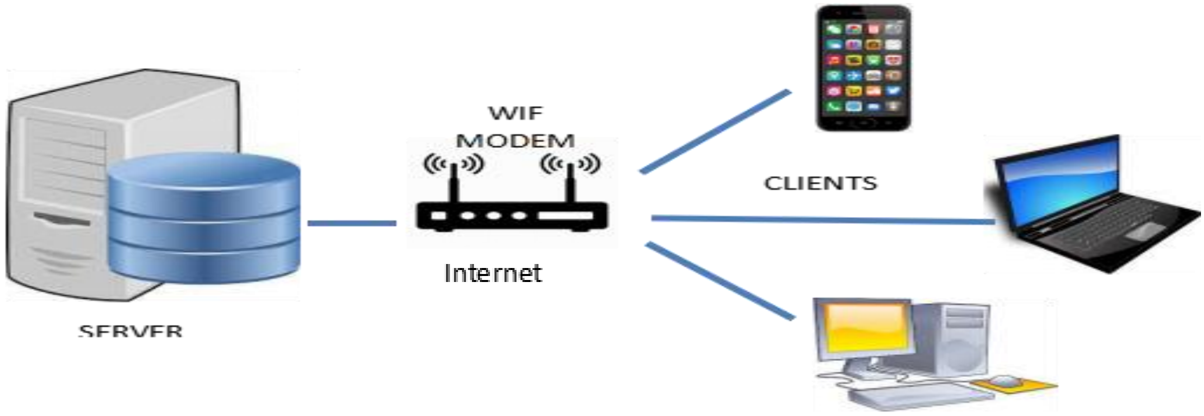

Figure 24. Network Model

Figure 24 represents the relationship of the 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 Corn Disease Identifier 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 corn plant in which aims to identify several types of corn 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 corn 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	4gb
Processor	Intel ® Core ™ i3-8145U CPU @ 2.10GHz 2.30 GHz
Storage	117gb Windows-SSD

4.3.3 Program Specification

Image-Based Corn Disease Identifier is capable of detecting varieties of corn 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 corn plant diseases. Using image processing to create an algorithm that will detect all of the corn 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 3.6

4.3.5 Deployment Diagram

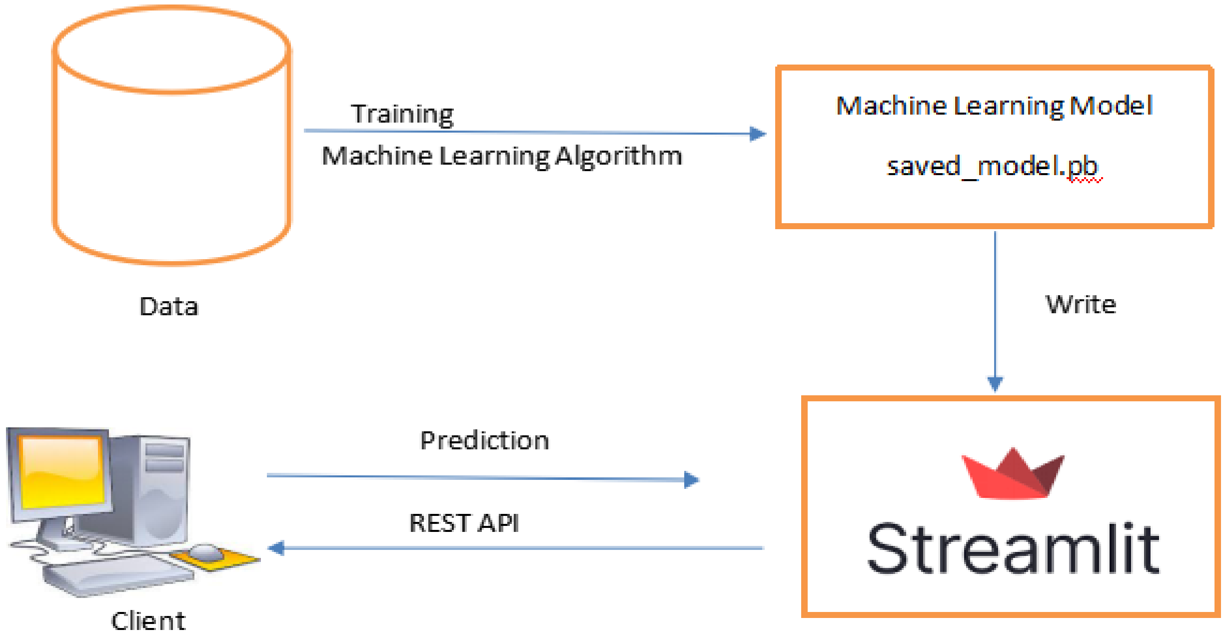

Figure 25. Deployment Diagram

4.3.6 Test Plan

Test Phase	Duration(days)	Tester	Reviewer	Date(s)	Status
Unit Testing	4 1/2 days	Mark RJ Marte	Mark Vincent Casilac	December 5- 9, 2021	Finish
Integration Testing	7 days	Mark RJ Marte	Mark Vincent Casilac	December 24-30,2021	Finish
Compatibility Testing	7 days	Mark Vincent Casilac	Roque Pajuyo	December 24-30, 2021	Finish
Performance Testing	1 1/2 days	Mark Vincent Casilac	Roque Pajuyo	January 7,2022	Finish
Stress Testing	7 days	Mark Vincent Casilac	Mark RJ Marte	January 9-15, 2022	Finish

Load Testing	2 days	Mark Vincent Casilac	Roque Pajuyo	January 20-22, 2022	Finish
System Testing	5 days	Mark Vincent Casilac	Roque Paajuyo	January 26-31,2022	Finish

Table 5. Test Plan

4.4 Testing

4.4.1 Unit Testing

To be able to determine the quality of the system, the classification model must be tested. The model was created using 4222 training images samples with 8 different classes from DateSet repository. It was combined together with 521 validation samples and trained for 100 epochs. The result of the training gained a total of 0.98544 or 98% highest training accuracy.

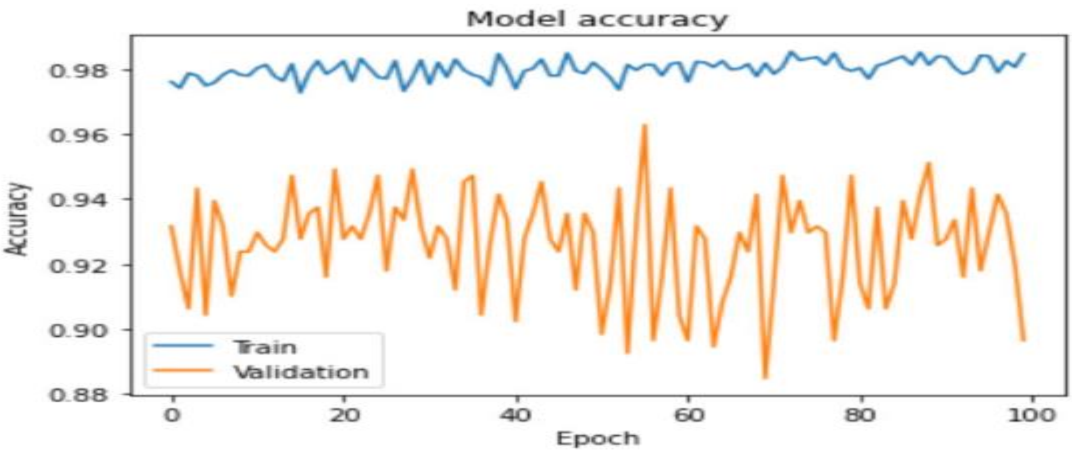

Figure 26. Model Accuracy

4.4.2 Integration Testing

The classification model was integrated to the Graphical User Interface (GUI) using streamlit framework. The model was tested using random images from the 521 test samples, captured images from webcams and phone cameras. The result of the test was similar to the performance during the model evaluation and concluded that it was a successful integration to the GUI.

4.4.3 Compatibility Testing

The application was tested in different computer devices and smartphones capable to view web pages to monitor its capability to operate in different devices. The application was deployed in the following devices:

Device Type	Model	Specification
Personal Computer	Lenovo i3	Windows 10, Core i3
Laptop	Acer Aspire 3	Windows 10, Core i5
Laptop	Dell Inspiron 3431	Windows 7, Celeron D
Android	Huawei Y6 Pro	Android 9, 3gb RAM
Android	Samsung J730	Android 9, 2gb RAM
Iphone	6S Plus	iOs 12.5.5, 2gb RAM
Android	Cherry Mobile Flare S8	Android 6, 1gb RAM

Table 6. Compatibility Testing

Deployment of the application to the devices stated on the table above was successful and works in its expected performance. There are cases on some android devices where the application seems to be a bit slow in showing and predicting the image due to low memory (RAM) installed on those devices. The suggested android device must have at least 1gb of RAM.

4.4.4 Performance Testing

Figure 27. Desktop-Based Prediction Output

Figure 27 shows output a desktop sample output of a corn leaf image taken from the internet with a common rust disease, the application was able to predict the disease with a 100% probability.

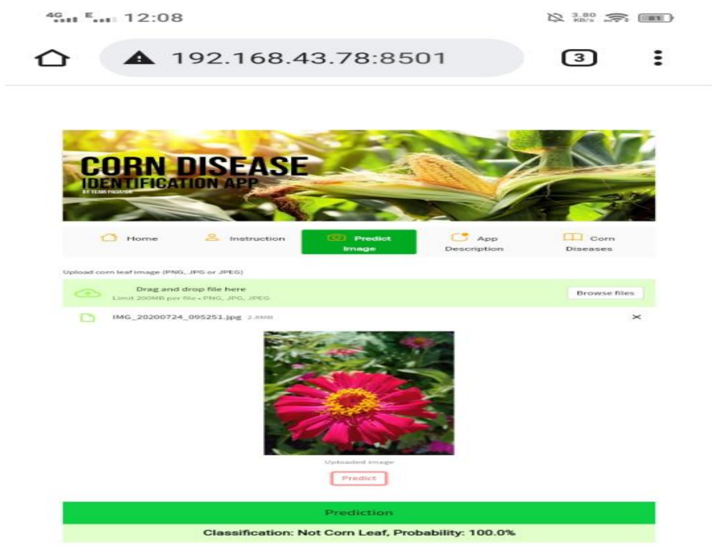

Figure 28. Smartphone-Based Prediction Output

While figure 28 shows a smartphone sample output of a mouse where the image was taken from the phone camera and directly upload to the application. The application was able to predict that uploaded image is not a corn leaf with 100% probability.

4.4.5 Stress Testing

The test for the application overall performance was successful, but it is also important to test the capability of the system when it is used beyond its expected usage. The application only caters three file formats, PNG, JPG and JPEG. Hence, the application was tested using different file formats that was considered as an invalid input, the expected output was achieve by giving an error message that such a file is not allowed on the system.

Figure 29. Error Message

4.4.6 Load Testing

The application was test by simulating multiple users that will access the it simultaneously via local host network. The test was conducted using 8 different devices (clients) connected to a single MODEM/ WIFI connection, the test was successful, the response time between the computer server and the clients is fast and the result was given accurately as expected. And the application can identify either uploaded image was a corn leaf or not.

4.4.7 System Testing

The application was tested using six different methods, with all of the test was all successful, it can be concluded the overall system is successful. The application was deployed on a single desktop unit connected through a local host network, access it using web browsers on different devices and tested its capability to predict. The application was able to perform a result as expected.

CONCLUSION AND RECOMMENDATIONS

The importance of advanced technology in this modern world is a way to accomplish things more accessible and easier. This system will bridge the gap between a traditional technique that the farmer does and the interest of using a advanced technology in identifying a corn disease. All the objectives of this study were successfully achieved. The system is able to identify a corn disease and the features were effective for recognizing a corn leaf disease. The study was able to develop a corn leaf disease recognizer with an accuracy 98.54%.

However, this study has a lot of rooms for improvement, first is to further improve the performance of the classification model and also consider to include other currently discovered corn leaf diseases. The system developed in this study was only able to recognized 6 corn leaf diseases, and it can identify if the uploaded image is not a corn leaf. It is hereby recommended that the system include other corn leaf diseases

IMPLEMENTATION PLAN

Project Implementation Checklist

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

No.	**Tasks**	**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

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

Implementation contingency

The table below shows the projects implementation contingency plan. The following are the listed task and contingencies that the proponents intended contingency implementation for each possible problem that would prevent the completion of the project.

No.	**Task**	**Contingency**
1.	System Presentation Session	During the session/meeting the system presentation plan should have backup.
2.	Data Gathering	If the images are not accepted, gather clear images that based on the data.
3.	System Testing	During the system testing. The system source code should have backup to make it testable and safer for testing.
4.	Data Recovery Strategies	Identify possible causes. Store all data resources and examine any possible loophole.

Table 8. Implementation contingency

BIBLIOGRAPHY

Sumita Mishra, Rishabh Sachan, And Diksha Rajpal, 2020 “Deep Convolutional Neural Network based Detection System for Real-Time Corn Plant Disease Recognition” International Conference on Computer Intelligence and Data Science.

Fedra Trujillano, Andres Flores, Carlos Saito, Mario Balcazar, And Daniel Racoceanu, 2018 “Corn Classification Using Deep Learning with UAV Imagery. An Operational Proof of Concept” Department of Engineering Pontificia Universidad Catolica del Peru, Lima, Peru.

Zhang Z., He X., Sun X., Gou L., Wang J., Wang F., 2015 “Image Recognition of Maize Leaf Disease Based on GA-SVM” Chemical Engineering Transaction.

Koushik Bhattacharyya, Ram Lal, 2020 “Classification of Leaf Disease using Image Processing and Machine Learning” International Research Journal of Innovations in Engineering & Technology.

Prakuti Bhatt, Sanat Sarangi, 2019 “Detection of Disease and Pests on Images Captured in Uncontrolled Conditions From Tea Plantations” researchgate.net.

Cueva F M Dela, Castro A M De, And Torres R L De, 2020 “Peronosclerospora Philippinensis (Philippine Downey Milder of Maize) Invasive Species Compendium.

Kumar, Sashin, Sumita Mishara, And Pooja Khanna, 2017 “Precision Sugarcane Monitoringg Using SVM Classifier” Procedia Computer Science, Vol. 22: 881-887.

Dechant, 2017 “Automated Identification of Northern Leaf Blight-Infected Miaze Plants from Field Imaginery Using Deep Learning” Phytopathology, Vol.107, no.11, pp.1426-1432.

Jayme Garcia, Arnal Barbedo, 2019 “Plant Disease Idnetification from Individual Lesions and Spots Using Deep Learning” Biosystems Engineering, Volume 180, Pages 96-107.

Jonah Flor Orano, Chris Jordan Aliac, Elmer Maravillas, And Jannie Fleur Orano, 2018 "JackFruit Phytophthora Palmivora (Butler) Disease Recognizer Uisng Mamdani Fuzzy Logic" researchgate.net.

Enquhone Alehegn, 2017 "Maize Leaf Diseases Recognition and Classification Based on Imaging and Machine Learning Techniques" semanticsholar.org.

N. Kanaka Durga, G. Anuradha, 2019 "Plant Disease Identification Using SVM and ANN Algorithms" International Journal of Recent Technology and Engineering.

Prakruti Bhatt, Sanat Sarangi, Anshul Shivhare, Dinesh Singh, 2019 "Identification of Disease in Corn Leaves Using Convolutional Neural Networks and Boosting" International Conference on Pattern Recognition Applications and Methods.

APPENDICES

APPENDICES A

RELEVANT SOURCE CODE

Model Training Source Code

```
In [1]: from keras import optimizers
        from keras.preprocessing.image import ImageDataGenerator
        from keras.models import Sequential
        from keras.layers import Conv2D, MaxPooling2D
        from keras.layers import Activation, Dropout, Flatten, Dense
        from keras import backend as K
        from keras.callbacks import EarlyStopping, ModelCheckpoint
        from tensorflow.keras.layers import BatchNormalization
```

```
In [2]: # image dimension
        img_width, img_height = 64, 64

        # training and validation set directory
        train_data_dir = 'DataSet/Training'
        validation_data_dir = 'DataSet/Validation'

        num_train_samples = 4222
        num_validation_samples = 521

        epochs = 20
        batch_size = 32

        input_shape = (img_width, img_height, 3)
```

```
In [3]: # this is the augmentation configuration use for training
        train_datagen = ImageDataGenerator(
            rotation_range=30,
            width_shift_range=0.2,
            height_shift_range=0.2,
            rescale=1./255, #to normalize the data
            shear_range=0.2,
            zoom_range=0.2,
            horizontal_flip=True
        )
```

```
In [4]: # this is the augmentation configuration use for testing:only rescaling
        test_datagen = ImageDataGenerator(rescale=1./255)

        train_generator = train_datagen.flow_from_directory(
            train_data_dir,
            #color_mode = 'grayscale',
            target_size=(img_width, img_height),
            batch_size=batch_size,
            class_mode='categorical')

        validation_generator = test_datagen.flow_from_directory(
            validation_data_dir,
            #color_mode = 'grayscale',
            target_size=(img_width, img_height),
            batch_size=batch_size,
            class_mode='categorical')
```

```
In [5]: #Building the model
model = Sequential()
model.add(Conv2D(32, (3, 3), input_shape=input_shape))
model.add(Activation('relu'))
model.add(MaxPooling2D(pool_size=(2, 2)))

model.add(Conv2D(64, (3, 3)))
model.add(Activation('relu'))
model.add(MaxPooling2D(pool_size=(2, 2)))

model.add(Conv2D(128, (3, 3)))
model.add(Activation('relu'))
model.add(MaxPooling2D(pool_size=(2, 2)))

model.add(Conv2D(128, (3, 3)))
model.add(Activation('relu'))
model.add(MaxPooling2D(pool_size=(2, 2)))

model.add(Flatten())

# Fully connected Layer
model.add(Dense(128))
model.add(BatchNormalization())
model.add(Activation('relu'))
#model.add(Dropout(0.5))
model.add(Dense(128))
model.add(BatchNormalization())
model.add(Activation('relu'))
model.add(Dropout(0.5))
model.add(Dense(8))
model.add(Activation('softmax'))

model.compile(loss='categorical_crossentropy',
              optimizer='adam',
              metrics=['accuracy'])

# to print the summary of the Layers
model.summary()
```

```
In [32]: from keras.models import load_model

new_model = load_model("Model")
EPOCHS=100
checkpoint = ModelCheckpoint(filepath, monitor = 'accuracy', verbose = 1, save_best_only = True, mode = 'max')
history = new_model.fit(
    train_generator,
    steps_per_epoch=num_train_samples // batch_size,
    epochs=EPOCHS,
    validation_data=validation_generator,
    validation_steps=num_validation_samples // batch_size,
    callbacks = [checkpointer]
)
```

```
In [33]: model.save('Model')

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

```
In [35]: #TRAINING HISTORY VISUALIZATION
import matplotlib.pyplot as plt


#TRAINING HISTORY VISUALIZATION

# Plot training & validation accuracy values
plt.plot(history.history['accuracy'])
plt.plot(history.history['val_accuracy'])
plt.title('Model accuracy')
plt.ylabel('Accuracy')
plt.xlabel('Epoch')
plt.legend(['Train', 'Validation'], loc='lower left')
plt.show()

# Plot training & validation loss values
plt.plot(history.history['loss'])
plt.plot(history.history['val_loss'])
plt.title('Model loss')
plt.ylabel('Loss')
plt.xlabel('Epoch')
plt.legend(['Train', 'Validation'], loc='upper left')
plt.show()
```

```
In [37]: model.save('Model')

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

Figure30. Model Training Source Code

Web Application Main File Codes

```python
from App_Pages import Home,Instruction,AppDescription,CornDiseases,Predict
import streamlit as st
import streamlit.components.v1 as components
from streamlit_option_menu import option_menu


st.set_page_config(

    page_title="Corn Disease Identification App",
    page_icon="App Images/corn.ico",
    layout="wide",
    initial_sidebar_state="expanded",
)
st.markdown('<style>body{text-align: center;}</style>', unsafe_allow_html=True)


hide_menu_style = """
        <style>
        #MainMenu {visibility: hidden;}
        footer {visibility: visible;}

        footer:before{
            content: 'Team Padayon @ 2021-2022: IBCDI';
            color: #FF4B4B;
            display: block;
            position: relative;
            padding 2px;
            top: 3px;
        }
        </style>
    """
st.markdown(hide_menu_style,unsafe_allow_html=True)
```

```python
st.image('App Images\Header.jpg',use_column_width=True)

choose = option_menu("", ["Home", "Instruction","Predict Image", "App Description", "Corn Diseases"],
                     icons=['house', 'person lines fill','camera fill', 'app-indicator', 'book'],
                     menu_icon="menu-button-fill", default_index=0, orientation= 'horizontal',
                     styles={
        "container": {"padding": "5!important", "background-color": "#fafafa"},
        "icon": {"color": "orange", "font-size": "25px"},
        "nav-link": {"font-size": "16px", "text-align": "center", "margin":"0px", "--hover-color": "#eee"},
        "nav-link-selected": {"background-color": "#02ab21"}
    }
    )



if choose == "Home":
    Home.app()
elif choose == "Predict Image":
    Predict.app()
elif choose == "App Description":
    AppDescription.app()
elif choose == "Corn Diseases":
    CornDiseases.app()
elif choose == "Instruction":
    Instruction.app()
```

Figure 31. Web Application Main File Codes

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 = 64
    classes = [
    'Common Rust',
    'Eye Spot',
    'Gray Leaf Spot',
    'Northern Leaf Blight',
    'Not Corn Leaf',
    'Southern Rust',
    'Tar Spot',
    'Healthy']
    model_path = r'Model'
    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
```

Figure 32. Model File Codes

Home Page File Codes

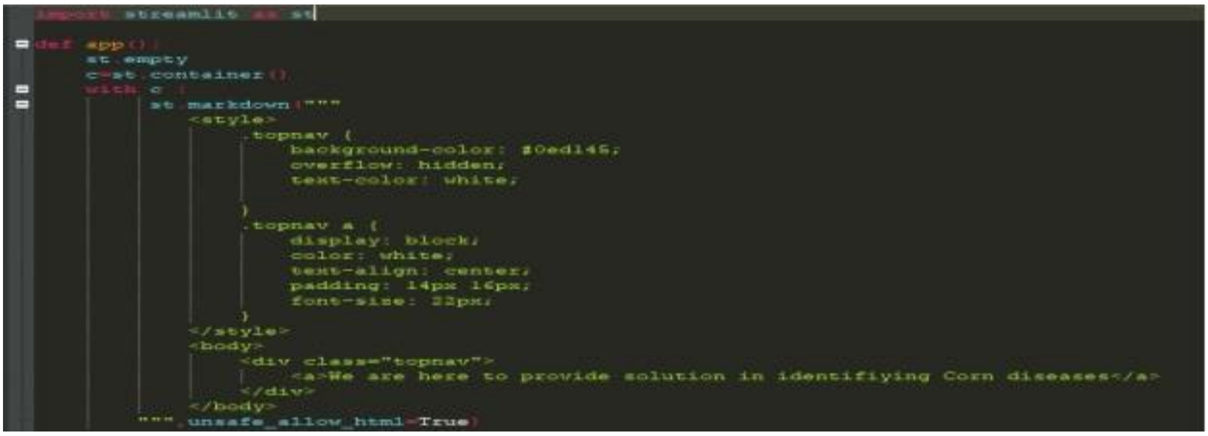

Figure 33. Home Page File Codes

Instruction Page File Code

```
import streamlit as st

def app():
    st.empty()
    c=st.container()
    with c :
        st.markdown("""
        st.image('App Images/I1.png',use_column_width=True)
        st.markdown("""
        st.image('App Images/I2.png',use_column_width=True)
        st.markdown("""
        st.image('App Images/I3.png',use_column_width=True)
        st.markdown("""
        st.image('App Images/I4.png',use_column_width=True)
        st.markdown("""
        st.image('App Images/I5.png',use_column_width=True)
        st.text('')
        st.text('')
        st.text('')
        st.text('')
        st.markdown("""

        st.image('App Images/I6.png',use_column_width=True)
        st.markdown("""
        st.image('App Images/I7.png',use_column_width=True)
        st.markdown("""
        st.image('App Images/I8.png',use_column_width=True)
        st.markdown("""
        st.image('App Images/I9.png',use_column_width=True)
```

Figure 34. Instruction Page File Codes

Predict Page File Code

```python
import streamlit as st
from model import predict

import requests
from streamlit_lottie import st_lottie

def load_lottie(url):
    r = requests.get(url)
    if r.status_code !=200:
        return None
    return r.json()

def app():
    st.empty
    st.text("")
    img = st.file_uploader(label='Upload corn leaf image (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, channels = "RGB")
        col3.text("")
        predict_button = st.button(label='Predict')
        if predict_button:
            st.text('')
            st.text('')
```

```python
            try:
                prediction_class, prediction_probability = predict(img)
                c=st.container()
                with c :
                    st.markdown("""
                        <style>
                            .topnav {
                                background-color: #0ed145;
                                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;
                        font: bold 20px Arial;
                        background-color: #e1ffca;
                    }}
                    </style>
                    <p class="a">{a}</p>
                    """
                st.markdown(html_pre,unsafe_allow_html=True)
```

```python
            except ValueError:
                st.markdown("""
                        <style>
                            .topnav {
                                background-color: #ff4b4b;
                                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: #e1ffca;
                            }
                            .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 inputed is invalid for image reshaping and object detection.
                                <p>Please select another image. Thank you!</p></a>
                            </div>
                        </body>
                        """,unsafe_allow_html=True)
```

Figure 35. Predict Page File Codes

App Description File Codes

```
import streamlit as st


def app():
    st.empty()
    c=st.container()
    with c:
        st.markdown("""
        <style>
            #site_content{
                    width: 100%;
                    overflow: hidden;
                    background-color: #elffca;
                }
            .topnav {
                background-color: #0ed145;
                overflow: hidden;
            }
            .topnav a {
                display: block;
                color: #f2f2f2;
                text-align: left;
                padding: 14px 16px;
                text-decoration: none;
                font-size: 22px;
            }
            .Paragraph {
                background-color: #elffca;
                overflow: hidden;
            }
            .Paragraph a {
                display: block;
                color: black;
                text-align: Left;
                padding: 14px 16px;
                font-size: 17px;
            }
        </style>
        <body>
            <div class="topnav">
                <a>Technology Development</a>
            </div>
            <div class="Paragraph">
                <a>First, with the development of technology, the use of deep learning and image recognition
                    technology for plant disease detection has become an important research direction. This app,
                    is implementing a suitable and fast identification system with machine learning can solve the gap in
                    identifying and classifying the wide variety of corn diseases from images of plant leaves.
                    The identification model focused on using class labels for training images, and built a fine-grained
                    image classification system- a recognition method for corn disease images.</a>
            </div>
            <div class="topnav">
                    <a>App's Purpose</a>
                </div>
                <div class="Paragraph">
                    <a><p>In agriculture environment, image-based corn disease identifier is an advanced technology used to overcome
                    the problems related with all existing techniques of corn disease detection. Image-based corn decease identifier
                    provides very fast and more accurate result which help in disease management. Thus, this App serves as assistance
                    to farmers in preventing, manage and distinguish the variety of corn diseases in a short period of time.
                    We, the proponents of this App are in task of gathering available data sets of corn disease images in which this data
                    set will be used for training the system for it to be able to identify a variety of corn diseases. The system will accept
                    an image input from the user that will undergo object detection in which it will identify all corn diseases that is presented
                    in the image. This project is designed to identify a variety of corn disease. With the help of Image processing,we will implemented
                    an algorithm in which we can detect all of the corn disease in the provided image and identify it individually.
                    </p></a>
                </div>
                <div class="topnav">
                    <a>App's Technicality</a>
                </div>
                <div class="Paragraph">
                    <a><p>The Image-Based Corn Disease Identifier is a Computer-Based software application that identifies the disease of a corn plant.
                    The user can upload an image of a corn plant leaves so that the system can process it and the system can identify corn plant disease.
                    We, the proponents aimed for this software to be capable of running without the use of internet connection. This goal will be 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 corn plant diseases.</p></a>
                </div>
        </body>
        """,unsafe_allow_html=True)
    st.image('App Images\CNN.png',use_column_width=True)
    st.markdown("""
    st.image('App Images\HTW.PNG',use_column_width=True)
    st.markdown("""
```

Figure 36. App Description Page File Codes

Corn Diseases File Code

```python
import streamlit as st


def app():
    st.empty
    c=st.container()
    with c :
        st.markdown("""
        <style>
            .topnav {
                background-color: #0ed145;
                overflow: hidden;
            }
            .topnav a {
                display: block;
                color: #f2f2f2;
                text-align: left;
                padding: 14px 16px;
                text-decoration: none;
                font-size: 20px;
            }
            .Paragraph {
                background-color: #e1ffea;
                overflow: hidden;
            }
            .Paragraph a {
                display: block;
                color: black;
                text-align: left;
                padding: 14px 16px;
                font-size: 17px;
            }
        </style>
        <body>
            <div class="topnav">
                <a>What is Corn/Maize crops?</a>
            </div>
            <div class="Paragraph">
                <a><p>Maize, Zea mays, is an annual grass in the family Poaceae and is a staple food crop grown all over the world.
                he maize plant possesses a simple stem of nodes and internodes. A pair of large leaves extend off of each internode
                and the leaves total 8-21 per plant. The leaves are linear or lanceolate (lance-like) with an obvious midrib (primary vein)
                and can grow from 30 to 100 cm (11.8-39.4 in) in length. The male and female inflorescences (flower bearing region of the plant) a
                re positioned seperately on the plant. The male inflorescence is known as the 'tassel' while the female inflorescence is the 'ear'
                The ear of the maize is a modified spike and there may be 1-3 per plant. The maize grains, or 'kernels', are encased in husks and total 30-1000 per ear.
                The kernels can be white, yellow, red, purple or black. Maize is an annual plant, surviving for only one growing season and can
                reach 2-3 m (7-10 ft) in height.</p></a>
                <a style= "background-color: #aae27f" >Foliar Fungal Diseases</a>
            </div>
            <div class="Paragraph">
                <a><p>Several diseases are economically important for corn production. Most of the major corn diseases
                are foliar - meaning they affect the leaves - which vary from year to year because they are strongly influenced by
                weather conditions. Thus, accurate identification and an awareness of potential disease losses are essential for continued
                successful corn production. </p></a>
            </div>
        </body>
        """,unsafe_allow_html=True)




    st.text('')
    #Southern Rust
    c=st.container()
    with c :
        st.markdown("""
        <style>
            .topnav {
                background-color: #0ed145;
                overflow: hidden;
            }
            .topnav a {
                display: block;
                color: #f2f2f2;
                text-align: left;
                padding: 14px 16px;
                text-decoration: none;
                font-size: 22px;
            }
            .Paragraph {
                background-color: #e1ffea;
                overflow: hidden;
            }
            .Paragraph a {
                display: block;
                color: black;
                text-align: left;
                padding: 14px 16px;
                font-size: 17px;
            }
        </style>
        <body>
            <div class="topnav">
                <a>1. Southern Rust</a>
            </div>
            <div class="Paragraph">
                <a><p>Southern rust is caused by the fungus Puccinia polysora. Although generally considered a tropical disease,
                southern rust can occur in important corn production areas of the United States and Canada. Symptoms are similar
                to common rust, but pustules are smaller and occur almost exclusively on the upper leaf surface. Pustules are usually
                circular or oval, very numerous, and densely scattered over the leaf surface. Spores are orange
                when they erupt from the pustule. As pustules age, they become chocolate brown to black, often forming dark
                circles around the original pustule.</p></a>
                <a style= "background-color: #aae27f" >Southern Rust Cycle</a>
            </div>
            <div class="Paragraph">
                <a><p>Southern rust is caused by the fungus Puccinia polysora, which only infects corn.
                Pustules of southern rust are small (0.2 to 2 mm in diameter), circular to oval and light cinnamon
                brown to orange, they frequently form on the upper leaf surface and very rarely on the lower leaf surface
                (Figure 2). Southern rust pustules may occur on leaves, stalks, sheaths, and husks.
                <p>Southern rust is easily overlooked by the casual observer early in the season because initial infections are typically only one to two pustules per plant
                (Figure 1: Cycle). The absence of sporulation on the lower leaf surface early in the season is an indication of southern rust.
                As indicated earlier, rust sporulation on the lower leaf surface is associated with common rust, a minor disease. Early-season
                southern rust pustule development is most frequently observed in the field at mid-canopy (4 to 5 feet from the ground) along the edge
                of the field. Free moisture as dew or light rain is necessary for rust spores to germinate and infect. Symptoms appear about 3 to 6 days
                after infection, and by 7 to 10 days the pustules may rupture to expose more rust spores. Thus, new infections can occur very rapidly after
                the initial infection when conditions favor disease. Conditions that favor disease develop-ment consist of high temperatures (80° to 90°F),
                high relative humidity and frequent rainfall/ heavy dew. Even in hot summer conditions with temperatures above 100°F, pustules continue to
                sporulate, hence the name southern rust.</p></a>
            </div>
        </body>
        """,unsafe_allow_html=True)
    with st.expander("View Image"):
        st.image('App Images/Sr_cycle.png',use_column_width=True)
        st.image('App Images/Sr.png',use_column_width=True)
    st.text('')
```

Figure 37. Corn Diseases Page File Codes

Training Plot in Jupiter Note Book

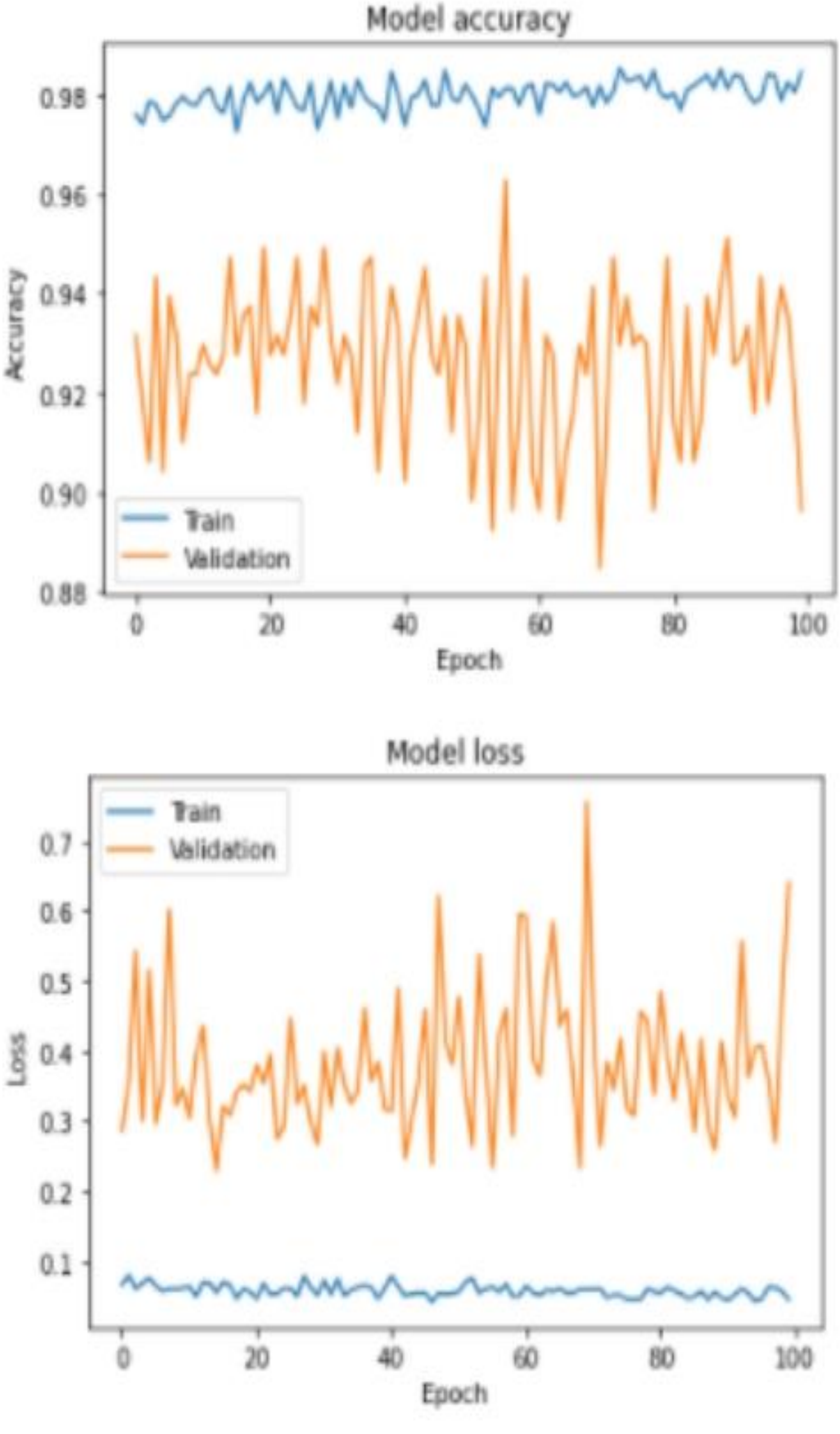

Figure 38. Training Plot in Jupiter Note Book

CURRICULUM VITAE

ANGELE ROSE M. DEJESICA

Himay-angan, Liloan, Southern Leyte
Cell number: 09683338917
E-mail Address: dejesicaangele15@gmail.com

OBJECTIVES

To be in a team in which I can contribute my knowledge with my passion and skills in creating and building a system that provide an opportunity to capitalize my skills and abilities.

PERSONAL INFORMATION:

NICKNAME: Gel

BIRTHDAY: January 15, 2000

AGE: 22

NATIONALITY: Filipino

RELIGION: Roman Catholic

CIVIL STATUS: Single

FATHER'S NAME: Reynaldo J. Dejesica

MOTHER'S NAME: Mercedita M. Dejesica

EDUCATIONAL BACKGROUND:

TERTIARY: SOUTHERN LEYTE STATE UNIVERSITY

Bachelor of Science in Information Technology

Major in Networking

Sogod, Southern Leyte

Ongoing

SECONDARY: SOUTHERN LEYTE STATE UNIVERSITY - CBM

Accountancy Business and Management

San Juan, Southern Leyte

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

MARK RJ MARTE

Bogo, Tommas Oppus, Southern Leyte
Cell number: 09058172767
Email Address: **markrjmarte9@gmail.com**

OBJECTIVES

To be in a team in which I can contribute my knowledge with my passion and skills in creating and building a system that provide an opportunity to capitalize my skills and abilities.

PERSONAL INFORMATION:

NICKNAME: Mart

BIRTHDAY: June 09,1999

AGE: 22

NATIONALITY: Pilipino

RELIGION: Roman Catholic

CIVIL STATUS: Single

FATHER'S NAME: Marcus Antonio Marte

MOTHER'S NAME: Elbie Marte

EDUCATIONAL BACKGROUND:

TERTIARY: SOUTHERN LEYTE STATE UNIVERSITY

Bachelor of Science in Information Technology

Major in Networking

Sogod, Southern Leyte

Ongoing

SECONDARY: Daun Agustin F. Stanio National High School

TVL- Computer Hardware Service

Tommas Oppus, Southern Leyte

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

ROQUE PAJUYO

Tigbao, Libagon, Southern Leyte
Cell number: 09150592146
Email Address: roquepajuyo77@gmail.com

OBJECTIVES

To be in a team in which I can contribute my knowledge with my passion and skills in creating and building a system that provide an opportunity to capitalize my skills and abilities.

PERSONAL INFORMATION:

Personal Information:

NICKNAME: Roq

BIRTHDAY: September 13, 1999

AGE: 22

NATIONALITY: Filipino

RELIGION: Roman Catholic

CIVIL STATUS: Single

FATHER'S NAME: Leonilo Pajuyo

MOTHER'S NAME: Helen Pajuyo

EDUCATIONAL BACKGROUND:

TERTIARY: SOUTHERN LEYTE STATE UNIVERSITY
Bachelor of Science in Information Technology

Major in Networking

Sogod, Southern Leyte

Ongoing

SECONDARY: SOUTHERN LEYTE STATE UNIVERSITY - MAIN CAMPUS

Technical Vocational Livelihood - Computer Hardware Servicing

Sogod, Southern Leyte

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

MARK VINCENT CASILAC

Rizal, Sogod, Southern Leyte
Cell number: 09753442050
Email Address: casilacmarkvincent@gmail.com

Objectives

To be in a team in which I can contribute my knowledge with my passion and skills in creating and building a system that provide an opportunity to capitalize my skills and abilities.

PERSONAL INFORMATION:

NICKNAME: Lhao

BIRTHDAY: April 06, 2000

AGE: 21

NATIONALITY: Filipino

RELIGION: Roman Catholic

CIVIL STATUS: Single

FATHER'S NAME: Alvin Casilac

MOTHER'S NAME: Clarita Escano

EDUCATIONAL BACKGROUND:

TERTIARY: SOUTHERN LEYTE STATE UNIVERSITY
Bachelor of Science in Information Technology
Major in Networking
Sogod, Southern Leyte
Ongoing

SECONDARY: SOUTHERN LEYTE STATE UNIVERSITY - MAIN CAMPUS
Technical Vocational Livelihood - Computer Hardware Servicing
Sogod, Southern Leyte

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

JAY MANGUILIMUTAN

Zone 5, Sogod, Southern Leyte
Cell number: 09678255270
Email Address: jayobbus24@gmail.com

OBJECTIVES

To be in a team in which I can contribute my knowledge with my passion and skills in creating and building a system that provide an opportunity to capitalize my skills and abilities.

PERSONAL INFORMATION:

NICKNAME: Jay

BIRTHDAY: September 24, 1999

AGE: 22

NATIONALITY: Filipino

RELIGION: Roman Catholic

CIVIL STATUS: Single

FATHER'S NAME: Rolando Manguilimotan

MOTHER'S NAME: Rosanna Manguilimotan

EDUCATIONAL BACKGROUND:

TERTIARY: SOUTHERN LEYTE STATE UNIVERSITY

Bachelor of Science in Information Technology

Major in Networking

Sogod, Southern Leyte

Ongoing

SECONDARY: SOUTHERN LEYTE STATE UNIVERSITY - MAIN CAMPUS

Technical Vocational Livelihood - Computer Hardware Servicing

Sogod, Southern Leyte

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

Republic of the Philippines

SOUTHERN LEYTE STATE UNVERSITY
Sogod, Southern Leyte
Website: www.slsuonline.edu.ph
Email: slsumaincampus@gmail.com
op@slsuonline.edu.ph
Telefax No. (053) 382-3294

College of Computer Studies and Information Technology

CAPSTONE PROJECT HEARING NOTICE

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

DEPARTMENT: CCSIT
Research Title: IMAGE-BASED CORN DISEASE IDENTIFIER

Proponents:

Angele Rose Dejesica
Mark RJ Marte
Roque Pajuyo
Mark Vincent Casilac
Jay Manguilimotan

CERTIFICATION

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

ALEX C. BACALLA
Panel Chairman

GERALDING MANGMANG
Panel 1

JAMES BRIAN FLORES
Panel 2

APPROVE BY:
ALEX C. BACALLA
Dean CCSIT