CHAPTER 1 INTRODUCTION TO THE STUDY

Background of the Study and Theoretical Framework

Rice holds paramount importance as the predominant staple crop in Asia, specifically in the Philippines. The agricultural sector generates 14 percent of the country's GDP and employs 13 million people (32% of the total workforce) (Arnaoudov et al., n.d.). Unfortunately, when various insect pests infest rice, both quantity and quality may be lost.

Farmers worldwide use pesticides to prevent agricultural damage caused by insect pests. However, farmers also rely on insect pollinators to increase agricultural yields and other insects as natural pest adversaries (Kirkeby, 2021). Crop insect identification poses a challenge for farmers because insect pest attacks cause crop damage and quality degradation (He, 2019).

These challenges arise due to similarities among insect species and their lack of information about insect pests and the damage they carry on rice. Furthermore, pesticide misuse and crop protection malpractice have shown to cause more harm than good, resulting in significant economic losses and severe environmental degradation (Guian et al., 2021).

Therefore, identifying insect pests and beneficial insects accurately to target pesticides only on insect pests were necessary to avoid sustained economic damage and retain beneficial insects in the rice fields.

As a result of the growing interest in sustainable agriculture, some researchers discovered that its application to diagnose crop diseases and pests had expanded (He, 2019). Several studies have been conducted to develop deep learning model-based pest detection, with the results indicating that they are more capable of adapting to complicated field conditions than traditional detection methods. Due to the rapid advancement of deep learning in object detection, numerous deep detection models have been presented in recent years. Typical detectors include the Faster R-CNN (Liu, 2018), the R-FCN (Xue & Li, 2018), the YOLO (you only look once) (Shaifee et al., 2017), and the SSD (single-shot multibox detector) (Liu, 2016), among others. The general assessment of these two-stage detectors is that they are highly precise in detection but have a high computational cost. On the other hand, one-stage detectors such as YOLO and SSD are less accurate but faster, making them suitable for mobile devices (He, 2019). Moreover, the Single Shot MultiBox Detector (SSD) is an algorithm that uses a single shot to detect several objects within an image, while the MobileNet is an identification and classification neural network (Ileladewa, 2020).

Furthermore, this study aimed to develop a mobile application named Inspestor, which employs SSD MobileNet, a Deep Learning model, to identify insect pests in rice fields and recommend pesticides. This study aimed to develop a mobile application that give farmers and other essential users insect pest information, such as the insect pest's name and recommended pesticide. In this study, the SSD MobileNet model based on deep learning is used to identify insect pests on rice fields, along with prescribed Department of Agriculture-approved pesticides. The data utilized to train the models came from an image collection gathered from in-field traps collected by the researchers.

The proposed system for Pest Classification and Pesticide Recommendation System by Kyaw et al. (2019) is a significant step forward in the pest control industry. This system is based on the Convolutional Neural Network model, GoogLeNet, which is a commonly used model in deep learning for image processing. The system aimed to provide users with easy access to information on pests and the corresponding pesticides to be used for effective pest control.

The framework of the system involves two stages: training and testing. In the training stage, a dataset of 1265 pest images are used to train the model. The training data consists of four types of pest images, which are used to train the CNN model. The model then extracts features from the pest images and stores them in a CNN feature set.

In the testing stage, the user inputs the test pest image, which is classified by the CNN model. The system then provides the results of the pest classification and recommends the most suitable pesticide for the identified pest. This system has the potential to revolutionize the pest control industry by providing a more efficient and accurate way of identifying pests and recommending appropriate pesticides.

However, the proposed Insect Pest Identification App with prescribed pesticide using SSD MobileNet model based on deep learning is anchored to be more advanced and sophisticated than the system proposed by Kyaw et al. (2019). The use of the SSD MobileNet model is an improvement over the GoogLeNet model, as it is a more accurate and efficient object detection algorithm. Additionally, the research study used a larger dataset of 24,000 images to train the model, which is almost 20 times larger than the dataset used in the study of

Kyaw et al. (2019). This will likely result in a more accurate and reliable model that can identify a wider range of pests.

Furthermore, the proposed app provides prescribed pesticide recommendations based on the identified pest, which goes beyond the scope of the system proposed by Kyaw et al. (2019). This additional feature provides more comprehensive and personalized guidance for users, making the app a valuable tool for pest control professionals and farmers.

Overall, the use of advanced deep learning models, larger datasets, and the inclusion of prescribed pesticide recommendations in the proposed system and app have the potential to significantly improve pest control practices and help reduce the negative impact of pests on agriculture and the environment.

Figure 1 illustrates the structure of processing information of the mobile application using the Input-Process-Output (IPO) Model. The inputs include the insect pests found on rice fields and the corresponding pesticides. This input is necessary in order to generate the output. The process begins with collecting insect pest names and pesticide data, followed by the development and training of a TensorFlow model to categorize the insect pest's image, and finally, the development of the prototype. This procedure was necessary in order to obtain the result. Lastly, the output provides users with the insect pest's name and recommended pesticide.

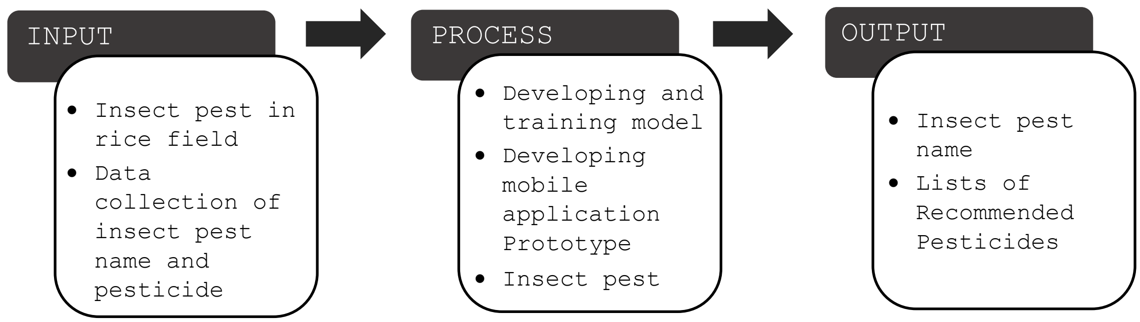


Figure 1. Input-Process-Output (IPO) Model of the System

Objectives of the Study

At the end of the study, the researchers developed a mobile application for Insect Pest Identification with Prescribed Pesticide in Rice fields Using SSD MobileNet Model on Deep Learning.

Specifically, it aimed to:

1. develop a system that will utilize SSD MobileNet Model to detect and identify insect pests in rice fields;
2. develop a mobile application that gives farmers information about the insect pest's name and recommended pesticides;

3. together with an IT expert, evaluate the application's accuracy detection based on Mean Average Precision (mAP);and
4. evaluate the application performance based on ISO 25010 along with an IT Expert, Department of Agriculture and Farmers.

Significance of the Study

The goal of this research was to create a mobile application for identifying insect pests and prescribing pesticides on rice fields.

This research involved using an app to capture an image of an insect pest, analyzing it using object detection and deep learning algorithms, and providing information on the insect pest collected as well as the appropriate pesticide to use in eliminating it.

Specifically, the following sectors or groups may this benefit from the results of the study:

- Farmers. This study increases understanding of the farmers in the various types of insect pests that may be found on rice fields, as well as the best pesticides to eradicate them.

- Department of Agriculture (DA) Region VI. Through this study, the DA may utilize the app as a tool to promote initiatives or advocacies aimed at teaching farmers how to cope with rice field infestations.
- Fertilizer and Pesticides Authority (FPA). This study might provide an innovative platform for FPA to inform key users on pesticide recommendation. Nonetheless, they may utilize the mobile app to determine proper pesticide and its general information and management steps in order to avoid significant financial losses and major environmental damages while also preserving beneficial insects.
- Other essential users. Agriculturists and common users who can use the mobile app in this study can learn about various insect pests found on rice fields and its recommended pesticide.
- Future researchers. This study covers information involving insect pest identification and elimination by means of Department of Agriculture-approved pesticide recommendations. As a result, this research can be used as a baseline for future discussions about the capabilities of deep learning and object detection in agricultural sectors.

Definition of Terms

To aid comprehension, the following terms were conceptually and operationally defined:

Deep Learning -- refers to the type of machine learning and artificial intelligence (AI) that imitates the way how humans gain certain types of knowledge (Burns & Brush, 2021).

In this study "deep learning," referred to a technique for providing an application with highly accurate object detection and image classification.

Insect Pest -- refers to insects or other invertebrates damaging plants or plant products (Insect Pests Definition, 2018).

In this study "insect pest," referred to the subject in this study that will be identified using the mobile application to prescribe a pesticide recommendation.

Mean Average Precision -- refers to the most meaningful metric for object detectors, instance, and semantic segmentation (mAP (Mean Average Precision) - Hasty visionAI Wiki, 2021).

In this study "mean average precision," referred to an evaluation metric in this study to measure the application's performance based on accuracy.

MobileNet Model -- pertains to a network model using depthwise separable convolution as its basic unit (Wang et al., 2020).

In this study "MobileNet model," referred to a model designed to run efficiently on TensorFlow for mobile applications.

Pesticide -- pertains to an agent used to destroy pests (Merriam-Webster. n.d.).

In this study "pesticide," referred to the chemicals used by farmers to eliminate insect pests on rice fields.

Prescribed -- pertains to officially telling someone to use (a medicine, therapy, diet, etc.) as a remedy or treatment (Merriam-Webster. n.d.).

In this study "prescribed," referred to the most suggested pesticides to employ in this study's application to help control insect pests on rice fields.

Rice Fields -- refers to a field in which rice is grown (Collins English Dictionary, 2022).

In this study "rice fields," referred to an area that will be covered in this study where the insect pest's infestations occur.

Single Shot Detector -- refers to taking one single shot to detect multiple objects within the image (Pokhrel, 2022).

In this study "single shot detector," referred to a CNN algorithm model that used a single shot detector to detect insect pests within an image.

Supervised Algorithm -- refers to an algorithm that depend on data that is accurately labeled and was under the direction of a developer or programmer (Seldon, 2021).

In this study "supervised algorithm," referred to the technique used to develop the training model in order to build a model with a high level of accuracy.

Tensorflow -- refers to a free software library focused on machine learning created by Google (Techopedia, 2018).

In this study "tensorflow," referred to a library of workflows for developing and training the SSD MobileNet model.

Delimitation of the Study

The study was designed to develop a mobile application that could detect insect pests in rice fields with prescribed pesticides using the SSD MobileNet Model on Deep Learning. It focused on detecting insect pests on rice fields using a mobile camera. The study's scope included a total of 25 respondents, 18 of whom were farmers from Barangay Buga, Leon, Iloilo and 7 were technical staff from Department of Agriculture – Region VI.

Though the app was centered on ways to aid farmers in accurately identifying insect pests and its proper pesticides, it is limited to only six major insect pests in the adult stage. The system can only accept a list of six common insect pests in the adult stage, such as Rice Grain Bug, Rice Black bug, Rice Bug, Brown Planthopper, Green Leafhopper, and Leaffolder. Moreover, this study involved the use of Kotlin and Python as the programming languages, as well as Android Studio and Google Colab as IDEs. A convolutional neural network with supervised algorithm technique is used to train an SSD MobileNet model to classify six types of insect pests and recommend appropriate pesticides using a dataset of 24,000 images.

The mobile app will run on the Android operating system only, with a minimum specification of Android 7 and API Level 24. The application is offline, so the functionality of the system is not dependent on the internet.

CHAPTER 2 REVIEW OF RELATED STUDIES

Review of Existing and Related Studies

Deep Learning Detector for Pests and Plant Disease Recognition

The study of Ileladewa (2020) aimed to create a framework for classifying plants, detecting diseased spots on their leaves, and then deploying the framework in a mobile application using deep learning techniques. This research combines Single Shot MultiBox Detector and MobileNet (SSD MobileNet), where SSD is an algorithm that detects multiple items within an image with a single shot and MobileNet is a neural network for recognition and classification. The system is trained on a large dataset of PlantVillage photos of damaged and healthy plants of various classifications. According to the study's findings, the proposed system was capable of recognizing and detecting a variety of pests and diseases that had been trained in the model, as well as dealing with the complexity of a plant's surrounding environment.

The study of Deep Learning Detector for Pests and Plant Disease Recognition had similarities with the current study titled, Insect Pest Identification with Prescribed Pesticides in Rice fields Using SSD MobileNet Model on Deep Learning. Both studies employed deep learning techniques for insect pest identification. The two studies aimed to create a framework that can classify plants, detect diseased spots, and identify various pests and diseases across different plant classifications. The two studies differ not only in the crops being studied but also in their objectives and scope. In contrast, our proposed study's primary objective was to develop a mobile application that provides insect pest information, including the name of the pest and the recommended pesticide, specifically for rice fields.

Remote Insects Trap Monitoring System Using Deep Learning Framework and IoT

According to Ramalingam et al. (2020), a proposed system was tested in real-time using four-layer IoT with images of insects captured through sticky trap sheets in the built environment. As a result of recent advances in Artificial Intelligence (AI) and the Internet of Things (IoT), numerous maintenance activities can be automated, significantly increasing efficiency and safety.

Using IoT and Deep Learning (DL) frameworks, this work presents a real-time remote insect trap monitoring system and method for insect detection. The object detection framework was trained on images of insects found in the built environment and farm fields before being deployed in IoT. Insects discovered in agricultural fields were also screened using a different insect picture database.

The experimental findings demonstrated that the suggested system could automatically identify insects in the built environment and farm fields with an average accuracy of 94 percent.

The study by Ramalingam et al. (2020) and this current study share some similarities and differences. Both works emphasize the need for accurate identification of insect pests to avoid economic damage and protect beneficial insects. Both works also highlight the use of advanced technologies such as AI, IoT, and deep learning to develop systems for insect detection and monitoring. However, the two works differ in their focus and scope. The related study by Ramalingam et al. (2020) primarily targets insect pests in built environments and farm fields, while our proposed study centers on insect pests in rice fields. Additionally, this current study provides a background on the economic and environmental impact of pesticide misuse and crop protection malpractice. Overall, both works contribute to the advancement of sustainable agriculture by introducing novel and innovative approaches to insect pest detection and monitoring.

Object Detection in A Remote Insect Trap Monitoring System Using an On-The-Edge Deep Learning Platform (Alertrap)

The study of Le et al. (2021), proposed a system that applies many types of real-time object identification algorithms to the system's detection accuracy, power efficiency, and delay reduction when identifying alive and dead fruit flies in the trap. This study employs the Yolov4-tiny and single shot detector (SSD) architectures, as well as numerous state-of-the-art backbone feature extractors, such as MobileNetV1 and MobileNetV2, to present a feasible solution to the real-time detection challenge. According to the findings of this study, YOLOv4-tiny has the best overall performance among the three model candidates. Nonetheless, in a variety of synthetic disturbance test settings, the SSD MobileNet V2 model outperforms the YOLOv4-tiny model. Additionally, SSD models exceed YOLOv4-tiny in terms of processing speed, enabling very accurate real-time detection applications.

The study by Le et al. (2021) and this study share several similarities and differences. Both works emphasized the need for accurate identification of insect pests to avoid economic damage and protect beneficial insects. Both works also highlight the use of advanced technologies, particularly deep learning, to develop systems for insect detection and monitoring. However, the two works differ in their focus and scope. The study by Le et al. (2021) primarily targets fruit flies in a remote trap monitoring system, while our proposed study centers on insect pests in rice fields. Additionally, this current study provides a background on the economic and environmental impact of pesticide misuse and crop protection malpractice, which was not mentioned in the study. Moreover, the study by Le et al. (2021) evaluates the performance of different deep learning models for object detection, while the current study aimed to develop a mobile application for insect pest identification using the SSD MobileNet model. Overall, both works contribute to the advancement of sustainable agriculture by introducing novel and innovative approaches to insect pest detection and monitoring, using deep learning algorithms and real-time object detection technology.

Plant Diseases and Pest's Detection Based on Deep Learning: A Review

The study of Liu et al. (2021) summarized the research on plant diseases and pest detection based on deep learning in recent years from three perspectives: classification network, detection network, and segmentation network, with the merits and disadvantages of each technique outlined. In general, there are two types of deep learning-based plant disease and pest detection networks: two-stage networks like Faster R-CNN and one-stage networks like SSD and YOLO. Because the program must forecast in real-time on a mobile CPU, a MobileNet and SSD-based app was developed to aid in model parameter identification. The study examined 108 papers and discovered that many researchers used Faster R-CNN to directly locate diseases and pests. Zhou et al. (2019) discovered that the highest detection accuracy was 98.26%/0.53 s.

The study on plant diseases and pest detection based on deep learning by Liu et al. (2021) has similarities to our proposed study on rice pest detection through deep learning in that both discuss the use of deep learning-based models for pest detection. Both papers also mention the advantages and disadvantages of different deep learning models and techniques used in object detection.

However, Liu et al. (2021) focused on plant diseases and pest detection while the introduction specifically dealt with insect pests in rice fields. Additionally, Liu et al. (2021) focused on a comprehensive review of various research papers on plant diseases and pest detection, while our proposed study focused on the need for accurate insect pest identification and targeted pesticide use for sustainable agriculture. Lastly, the study by Liu et al. (2021) presented a mobile-based approach using MobileNet and SSD-based apps to aid in model parameter identification, while our proposed study had a mobile application that can give farmers and essential users insect pest information, such as the insect pest's name and recommended pesticide, using SSD MobileNet model-based deep learning.

A Review of the Challenges of Using Deep Learning Algorithms to Support Decision-Making in Agricultural Activities

The study of Alibabaei et al. (2022) presented recent work on the application of deep learning to agriculture and biodiversity, as well as some of the challenges that this field faces. Reducing agrochemical use, reducing pesticide use, practicing organic farming, using appropriate crop rotations, cultivating small-scale fields, and preserving natural spaces between agroecosystems are all ways to achieve sustainable agriculture and biodiversity promotion in agricultural systems. This can be accomplished by combining cutting-edge IoT technology with new biodiversity algorithms and an AI model. They can be used to detect and regulate species, as well as to improve the state of the ecosystem consequently, productivity without resorting to environmentally destructive activities.

The uniqueness of the application of DL models in agriculture and the challenges identified underline the necessity for additional research. In agriculture, CNN is the most extensively used deep learning model. This article discusses current scientific advances in deep learning and its application to agriculture, as well as some of the obstacles and potential solutions associated with the use of deep learning algorithms in agriculture. This research suggests that by incorporating new methods from deep learning, it is possible to achieve higher accuracy and shorter inference times while also making the models relevant for real-world applications. The use of novel methods, such as attention mechanisms, new lightweight models, and single-stage detection models, can dramatically improve the model's performance, as a small increase in accuracy and run time can significantly improve outcomes.

Both the study of Alibabaei et al. (2022) and the current study focused on the challenges of agriculture and the need for sustainable agriculture. The related study explores the application of deep learning algorithms in agriculture, including biodiversity, and identifies the challenges in this field. On the other hand, this study discussed the challenges that farmers face in identifying insect pests accurately and the need for targeted use of pesticides to prevent economic losses and environmental damage. Both also emphasize the need for accurate identification and monitoring of agricultural pests and the potential of deep learning models to address these challenges. However, the study of Alibabaei et al. (2022) focuses on the potential of deep learning models to address challenges in agriculture and biodiversity, while tour proposed study centers on the challenges that farmers face in crop protection. The study of Alibabaei et al. (2022) also provides insights into the use of cutting-edge IoT technology with new biodiversity algorithms and an AI model to detect and regulate species and preserve the ecosystem's state. In contrast, the current study discussed the challenges faced by farmers in identifying insect pests accurately and the potential of deep learning models in object detection. Moreover, the current study described the development of a mobile application for insect pest identification using the SSD MobileNet model based on deep learning.

In summary, both the study and our proposed study share similar themes related to sustainable agriculture and the need for accurate identification and monitoring of agricultural pests. However, the study of Alibabaei et al. (2022) explores the potential of deep learning models in addressing these challenges in agriculture and biodiversity, while the current study focused on the challenges faced by farmers in crop protection and the potential of deep learning models in insect pest identification.

PestNet: An End-to-End Deep Learning Approach for Large-Scale Multi-Class Pest Detection and Classification

According to Liu et al. (2019), PestNet is a deep learning-based system for large-scale multi-class pest identification and categorization. PestNet is comprised of three major components: (i) Channel-Spatial Attention (CSA), a novel feature extraction and enhancement module proposed to be fused into the backbone of a Convolutional Neural Network (CNN), (ii) Region Proposal Network (RPN), which is used to provide probable pest sites for regions based on feature maps collected from photos, and (iii) Position-Sensitive Score Map (PSSM) for pest categorization and bounding box Pest photographs were swept away from the pest collection tray as soon as they were taken. The photos are in JPG format and have a resolution of 2592 1944 pixels. Agricultural professionals photograph the pests and label them with boundary boxes.

The experimental results indicate that the proposed PestNet outperforms existing systems for multi-class pest detection, with a mean average precision (mAP) of 75.46 percent.

Both previously mentioned study and the current study focus on the challenges in identifying and categorizing insect pests and the need for sustainable pest management practices in agriculture. The related study proposes an end-to-end deep learning approach, PestNet, to identify and categorize pests in large-scale agricultural settings, while the current study discussed the challenges in crop insect identification and the potential harms of pesticide misuse.

The study utilized Channel-Spatial Attention (CSA), Region Proposal Network (RPN), and Position-Sensitive Score Map (PSSM) for pest detection, while the current study mentioned various deep learning models, such as Faster R-CNN, R-FCN, YOLO, SSD, and MobileNet, for pest detection. The experimental results of the study showed that PestNet outperforms existing systems for multi-class pest detection, while the current study aimed to develop a mobile application using the SSD MobileNet model for insect pest identification with prescribed pesticides on rice fields. Overall, both the study and our proposed study highlight the importance of accurate pest identification and sustainable pest management practices in agriculture.

Insect Identification Among Deep Learning's Meta-Architectures Using Tensorflow

The study of Patel and Bhatt (2019), utilized deep learning meta-architectures (Faster R-CNN, SSD Inception, and SSD MobileNet) to compare object detection in chosen flying insects, notably Phyllophaga spp., Helicoverpa armigera, and Spodoptera litura. The current study evaluated selected meta-architectures correctness using a small insect dataset. The meta-architecture was evaluated in the same environment for all three architectures.

The related study's findings indicate that the state-of-the-art CNN meta-architecture Faster-RCNN outperforms other architectures, with an identification accuracy of 95.33 % and a sensitivity of 91.06 % in chosen pest detection operations. Furthermore, SSD MobileNet was discovered to have a high level of detection accuracy. Despite the tiny sample size, the study achieved high accuracy in detecting selected pests using the Faster-RCNN and SSD MobileNet architectures.

The study of Patel and Bhatt (2019) and the current study proposed system focus on the identification of insect pests in agricultural settings. The related study utilized deep learning meta-architectures, while the current study discusses the application of deep learning models in pest detection. Both also acknowledge the challenges of identifying insect pests due to their similarities and lack of information. Moreover, both studies highlight the negative impact of pesticide misuse and the need for sustainable agriculture. However, the current study goes further to discuss the importance of preserving beneficial insects and the use of mobile applications to disseminate insect pest information to farmers. The related study, on the other hand, provides specific findings on the performance of different deep learning architectures in pest detection, whereas the current study presents a broader overview of the use of deep learning in agriculture.

Identification of Maize Leaves Infected by Fall Armyworms Using UAV-Based Imagery and Convolutional Neural Networks

Ishengoma et al. (2021) sought to precisely detect maize leaves infected by fall armyworms (faw) using automatic recognition algorithms based on convolutional neural networks (CNNs), specifically VGG16, VGG19, InceptionV3, and MobileNetV2.

These models examined infected maize leaves obtained using remote sensing technology from an unmanned aerial vehicle (UAV). Shi-Tomas corner detection algorithms were used to collect both original and modified photos for the models.

In both instances, the CNN models under evaluation exceeded previously proposed models in terms of accuracy. Furthermore, the accuracy of VGG16, VGG19, InceptionV3, and MobilenetV2 models trained on updated images increased from 96 percent, 93.08 percent, 96.75 percent, and 98.25 percent to 99.92 percent, 99.67 percent, and 100 percent, respectively.

Both the related study and the current study discussed the challenges of identifying insect pests in agricultural settings and the potential of deep learning models to assist in this task. The study focuses specifically on identifying maize leaves infected by fall armyworms using UAV-based imagery and CNN models, while the current study discussed the importance of rice as a staple crop and the need to accurately identify insect pests in rice fields. Both sources also touch on the potential negative effects of pesticide misuse and the importance of sustainable agricultural practices.

However, the approaches used in the study and our proposed system differ. The related study utilized remote sensing technology and specifically evaluated the performance of four different CNN models. In contrast, the current study discussed the broader field of deep learning-based pest detection and highlights the strengths and weaknesses of different types of detection models. Additionally, while the related study focused on developing a mobile application for identifying insect pests on maize leaves, the current study emphasized the need for accurate identification in general and does not discuss specific applications.

Smart Iot-Based System for Detecting RPW Larvae in Date Palms Using Mixed Depthwise Convolutional Networks

The study of Karar et al. (2021) used Python code programming with the Tensorflow and Keras packages to implement in proposed MixConvNet classifier and other transfer learning models. Three transfer learning models, EfficientNetB0, MobileNetV2, and Xception, achieved classification accuracy rates ranging from 95.17 to 95.58%.

The lowest classification accuracy is 94.77% for the Densenet-121 model. The MobileNet-V2 presents the classifier's smallest size of 14 MB and relatively low classification accuracy of 93.65. Nevertheless, our proposed MixConvNet classifier has a moderate size of 32 MB with the highest accuracy value. The main prospect of this research work is utilizing edge computing services based on lightweight deep learning models integrated with a developed mobile application for guiding farmers and agricultural experts.

The study of Karar et al. (2021) and the current study have similarities and differences in terms of their research focus and methodology. Both studies aimed to address agricultural challenges caused by insect pests, but the former focuses on detecting RPW larvae in date palms using smart IoT-based systems, while the current study aimed to develop a mobile application for insect pest identification and prescribed pesticides on rice fields. The two studies differ in terms of their deep learning models and datasets used. Karar et al. (2021) utilized Python code programming with the Tensorflow and Keras packages to implement a proposed MixConvNet classifier and other transfer learning models to detect RPW larvae, while the current study discussed the use of deep learning models such as the Faster R-CNN, R-FCN, YOLO, SSD, and MobileNet for insect pest identification. In terms of datasets, Karar et al. (2021) utilized in-field trap images of RPW larvae, while the current study did not mention a specific dataset used for insect pest identification. Overall, both studies demonstrated the potential of deep learning in addressing agricultural challenges caused by insect pests.

Pest Classification and Pesticide Recommendation System

The study of Kyaw et al. (2019) proposed a system that uses the convolutional neural network (CNN) model, which is commonly used when applying deep learning to image processing, to classify pests and then recommends the most appropriate pesticide based on the insect type. The purpose of this research is to make it easier for users to learn about pests and pesticides that should be used. To learn the training data, the GoogleNet Convolutional Neural Network model is used. After that, the features are saved in a CNN feature set.

The user must enter the test pest picture during the testing procedure. CNN will classify the user's pest image, and the system will tell the user what sort of pest it is. Finally, the algorithm will provide the most probability response to which pest category the pest belongs to and the best insecticide to use. Using a public dataset of 1265 bug photos, a neural network and supervised algorithms are trained to classify four types of pest species and recommend appropriate treatments.

The study of Kyaw et al. (2019) and the current study share a common goal of aiding farmers in identifying and managing insect pests in agricultural settings. Both studies recognized the importance of accurate identification of insect pests to prevent economic loss and environmental damage caused by misusing pesticides. However, the methods used in the two studies differ. While Kyaw et al. (2019) utilized a convolutional neural network (CNN) model to classify pests and recommend pesticides, the current study explored the use of deep learning model which is the SSD MobileNet, for insect pest detection. Moreover, the current study aimed to develop a mobile application for insect pest identification, whereas the study of Kyaw et al. (2019) focused on training a neural network to classify pest images and provide recommendations. Both studies, however, showed the potential of using deep learning in agriculture and highlight the importance of accurately identifying insect pests to improve crop management.

CHAPTER 3 RESEARCH DESIGN AND METHODOLOGY

Description of the Proposed Study

The proposed system, Insect Pest Identification App with Prescribed Pesticide on Rice Fields Using SSD MobileNet Model on Deep Learning, aimed to develop a mobile application that gives farmers pest information, such as the insect pest's name and recommended pesticide.

The application works on a mobile device created in Kotlin as the programming language and Android Studio as the IDE. Meanwhile, the system was developed using Python as the programming language and Google Colab as the IDE for the training model development process.

The primary users of the application are farmers. The captured image of the insect pest serves as the input.

After the system analyzes and interprets the input, it will display an output to the user's device containing the insect pest's name and its recommended pesticide. The researchers employed because it helps collect, analyze, and interpret large amounts of data. The researchers used six (6) classes of adult insects and employed a large amount of training data for each class to achieve a high rate of accuracy. Each insect underwent image preprocessing, which consists of 4,000 resized and padded images. The researchers manually captured diverse images of insect pests present from rice fields as they labeled the images using Python to train the model in Google Colab. They also used in-field traps to catch major insect pests in the adult stage collected at Brgy. Tina-an Norte, Leon, Iloilo.

The researchers also sought data from government agencies, specifically the Department of Agriculture (DA) - Region VI, through an online and face-to-face interview with Mr. Ryan V. Rasgo, Center Chief, Regional Crop Protection Center.

The DA provided the researchers with a variety of documents on the various classes of insect pests, such as booklets and images, as well as a PDF file from the Fertilizer and Pesticide Authority, which contained the various types of pesticides, and which insect pests they would be useful in eradicating. Approximately 24,000 photos were used to train the models for each class of insect pest, which were photographed manually and intricately at various angles using a mobile phone.

Assumptions and Preconditions

In conducting this study, the following assumptions and preconditions were made:

The assumptions were:

1. The Department of Agriculture officials would identify and confirm the insect pests collected in the rice fields to ensure that the data collected is reliable and valid.

2. The mobile application would recommend a pesticide to the detected insect pest, following the FPA approved pesticides lists.

The preconditions were:

1. The supported operating system for the mobile application was Android only. When capturing an image, the background was limited to three options: white, palm, or rice leaves.

The researchers and DA technical staff recommended that the palm was the best suited background in capturing images to ensure that the insect pest wouldn’t fly easily.

2. In order to detect insect pests accurately, proper lighting must be used. In low-light areas, it is preferable to use a camera flash, lightbulb, or flashlight to provide the necessary amount of light for a precise and clear image.

Specifically, daytime with enough sunlight was more preferrable over cloudy and rainy weather conditions. To get a closer look at the insect pest, set the camera to focus and zoom in before taking the picture. The precision of detection depends on the image quality of the captured insect pest.

Methods and Proposed Enhancements

Sources of Information

Documentary Research Data. Starting with information gathering, the information and processes gathered to complete this study were specified.

The information acquired was crucial in the system's planning and implementation, and the internet is the key source of information. These documents comprise articles, journals, publications, dissertations, and research studies gathered from reputable online sources such as Google Scholar and ScienceDirect.

Tool and Techniques

Object Detection. Object detection was a computer vision approach for identifying and locating things in images and videos. Object detection can count objects in a scene, determine and track their precise locations, and precisely label them using this type of classification and localization. This study utilized the same method for object detection but introduced a custom dataset. Since object detection was a supervised machine learning problem, this study used a supervised machine learning algorithm. Supervised machine learning algorithms required direct supervision from a developer. The 24,000 images in the dataset consists of the six different types of insect pests with three different backgrounds are fed into the algorithms, together with the input and target output specified by the researchers. Following that, the system built the model based on the relationship between the input and output training data. The model was trained until it achieves a high level of accuracy. Furthermore, the TensorFlow object detection API is employed in this research. TensorFlow is the deep learning library that underpins all object detection algorithms. Instead of a raw CPU or memory, the object detection model on the GPU of Google Colab is used because it can be trained much faster and has more memory size needed for the trained model.

Software Development Process. MobileNet SSD Model is a network intended to perform object detection, and in the case of this study, the researchers incorporated deep learning techniques. Using the mobile app, the user needed to take one single shot to detect the type of insect pest in a captured or uploaded image. This research also included the use of IDEs such as Google Colab and Android Studio, as well as Python and Kotlin as programming languages in the development process. Some of the codes in model training were cloned from the GitHub repository and personally altered by the researchers into a program suitable for the app.

Software evaluation. The researchers used Mean Average Precision to evaluate the app's accuracy. Mean Average Precision (mAP) was a statistic for evaluating object detection models like Fast R-CNN, YOLO, Mask R-CNN, and so on. The mean of average precision (AP) values is calculated for recall levels ranging from 0 to 1. The current metric used by computer vision researchers to assess the robustness of object detection models is Mean Average Precision (mAP).

Proposed Enhancements

Recommended Pesticide. Based on the review of the related studies gathered by the researchers, most of the system's function was insect pest identification app only. Yet, the researchers added a prescribed pesticide feature as an enhancement along with the insect pest identification.

MobileNetSSD Model. In this study, the MobileNet SSD Model is used. It is an object detection model that used an input image to calculate an object's bounding box and category. Using MobileNet as a backbone, this Single Shot Detector (SSD) object detection model may enable quick object detection optimized for mobile devices (Cochard, 2021). MobileNet SSD is typically a machine learning model, but in this study, the researchers enhanced it by including deep learning algorithms.

Components and Design

System Architecture

Figure 2 illustrates the proposed system's architecture and its functioning process in a visual manner. The system's operation starts with the user capturing an image of an insect pest found in a rice field using their mobile phone. The user will then initiate the identification process by selecting the "OK" button. The collected image will be analyzed and evaluated using an SSD MobileNet model that has been trained with datasets of insect pests in TensorFlow model.

The analyzed image will undergo classification using an SSD MobileNet model to determine the insect pest's identity. Once the analysis and validation of the image are completed, the result will be sent to the user's device. The output will display the name of the identified insect pest and the recommended pesticide to control the pest.

Overall, the proposed system employs deep learning techniques to classify and identify insect pests found in rice fields, providing farmers with an efficient and effective solution to manage pest infestations. The proposed system can significantly reduce the time and effort required for pest identification, leading to timely and effective pest management. Additionally, the system can be easily integrated into existing farm management systems, allowing farmers to manage their crops more efficiently.

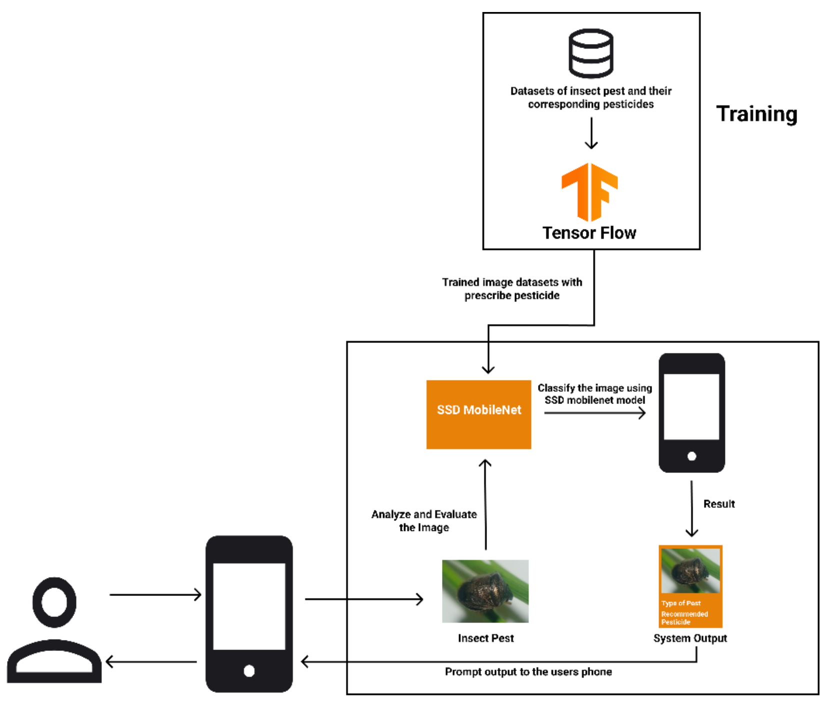


Figure 2. System Architecture of the System

Procedural Design

Figure 3 shows the Structured Flowchart of the mobile application. The user can either capture or upload an image of an insect pest from their phone's gallery to use the app. After submitting the image, the app will determine whether it is an insect pest or not. When the image was classified as an insect pest, the app will show the user an output that includes the insect pest's name as well as the recommended pesticide for eradicating it.

However, if the app was unable to recognize the image captured, it will display a "NOT IN THE LIST" message.

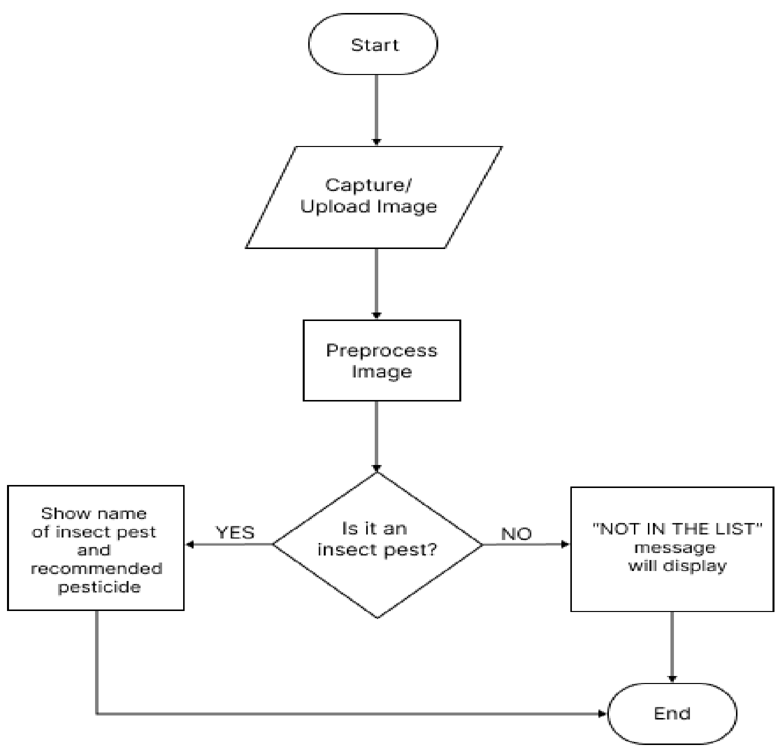


Figure 3. Procedural Design of the Proposed System

Object-Oriented Design

Figure 4 depicts the users and their interactions with the system using a Use Case Diagram.

Users can access the mobile application, encompassing farmers, who are the primary beneficiaries, and several other essential users such as students, educators, agriculture experts, and even home growers. The user was responsible for initiating the activity that the application will perform. The system will automatically process the output and send it back to the user once the user has entered the data required by the program.

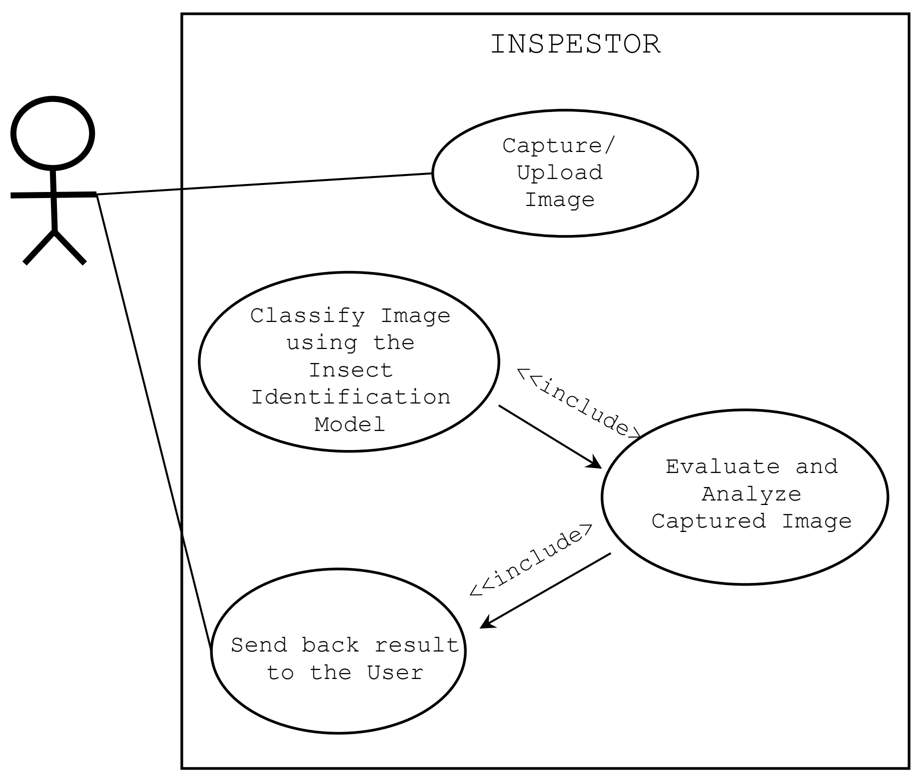


Figure 4. Use Case Diagram of the System

Process Design

The Data Flow Diagram depicts the detailed process design on how the system works and interacts with the user.

After the user takes or uploads an image, the app uses its TensorFlow Model to classify it. The system will then classify and analyze the image, and if it confirms that the image was an insect pest, it will provide information such as the pest's name and the recommended pesticide for eliminating it.

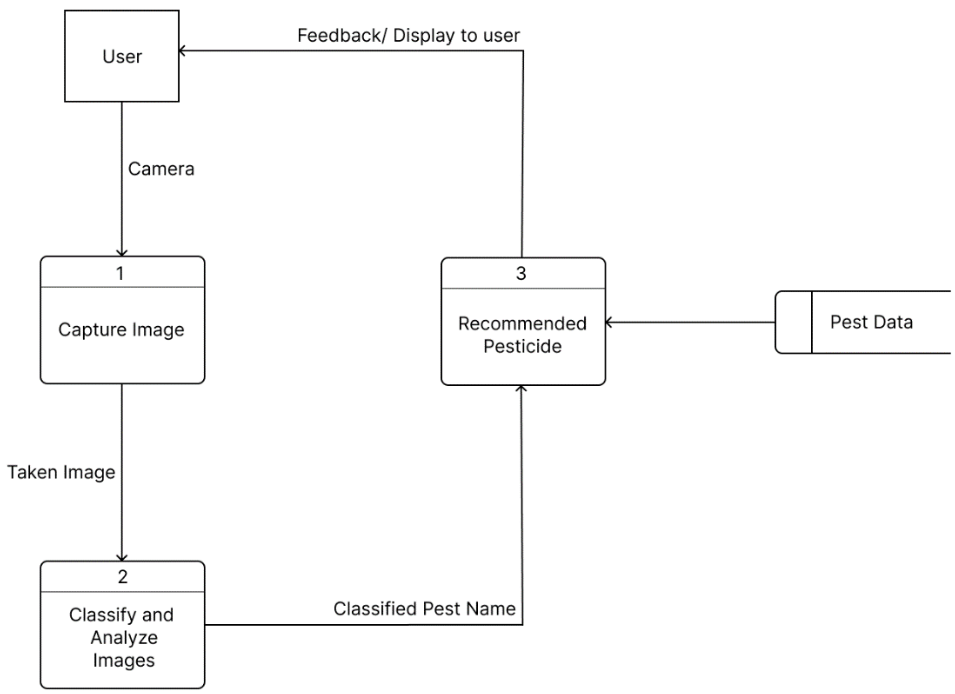


Figure 5. Data Flow Diagram of the System

System Development Life Cycle

Figure 6 illustrates the Agile Development model, which is the approach for software development in this study. It comprised the following phases: planning, data gathering, software requirements, designing/prototyping, coding, testing and feedback, and deployment.

In the planning phase, the researchers held a meeting, identified timely problems, and formulated a solution. The researchers presented project proposals to the panelists. After the approval of the proposal, the researchers assessed possible ways and ideas to develop the system, possible algorithms, programming language to use, and system design.

In the data phase, the researchers reviewed some related literature on the project, and researchers coordinated with a Department of Agriculture (DA) official for insights and recommendations for possible data gathering, and the researcher had conducted field data gathering.

During the software requirement phase, the researchers identified the software and hardware specifications that will be used in the project's development.

In designing the system/prototyping phase, the researchers design the system and use the prototype to lay out the design of the Graphical User Interface (GUI).

In the coding phase, the researchers used Python as a programming language to train the model and Kotlin programming language to program the mobile application. Using ISO 25010, the researchers tested the system's accuracy of identification, reliability, and application efficiency.

The researchers also asked for feedback on user experience from the farmers, D.A. official, and IT experts.

Deployment phase indicates that when the researchers have fixed all bugs and errors, it is ready to deploy.

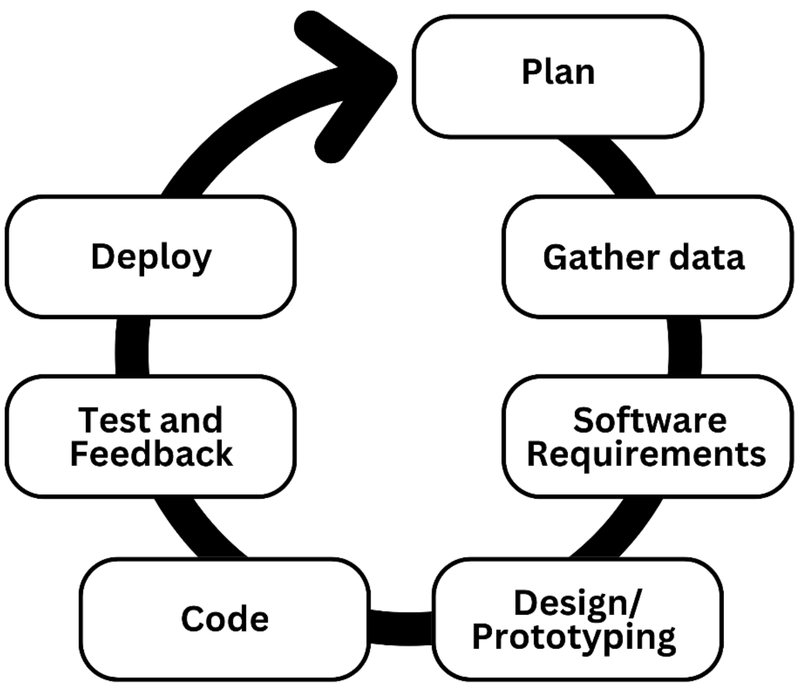


Figure 6. Agile Development Life Cycle

CHAPTER 4 RESULTS AND DISCUSSION

Implementation

The application was designed to provide users with insect pest information as well as pesticide recommendations.

The researchers proposed using this device as a portable tool to help with rice production in Iloilo.

Farmers are the primary beneficiaries; thus, all data in the mobile application about insect pests and recommended pesticides must be accurate and reliable. To ensure the accuracy of the data in the app, the researchers asked the assistance of the Department of Agriculture Region VI in gathering the necessary data prior to implementation and verifying the information listed and recommended in the software once it was deployed.

The designed application is only compatible with the Android mobile operating system, so the software application was tested on various Android smartphones to ensure that the program is working properly.

In the mobile application development, the following hardware specifications of the computer device were used:

In the training and development process of creating a Tensorflow Model, the researchers used Google Colab Pro running on a desktop with a hardware specification of CPU: AMD Ryzen 5 2400G with Radeon Vega Graphics, GPU: NVIDIA GeForce GTX 1060 6GB VRAM, RAM: 16 GB, and Storage: 2TB HDD

While in designing the user interface and overall layout of the mobile application, the researchers used a laptop with AMD Ryzen 5 3500U with Radeon Vega Mobile Gfx 2.10 GHz, installed RAM 16.0 GB (13.9 GB usable), system type 64-bit operating system, and x64-based processor.

Meanwhile, the software used in developing the mobile app is Kotlin as the programming language and Android Studio as the IDE.

Technical Specifications

In testing, the types of smartphones used in are Vivo Y31 with a specs of version 12, 8GB RAM, 128GB, 48MP, 2.0GHz Snapdragon SDM662 Octa-core, Asus Zenfone 3 Max ZC520TL with a specs of version 7, 3GB RAM, 32GB, 13MP Main Camera, Quad-core 1.25 GHz Cortex-A53, Samsung with specs of version 12, 4GB RAM, 128 GB, 48 MP, Octa Core CPU and etc.

Before the proposed system was implemented, a variety of techniques such as application performance based on ISO 25010 and accuracy detection based on Mean Average Precision (mAP) were used to determine its efficiency and efficacy.

The installation of the Inspestor on the user's mobile device is the first step.

The second step was to check if the app is running and evaluate each feature to ensure that it is working properly.

Maintenance is the final step. Its purpose was to keep all proponents up to date, including new pest and pesticide information that needs to be added, as well as other features and functionalities that need to be improved and/or developed in response to juror and critique requests.

System Inputs and Outputs

The preceding figures are a collection of user interfaces for the application. These interfaces functioned both the application's front-end design and a channel of communication with the user. The screenshots are as follows:

Figure 7. Logo of the mobile application

Figure 7 shows the logo for our mobile application, "Inspestor," which is short for "Insect Pest Detector" that represents the thesis.

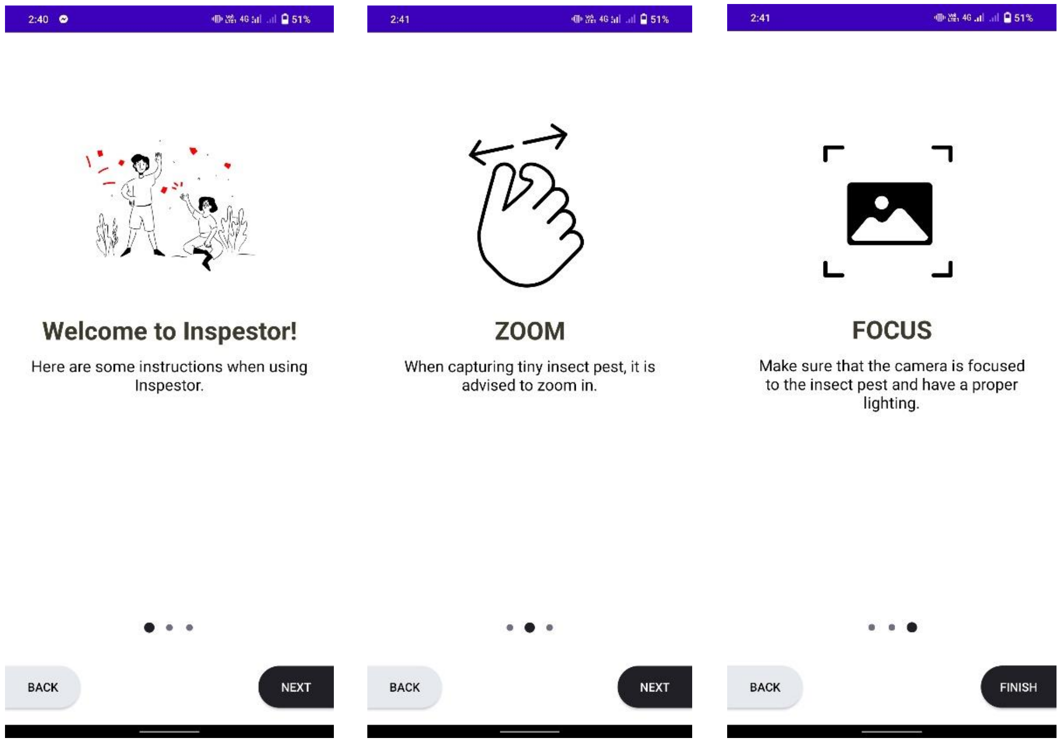


Figure 8. Onboard or Walkthrough Screen

Figure 8 shows the onboard or walkthrough screen that will display when the app was newly installed on the mobile device. It gives new users simple instructions on how to use the app. The user can click the "NEXT" button to go to the next slide or click the "BACK" button to go back to the previous slide.

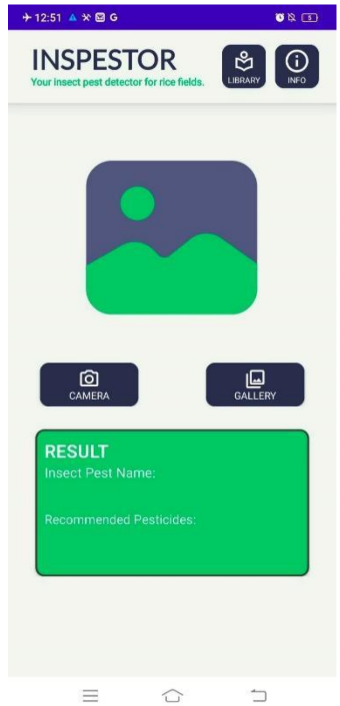


Figure 9. Homepage of the mobile application

Figure 9 displays the availability of the camera and gallery buttons because there was no image to be evaluated. In this illustration, the app requires the user to capture or upload an image of a rice-field-infesting pest.

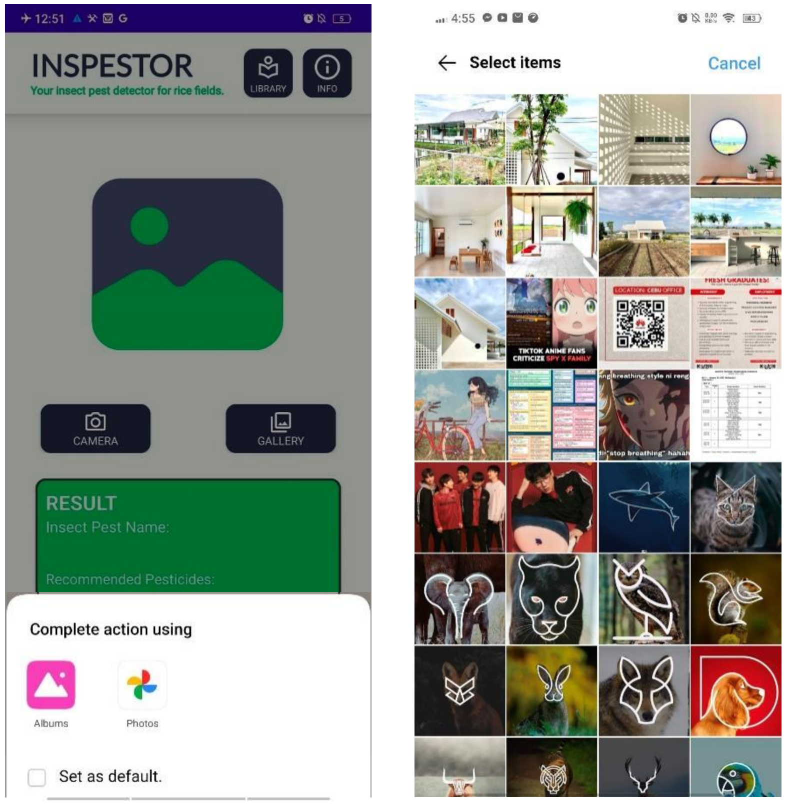


Figure 10. Selecting an image from the gallery

In Figure 10, the user can select any picture from the Gallery or the Albums.

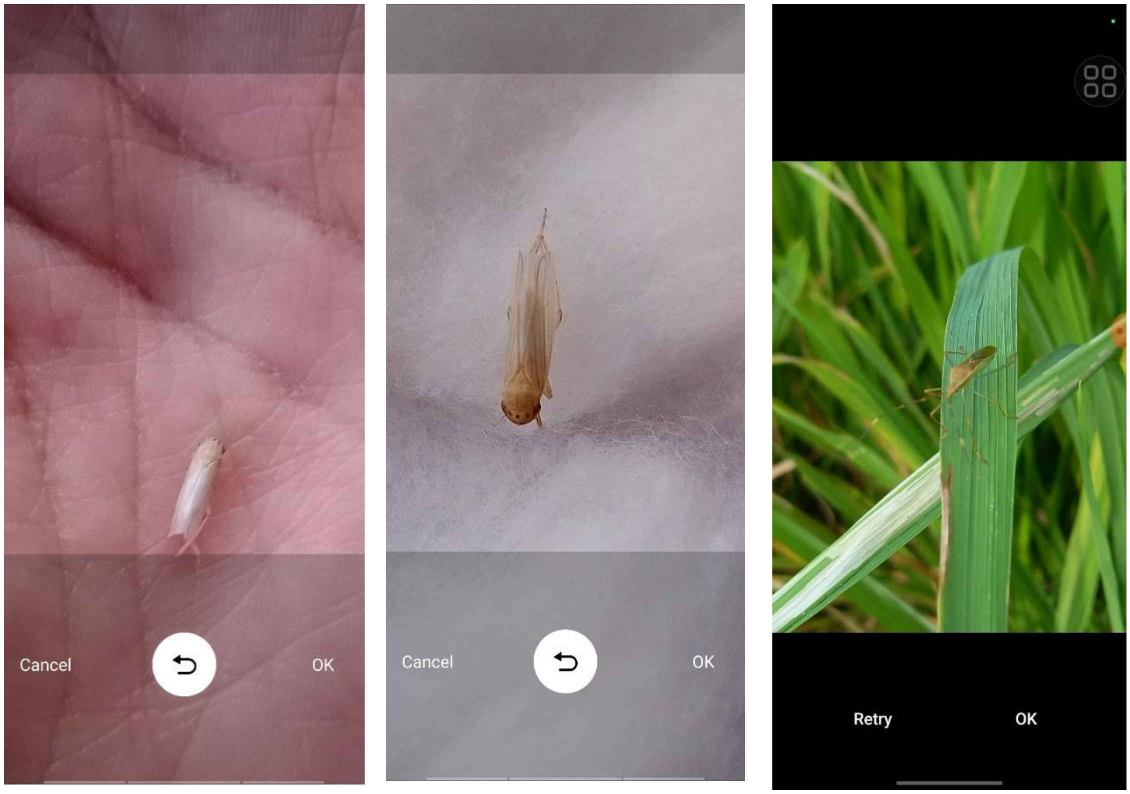


Figure 11. Capturing an Image through a mobile camera

In Figure 11, the user can take a photo using the phone's camera application. Then, it displayed the final captured image, which undergoes analysis and classification of images in the TensorFlow Model to classify the insect pest. Finally, the user can redo the image capture process according to his preferences.

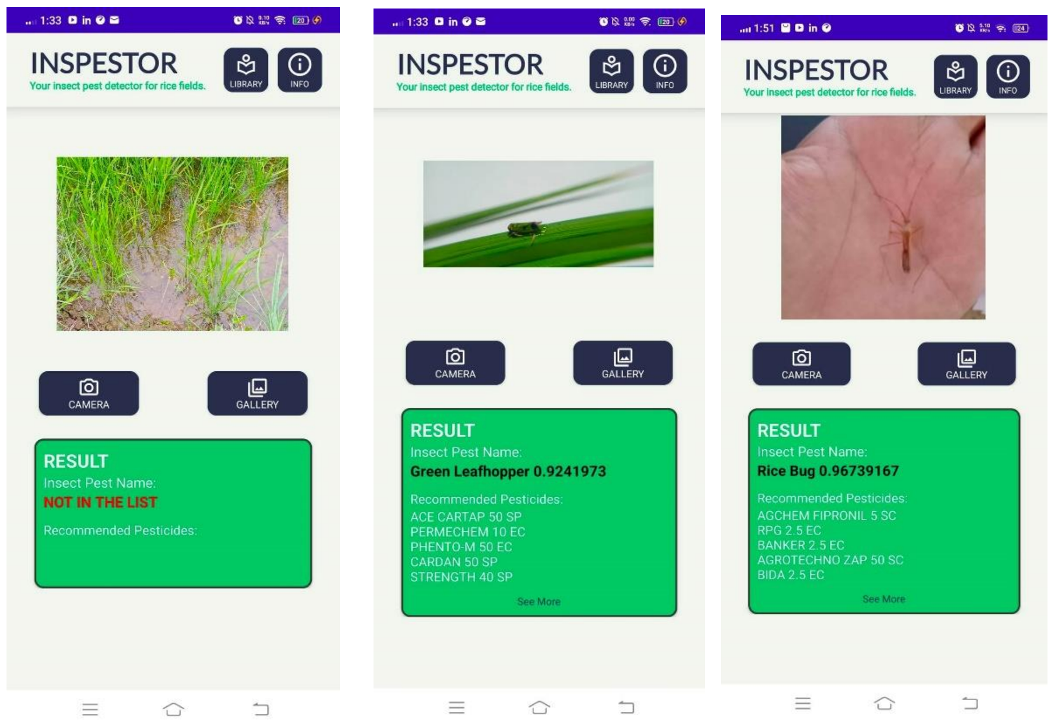
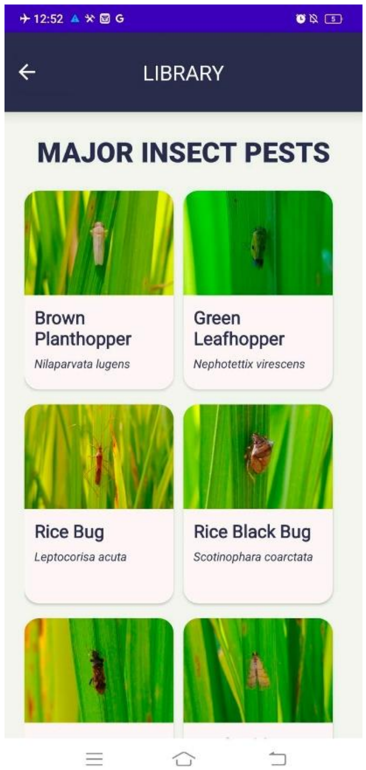


Figure 12. The final output of processing the image

Figure 12 displays the final output wherein TensorFlow Model categorized whether it was an insect pest or not on the image selected from the gallery (on the left) and the captured image of the brown planthopper (on the middle). Since a cat was not included in the training images, it was not considered an insect pest and will indicate "NOT IN LIST" on the app (on the left). While the result (on the right) displayed rice bug since it was part of the training model.



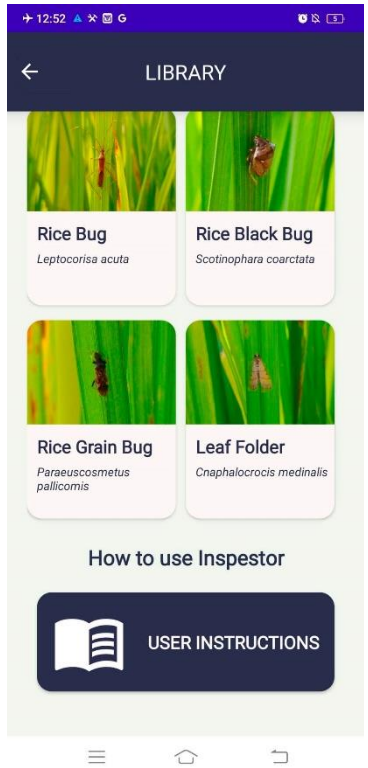


Figure 13. Insect Pest Library and User Instructions

Figure 13 depicts that the application's library feature, which displayed a list of the major insect pests used in this study. Each button was clickable, allowing users to read more about each insect pest. In addition, the application's user instruction button was presented and by clicking, users will be redirected to the next activity on how to use the application.

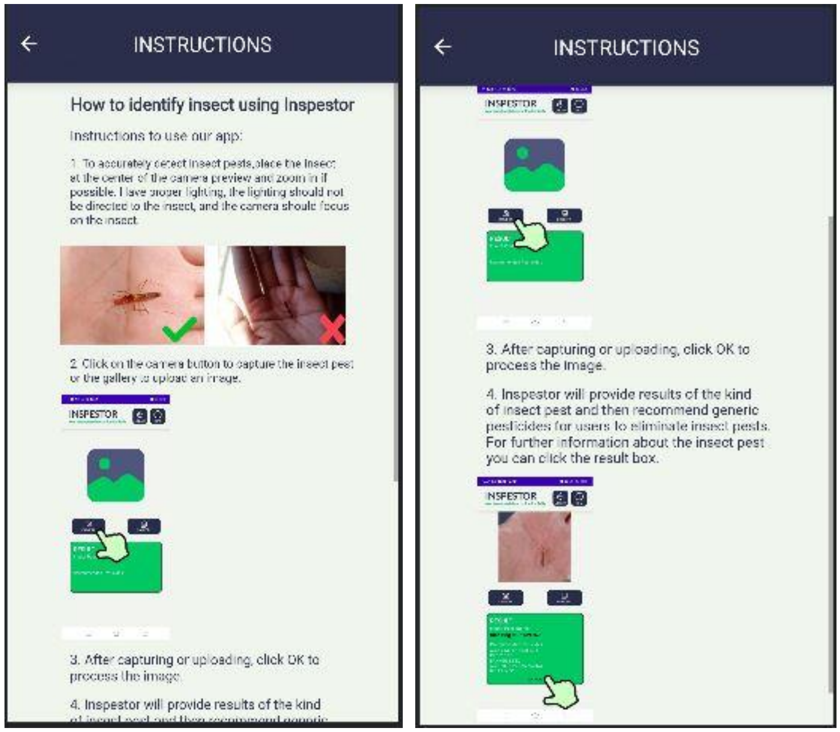


Figure 14. The User Instruction of the Application

Figure 14 displays how to use the application step by step to obtain a proper capture in order to generate a good result.

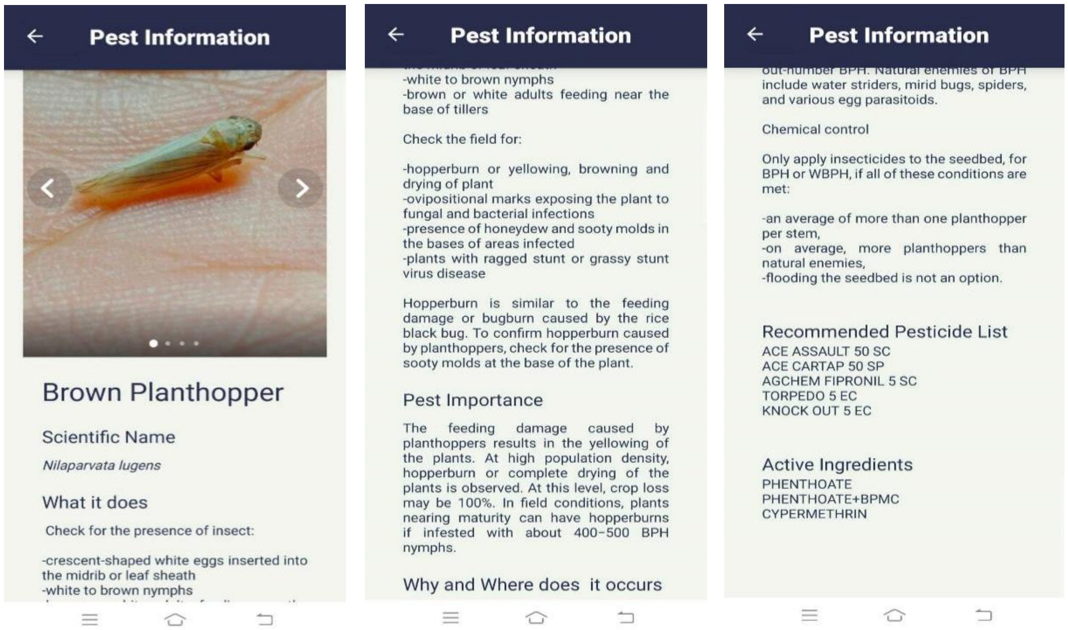


Figure 15. Pest Information of Insect Pest

Figure 15 shows the pest information for each of the six insect pests, which includes the Scientific Name, what it does, the Recommended Pesticide List, the Active Ingredients, and Pest Management. The information displayed was gathered from the Knowledge Bank website recommended by the Department of Agriculture and the Fertilizer and Pesticide Authority for the pesticide list.

Figure 16. About Us of the Application

Figure 16 depicts the application's information, including the researchers behind the app's development, as well as the reference where the information stated in the app was gathered.

Results Interpretation and Analysis

In this study, a total of 25 respondents were randomly selected. A group of 18 farmers and 7 Department of Agriculture—Region VI technical staff took part in testing the mobile application. To obtain the feedback of the participants, a printed questionnaire consisting of 20 questions was made.

In addition, the personal data that were collected were age, sex, signature, and what type of participants they were (farmers or technical staff); however, the name of the respondents was optional.

The respondents were fully informed about the study's objective, the scope of its use of the results, and the purpose of its use. For the farmers, the questionnaires were completed at Barangay Buga, Leon, Iloilo, where they reside while for the technical staff, the questionnaires were completed at the Regional Crop Protection Center (RCPC) office at the WESVIARC Hamungaya, Jaro, Iloilo City.

This mobile application may be useful in terms of functionality and reliability in detecting insect pests on rice fields because of the several trials that potential users might do with the system. Furthermore, the researchers employed the Mean Average Precision (mAP) to compute the classification metric of 24,000 photos of the six types of insect pests in order to assess the precision of the training model used in the mobile application.

Table 1

Training Model Accuracy using SSD MobileNet

Model	Batch Size	Epoch	Mean Average Precision (AP)	Average Recall (AR)	Dataset	Input Resolution
SSDMobileNetV2 FPNlite 40x640	16	50	71.6	76.9	24,000 images	640x640

The Single Shot Detector (SSD) MobileNet model's training model accuracy for various parameters is shown in Table 1. The SSDMobileNetV2 FPNlite model is employed in this investigation, and the batch size is set at 16. A dataset of 24,000 images with a resolution of 640x640 was used to train the model across 50 epochs.

The average recall (AR) and mean average precision (AP) measures were used to assess the model's performance. While the Average Recall measures the average recall across all classes, the Mean AP measures the average precision across all classes.

However, more investigation is required to verify these results and improve the model's effectiveness for various crop varieties and environmental factors.

Overall, Table 1 offers insightful information on how well the SSD MobileNet model performs in recognizing insect pests in rice fields. The findings imply that the proposed approach has the potential to be an effective tool for pest management in agriculture. To validate these results and improve the performance of the model for other crop varieties and environmental situations, additional study is nonetheless required.

Table 2

Confidence Level Accuracy on each Insect Pests

Insect Name	**Confidence Level**	**mAP**
Brown Planthopper	81%	71.6
Green Leafhopper	98%	
Leaffolder	98%	
Rice Black Bug	99%	
Rice Grain Bug	96%	
Rice Bug	99%	

The accuracy of the proposed methodology in identifying different types of insects commonly found in rice fields is shown in Table 2 below.

The results in Table 2 show that the model has a high accuracy in identifying most of the insect pests, with a confidence level of 98% or higher for Green Leafhopper, Leaffolder, Rice Black Bug, Rice Grain Bug, and Rice Bug. The highest confidence level is observed for Rice Bug, with a score of 99%.

The Mean Average Precision (mAP) has a value of 71.6%. The mAP gives an overall evaluation of the model's ability in identifying insect pests by measuring the average precision across all classes.

The results in Table 2 demonstrate that the proposed model is effective in identifying different insect pests in rice fields. The high confidence levels show that the algorithm can confidently and properly identify the majority of the pests.

Overall, Table 2 offers insightful information on how well the proposed model can identify various insect pests in rice fields. The findings imply that the suggested method has the potential to be a useful tool for agricultural pest control, allowing farmers to identify pests quickly and accurately and take the necessary precautions to prevent damage to their crops.

Table 3

Questionnaire for Respondents

	5 (Excellent)	4 (Very Satisfactory)	3 (Satisfactory)	2 (Fair)	1 (Poor)
1. The app can accurately detect the six types of insect pest. *(Ang app makadetect insakto sang anum nga peste nga insekto.)*					
2. The app's camera used in capturing insect pests is functioning well. *(Ang camera sang app nga gigamit sa pagkuha sang laragway sang mga peste nga insekto ga function tig insakto.)*					
3. The app features load quickly when navigated. (Ang features sang app dasig lng mag proseso kng pagamitun)					
4. Information about insect pests and recommended pesticides are reliable and adequately provided. *(Ang impormasyon bahin sa mga peste nga insekto kag ginarekomendar nga pestisidyo masaligan kag igo nga ginhatag.)*					
5. The app is compatible on my android device. *(Ang app tugma sa akong cellphone.)*					
6. The app detects insect pests faster and suggests appropriate pesticides.					

(Ang app dasig nga makadetect sang mga peste nga insekto kag parekomendar sang sakto nga pestisidyo.)					
7. The mobile application's loading speed meets my needs. *(Ang kadasigun sa pagproseso sang aplikasyon nalab-ot sa akong panginahanglan.)*					
8. The app is not complicated to use. (Ang app dili komplikado kng paggamitun.)					
9. The app's features like menus, buttons, etc. are user-friendly. *(Ang mga feature sa app parehus sa mga menu, pirindutan, kag iban pa dali lng kung gagamitun.)*					
10. The app's interface is clean, simple and consistent. *(Ang hitsura sang app limpyo, simple kag pare-pareho tulukan.)*					
11. Graphics, media elements, & content are clear and appealing. *(Klaro intindihon ang mga graphic, element sa media, kag mga unod nga impormasyon sang app.)*					
12. Background and text size are pleasing, compatible and easy to read. *(Ang background kag ang kadaku-on sang teksto manami tulukon, nagakaangay, kag dali basahon.)*					
13. The organization of contents and pages are precise and well organized. *(Maayo ang pagkay-o kag pagpasunod sang mga nasulod nga mga konteksto.)*					
14. Colors are used in an effective way. *(Epiktibo kag manami sa mata ang paggamit sang mga kolor.)*					

15. I am satisfied with the look and feel of the app. *(Nanami-an ako sa bilog nga hitsura sang app.)*					
16. The app is suitable to the target audience. *(Ang app naga-angay san na-target nga mga manug-gamit.)*					
17. This app will greatly aid farmers in rice production. *(Dako ang mabulig sang app sa produksyon sang paray.)*					
18. Incorrect use of keys/commands does not cause program to abort. *(Ang sala nga paggamit sang mga pirindutan indi rason para mapatay ang app.)*					
19. Aside from farmers, the app is also useful to other common users. *(Ini nga app, indi lamang mapuslan sang mga mangunguma kundi mangin mapuslanon man sa iban nga mga tawo nga gusto maggamit.)*					
20. The organization of content are precise and well presented. *(Maayo ang pag-pasunod kag pagpresentar sang nga unod nga impormasyon.)*					

Legend:

Scale	Description
4.21 - 5	Outstanding
3.41-4.20	Very Satisfactory
2.61-3.40	Satisfactory
1.81-2.60	Fair
1-1.80	Poor

The mean was used to determine the respondents' correspondence. The overall computed mean of the respondents was 4.58, which is ruled an "Outstanding" rate. This concludes that respondents favor the entirety of the application and have a positive response to its potential. In addition, responses to questions do not have fair or poor options from the respondents, indicating that none of them are dissatisfied with the application.

Specifically, the findings show that out of the 20 questions, item no. 20, "I am satisfied with the look and feel of the app." has the highest mean of 4.78 and is rated "Outstanding," which conveys that the users are satisfied with the app’s user interface. Moreover, item no. 6, "The app detects insect pests faster and suggests appropriate pesticides." had a mean of 4.36 with an "Outstanding" rating, which means that the results have satisfied the second objective of developing a mobile application that gives farmers information about the insect pest's name and recommended pesticides.

The second highest mean, with a mean score of 4.68 and an "Outstanding" rating, is tied on item no. 7, "The mobile application's loading speed meets my needs." and item no. 14, "The app’s interface is clean, simple, and consistent." which signifies that the app’s response time, processing time, and user interface meet the user’s requirements.

Item no. 4, "Information about insect pests and recommended pesticides are reliable and adequately provided." has the lowest rating with a mean value of 4.35, yet still falls under the "Outstanding" rating. This implies that the information presented in the mobile app is trustworthy and credible.

Table 4

ISO 25010 - Functional Stability

Indicator	**Mean**	**Description**
Functional Correctness	4.56	Outstanding

Functional Stability. The results, as shown in Table 4, conclude that the app has an overall functional stability mean score of 4.56 based on its Functional Correctness indicator. Results indicate that the application is capable of offering functions that meet the implied needs.

Table 5

ISO 25010 - Performance Efficiency

Indicators	**Mean**	**Description**
Time Behavior	4.60	Outstanding
Resource Utilization	4.44	Outstanding
Overall Mean	**4.52**	**Outstanding**

Performance Efficiency. The results shown in Table 5 revealed that the app has "outstanding" performance efficiency based on its overall mean score of 4.52. Its indicators are that Time Behavior is rated "Outstanding" with a mean of 4.60 and Resource Utilization is rated "Outstanding" with a mean of 4.44. This means that the mobile app performs well.

Table 6

ISO 25010 - Compatibility

Indicator	**Mean**	**Description**
Co-existence	4.64	Outstanding

Compatibility. The results shown in Table 6 reveal that the app has "Outstanding" compatibility based on its indicator Co-existence which garnered an overall mean score of 4.64. This revealed that the app is compatible with respondents' mobile devices.

Table 7

ISO 25010 - Usability

Indicators	**Mean**	**Description**
Operability	4.74	Outstanding
User Interface Aesthetics	4.61	Outstanding
Overall Mean	**4.68**	**Outstanding**

Usability. Table 7's findings reveal that the app has an overall mean rating of 4.68 and is deemed "Outstanding." With a mean score of 4.74 and 4.61, respectively, its indicators for Operability and User Interface Aesthetics are both regarded as "Outstanding." This demonstrates how top-notch the system's user interface and user experience are.

Table 8

ISO 25010 - Reliability

Indicator	**Mean**	**Description**
Fault Tolerance	4.36	Outstanding

Reliability. The results in Table 8 show that the app has "Outstanding" reliability based on its Fault Tolerance indicator mean score of 4.36. This means that the app is reliable and consistently performs well.

Table 9

ISO 25010 - Maintainability

Indicators	**Mean**	**Description**
Reusability	4.80	Outstanding
Analyzability	4.64	Outstanding
Overall Mean	**4.72**	**Outstanding**

Maintainability. The results in Table 9 indicate that the app has "Outstanding" maintainability based on its overall mean score of 4.72. Its indicators Reusability is "Outstanding" with a mean of 4.80 and Analyzability is "Outstanding" with a mean of 4.64. This revealed that the app is flexible and adaptive to changes in the environment and needs.

Table 10

Summary of ISO 25010 for Farmers and DA Technical Staff

Criteria	**Mean**	**Description**
Functional Stability	4.56	**Outstanding**

Performance Efficiency	4.52	**Outstanding**
Compatibility	4.64	**Outstanding**
Usability	4.68	**Outstanding**
Reliability	4.36	**Outstanding**
Maintainability	4.72	**Outstanding**
Overall Mean	**4.58**	**Outstanding**

Legend:

Scale	Description
4.21 – 5	Outstanding
3.41-4.20	Very Satisfactory
2.61-3.40	Satisfactory
1.81-2.60	Fair
1-1.80	Poor

The results in Table 10 indicate that the Inspestor achieved an overall "Outstanding" rating based on the ISO 25010 standard, garnering an overall mean score of 4.59. Precisely, among the six quality requirements, all of them achieved an "Outstanding" rating, whereas Maintainability achieved the highest mean score of 4.72.

The results satisfied the quality evaluation and thus attest to the app's quality in meeting implied needs for its users as evaluated by the respondents.

System Evaluation Results

In relation to the development and testing of the system, the researchers needed assistance from an IT expert to ensure that the mobile application performs well.

The system evaluation was conducted by one IT expert. The researchers sent a demo video of the mobile application based on the different test scenarios.

For this purpose, the researchers created a questionnaire form for software evaluation that covers six criteria based on ISO 25010. Functional Stability, Performance Efficiency, Compatibility, Usability, Reliability, and Maintainability were among the system evaluation criteria.

The evaluation form was made through Google Forms and consists of 20 questions. It was sent to the expert via Gmail.

SO/IEC 25010: SOFTWARE QUALITY EVALUATION

Kindly evaluate the degree of compliance of the software to the ISO/IEC 25010 by checking the column corresponding the degree to which you deemed the software being evaluated complied using the scale below after you access/run the mobile application.

* Required

1. Name (Last Name, First Name) *

2. Type of Respondent *

Check all that apply.

- [ ] Farmer
- [ ] IT Expert
- [ ] DA Technical Staff

3. Email *

____

Scale	Descriptive Rating	Qualitative Description
5	Outstanding	The performance almost always exceeds the job requirements. The faculty as an exceptional role model.
4	Very Satisfactory	The performance meets and often exceeds the job requirements.
3	Satisfactory	The performance meets the job requirements.
2	Fair	The performance needs some development to meet job requirements.
1	Poor	The faculty fails to meet job requirements.

Functional Suitability

This characteristic represents the degree to which a product or system provides functions that meet stated and implied needs when used under specified conditions.

4. Functional Correctness * 1 point

Degree to which a product or system provides the correct results with the needed degree of precision.

Check all that apply.

- [ ] Outsanding
- [ ] Very Satisfactory
- [ ] Satisfactory
- [ ] Fair
- [ ] Poor

Performance efficiency

This characteristic represents the performance relative to the amount of resources used under stated conditions.

5. Time Behavior * 1 point

Degree to which the response and processing times and throughput rates of a product or system, when performing its functions, meet requirements.

Check all that apply.

- [ ] Outstanding
- [ ] Very Satisfactory
- [ ] Satisfactory
- [ ] Fair
- [ ] Poor

6. Resource Utilization * 1 point

Degree to which the amounts and types of resources used by a product or system, when performing its functions, meet requirements.

Check all that apply.

- [ ] Outstanding
- [ ] Very Satisfactory
- [ ] Satisfactory
- [ ] Fair
- [ ] Poor

Compatibility

Degree to which a product, system or component can exchange information with other products, systems or components, and/or perform its required functions while sharing the same hardware or software environment.

7. Co-existence * 1 point

Degree to which a product can perform its required functions efficiently while sharing a common environment and resources with other products, without detrimental impact on any other product.

Check all that apply.

- [ ] Outstanding
- [ ] Very Satisfactory
- [ ] Satisfactory
- [ ] Fair
- [ ] Poor

Usability

Degree to which a product or system can be used by specified users to achieve specified goals with effectiveness, efficiency and satisfaction in a specified context of use.

8. Operability * 1 point

Degree to which a product or system has attributes that make it easy to operate and control.

Check all that apply.

- [ ] Outstanding
- [ ] Very Satisfactory
- [ ] Satisfactory
- [ ] Fair
- [ ] Poor

9. User Interface Aesthetics * 1 point

Degree to which a user interface enables pleasing and satisfying interaction for the user.

Check all that apply.

- [ ] Outstanding
- [ ] Very Satisfactory
- [ ] Satisfactory
- [ ] Fair
- [ ] Poor

Reliability

Degree to which a system, product or component performs specified functions under specified conditions for a specified period of time.

10. Fault Tolerance * 1 point

Degree to which a system, product or component operates as intended despite the presence of hardware or software faults.

Check all that apply.

- [ ] Outstanding
- [ ] Very Satisfactory
- [ ] Satisfactory
- [ ] Fair
- [ ] Poor

Maintainability

This characteristic represents the degree of effectiveness and efficiency with which a product or system can be modified to improve it, correct it or adapt it to changes in environment, and in requirements.

11. Reusability * 1 point

Degree to which an asset can be used in more than one system, or in building other assets.

Check all that apply.

- [ ] Outstanding
- [ ] Very Satisfactory
- [ ] Satisfactory
- [ ] Fair
- [ ] Poor

12. Analysability * 1 point

Degree of effectiveness and efficiency with which it is possible to assess the impact on a product or system of an intended change to one or more of its parts, or to diagnose a product for deficiencies or causes of failures, or to identify parts to be modified.

Check all that apply.

- [ ] Outstanding
- [ ] Very Satisfactory
- [ ] Satisfactory
- [ ] Fair
- [ ] Poor

13. Any comments, recommendations or suggestions? *

Figure 17. Questionnaire for IT Expert

Table 11

ISO 25010 – Functional Stability

Indicator		Mean	Description
Functional Correctness	Degree to which a product or system provides the correct results with the needed degree of precision.	5	Outstanding

Functional Stability. The results, as shown in Table 11, conclude that the app has an overall functional stability mean score of 5 based on its Functional Correctness indicator. Results show that the application is able to provide features that satisfy the indicated needs.

Table 12

ISO 25010 – Performance Efficiency

Indicators		Mean	Description
Time Behavior	Degree to which the response and processing times and throughput rates of a product or	**5**	Outstanding

	system, when performing its functions, meet requirements.		
Resource Utilization	Degree to which the amounts and types of resources used by a product or system, when performing its functions, meet requirements.	**5**	Outstanding

Performance Efficiency. The results shown in Table 12 reveal that the app has "outstanding" performance efficiency based on its overall mean score of 5. Its indicators include the ratings of "Outstanding" with a mean of 5 for both Time Behavior and Resource Utilization. This demonstrates the effectiveness of the mobile app.

Table 13

ISO 25010 – Compatibility

Indicators		Mean	Description
Co-existence	Degree to which a product can perform its required functions efficiently while sharing a common environment and resources with other products, without detrimental impact on any other product.	**5**	Outstanding

Compatibility. Table 13's findings showed that the app's indicator Co-existence, which had an overall mean score of 5, indicated "Outstanding" compatibility. This confirmed that the app is compatible with the mobile devices of the respondents.

Table 14

ISO 25010 - Usability

Indicators		**Mean**	**Description**
Operability	Degree to which a product or system has attributes that make it easy to operate and control.	**4**	Very Satisfactory
User Interface Aesthetics	Degree to which a user interface enables pleasing and satisfying interaction for the user.	**5**	Outstanding

Usability. Table 14 results show that the app has an overall mean rating of 4.5 and is regarded "Outstanding." With a mean score of 4 and 5, respectively, its indicators for Operability and User Interface Aesthetics are both regarded as "Outstanding," highlighting how excellent the system's user interface and user experience are.

Table 15

ISO 25010 - Reliability

Indicators		Mean	Description
Fault Tolerance	Degree to which a system, product or component operates as intended despite the presence of hardware or software faults.	**4**	Very Satisfactory

Reliability. According to the findings in Table 15, the app has "Outstanding" reliability based on its Fault Tolerance indicator mean score of 4. This demonstrates the app's reliability and continuously high performance.

Table 16

ISO 25010 - Maintainability

Indicators		Mean	Description
Reusability	Degree to which an asset can be used in more than one system,	5	Outstanding

	or in building other assets.		
Analyzability	Degree of effectiveness and efficiency with which it is possible to assess the impact on a product or system of an intended change to one or more of its parts, or to diagnose a product for deficiencies or causes of failures, or to identify parts to be modified.	5	Outstanding

Maintainability. The results in Table 16 indicate that the app has "Outstanding" maintainability based on its overall mean score of 5. Its indicators Reusability is "Outstanding" with a mean of 5 and Analyzability is "Outstanding" with a mean of 5. This demonstrated how adaptable the software is to changes in the environment and user needs.

Table 17

Summary of ISO 25010 for IT Expert

Criteria	Mean	Description
Functional Stability	5	Outstanding
Performance Efficiency	5	Outstanding
Compatibility	5	Outstanding
Usability	4.5	Outstanding
Reliability	4	Outstanding
Maintainability	5	Outstanding
Overall Mean	**4.75**	**Outstanding**

Legend:

Scale	Description
4.21 – 5	Outstanding
3.41-4.20	Very Satisfactory
2.61-3.40	Satisfactory
1.81-2.60	Fair
1-1.80	Poor

The results as shown in Table 17 indicate an overall "Outstanding" rating based on the ISO 25010 standard, garnering an overall mean score of 4.75. Precisely, among the six quality requirements, all of them achieved an "Outstanding" rating with a mean score of 5, except Usability which has a 4.5 mean score but is still rated as "Outstanding" and Reliability which has a mean score of 4, but is rated as "Very Satisfactory". The results satisfied the quality evaluation and thus attest to the app's quality in meeting implied needs for its users as evaluated by the respondents.

CHAPTER 5

SUMMARY, CONCLUSIONS, AND RECOMMENDATIONS

Summary of the Proposed Study Design and Implementation

The Insect Pest Identification App with Prescribed Pesticide on Rice Field using SSD MobileNet Model on Deep Learning was designed to provide users with information about the pest's name as well as a pesticide recommendation.

The researchers proposed an offline mobile application as a portable tool to help farmers in insect pest management.

Farmers are the primary beneficiaries, thus all data in the app about insect pests and recommended pesticides must be accurate and reliable.

The researchers used Figma to prototype the mobile software's User Interface (UI).

The researchers lay out the design of the GUI in the early stages of development by establishing the basic functionalities required, such as the user interface, user experience, codebase, and libraries.

During the review phase, the prototype was reviewed, and feedback on revisions and additional functionality to be developed was presented.

Enhancements were made throughout the updated and enhanced prototype phase.

In terms of image labeling, Python was used in the training model development process. TensorFlow and SSD MobileNet were used to create the training model. The Android Studio was the IDE used to create the mobile app, and Kotlin was the programming language.

Furthermore, the researchers seek the assistance of the Department of Agriculture Region VI in providing insect pest, as well as verifying the data presented in the app for validity and accuracy.

Summary of Findings

This study aimed to develop an insect pest identification app that would provide farmers with information on insect pests as well as recommended pesticides. The software can detect six different types of adult insect pests and offers a best-suited pesticide that targets specific insect pests found in rice fields.

The software had to be installed properly. The user's expertise with mobile devices spans from basic to advanced. The software runs on a mobile device that was built using

Android Studio and the Kotlin programming language. The training model was based on Tensorflow, an end-to-end open-source machine learning platform, and SSD MobileNet, a Single-Shot Multibox Identification network designed to perform object detection.

The analysis was based on the recorded images in the dataset so the precision was strongly dependent on the presence of sufficient images to support it.

The mobile application was aimed mostly at farmers, but it was also accessible to anyone who needed it. The mobile app can detect an insect pest more accurately when the image is captured with white, palm, or rice leaves as a background, preferably in portrait mode. However, captured images with rice leaves in the background have the least accuracy. Capturing images must be done during daylight or in areas with sufficient sunlight to ensure a smooth detection process. Capturing images in dark areas prevents the app from detecting the image. If the insect pest was too small to be detected, users can zoom the camera to enlarge the image. The image quality of the captured insect pest determined the precision of detection.

If the user captures another insect pest that is not included in the dataset, it will display a "NOT IN THE LIST" message. Moreover, the system cannot detect an insect that moves constantly. When taking pictures of an insect pest, it must be immobile because movements blur the pictures. Additionally, in an open field-testing scenario, it was crucial to check for wind speed when taking pictures since the wind makes the rice leaves move, which eventually disturbs the insect pest, which blurs the picture. Furthermore, the prescribed pesticides suggest commercially available brand names. Meanwhile, data on the pesticides' generic types or active ingredients can be found in the mobile app's library.

To assess the performance of the app, researchers generated an evaluation form that covers six ISO 25010 criteria and the accuracy detection based on the Mean Average Precision (mAP). The system evaluation criteria included Functional Stability, Performance Efficiency, Compatibility, Usability, Reliability, and Maintainability which were later evaluated by farmers and Department of Agriculture officials.

The overall mean of the app based on ISO 25010 is 4.58 with an "Outstanding" rating. Furthermore, the indicators Maintainability has the highest mean score of 4.36 and Reliability has the lowest mean score of 4.72, both of which achieve an "Outstanding" rating. Moreover, for the mean average precision of the system, it shows the result of 71.6

and an average recall of 76.9 and high-level result of confidence with 99% and least result of 81% of the insect pests.

Conclusions

After the application development, implementation and testing, the researchers concluded that the study met the objectives that were set for it.

1. It was created to detect and identify insect pests in rice fields using the SSD MobileNet Model.

2. It gives farmers information about the pest's name and recommended pesticides.

3. Its detection accuracy was evaluated using Mean Average Precision (mAP) in collaboration with an IT Expert.

4. Its application performance was evaluated based on ISO 25010 along with an IT Expert, Department of Agriculture and Farmers. The overall performance of the app based on the respondents (farmers and DA technical staff) is 4.58 with an “Outstanding” rating. On the other hand, the performance evaluation of the app based on ISO 25010 along with an IT expert is 4.75 with an "Outstanding" rating.

Recommendations

To improve the system, the researchers recommend the following:

1. In addition to the pesticide recommendation, a feature in which users were informed about natural insect pest control options if they prefer not to use chemicals may be introduced.
2. The program could be improved so that it can be downloaded and used on other mobile platforms, such as iOS.
3. Include different backgrounds for captured insect pests to accurately detect the image.
4. Add different types of insect pest that includes pre-adult stage and larvae stage in the dataset to make the app more reliable.
5. In data gathering, it was preferred to use a high-quality camera like DSLR to capture high resolution image of insect pest datasets to be used in training model.
6. Aside from SSD MobileNet Model, try to utilize other deep learning models/algorithm that also compatible in mobile device.

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Appendices

Appendix A

Letter to the Adviser

	INVITATION LETTER FOR ADVISER	Document No.	**WVSU-ICT-SOI-03-F03**
		Issue No.	**1**
		Revision No.	**0**
	WEST VISAYAS STATE UNIVERSITY	Date of Effectivity:	**April 27, 2018**
		Issued by:	**CICT**
		Page No.	**Page 100 of 142**

March 1, 2022
DEOCAMPO, NIKIE JO E.
Part- Time Instructor
CICT-West Visayas State University (Main)
Luna St, La Paz, Iloilo City, 5000 Iloilo

Dear Mr. Nikie Jo E. Deocampo,

The undersigned are BS Information Technology Research 1/Thesis 1 students of CICT, this university. Our thesis/capstone project title is *"Insect Pest Identification App with Prescribed Pesticide in Rice Fields Using Single Shot Detector MobileNet Model on Deep Learning"*.

Knowing of your expertise in research and on the subject matter, we would like to request you to be our **ADVISER**.

We are positively hoping for your acceptance. Kindly check the corresponding box and affix your signature in the space provided. Thank you very much.

Respectfully yours,

ALYZA MARIE TARRAZONA

CLARENCE GEALON

KHRYSMA DEI CALDINA

CLARNICK YAP

PAOLA BIANCA ZARRIZ

PS:

Advisers, are task to work with the students in providing direction and assistance as needed in their thesis/capstone project. They shall meet with the students weekly or as needed to provide direction, check on progress and assist in resolving problems until such a time that the students passed their defenses and submit their final requirements, as well as, preparing their evaluations and grades.

Action Taken:

○ I Accept.

○ Sorry. I don't accept.

Nikie Jo E. Deocampo
Signature over printed name of the Adviser

CC:
CICT Dean
Research Coordinator
Group
*To be accomplished in 4 copies

Appendix B

Letter to the Co-Adviser

	INVITATION LETTER FOR ADVISER	Document No.	WVSU-ICT-SOI-03-F03
		Issue No.	1
		Revision No.	0
	WEST VISAYAS STATE UNIVERSITY	Date of Effectivity:	April 27, 2018
		Issued by:	CICT
		Page No.	Page 1 of 2

March 18, 2022
MATEO, JOHN CRISTOPHER
Part-time Instructor
CICT-West Visayas State University (Main)
Luna St, La Paz, Iloilo City, 5000 Iloilo

Dear Mr. John Cristopher Mateo,

The undersigned are BS Information Technology Research 1/Thesis 1 students of CICT, this university. Our thesis/capstone project title is *"Insect Pest Identification App with Prescribe Pesticide in Rice fields Using Single Shot Detector Mobilenet Model on Deep Learning"*.

Knowing of your expertise in research and on the subject matter, we would like to request you to be our **CO-ADVISER**.
We are positively hoping for your acceptance. Kindly check the corresponding box and affix your signature in the space provided. Thank you very much.
Respectfully yours,

ALYZA MARIE TARRAZONA

CLARENCE GEALON

KHRYSMA DEI CALDINA

CLARNICK YAP

PAOLA BIANCA ZARRIZ

PS:
Advisers, are task to work with the students in providing direction and assistance as needed in their thesis/capstone project. They shall meet with the students weekly or as needed to provide direction, check on progress and assist in resolving problems until such a time that the students passed their defenses and submit their final requirements, as well as, preparing their evaluations and grades

Action Taken:

☒ I Accept.

☐ Sorry. I don't accept.

JOHN CRISTOPHER A. MATEO
Signature over printed name of the Adviser

CC:
CICT Dean
Research Coordinator
Group
To be accomplished in 4 copies

Appendix C

Letter to the Adviser Recommendation

	ADVISER'S ENDORSEMENT FORM (For Thesis Manuscript)	Document No.	**WVSU-ICT-SOI-03-F10**
		Issue No.	**1**
		Revision No.	**0**
	WEST VISAYAS STATE UNIVERSITY	Date of Effectivity:	**April 27, 2018**
		Issued by:	**CICT**
		Page No.	**Page 102 of 1**

Respectfully endorsed to the **Technical Editor**, the attached manuscript of the thesis entitled:

Insect Pest Identification App with Prescribed Pesticide in Rice fields Using SSD MobileNet Model on Deep Learning

Said manuscript has been presented to me for preliminary evaluation and guidance, and after a series of corrections/directions given which was implemented by the proponents whose names are listed hereunder and their thorough research, we have come to its completion.

Now therefore, I hereby **ENDORSE** the said thesis manuscript to the Technical Editor for **TECHNICAL EDITING**.

Nikie Jo Deocampo
Adviser's Name & Signature

John Cristopher Mateo
Adviser's Name & Signature

Date: January 5, 2023

Group Members:
1.Khrysma Dei Caldina
2.Clarence Gealon
3. Alyza Marie Tarrazona
4. Clarnick Yap
5. Paola Bianca Zarriz

Note: *This form should be accomplished and signed if the corrections and changes made by the adviser have beenimplemented and a new copy of the document have been printed for checking and submission to the next editor.*

Appendix D

Letter to the Technical Editor

	TECHNICAL EDITOR'S ENDORSEMENT FORM (For Thesis Manuscript)	Document No.	WVSU-ICT-SOI-03-F11
		Issue No.	1
		Revision No.	0
	WEST VISAYAS STATE UNIVERSITY	Date of Effectivity:	April 27, 2018
		Issued by:	CICT
		Page No.	Page 1 of 1

Respectfully endorsed to the **English Editor**, the attached manuscript of the thesis entitled:

Insect Pest Identification App with Prescribed Pesticide on Rice fields Using SSD MobileNet Model on Deep Learning

Said manuscript was presented to me and was reviewed and edited in terms of technical specifications, correctness of diagrams and other technical matters. The corrections and suggestions were carried and implemented by the proponents whose names are listed hereunder.

Now therefore, I hereby **ENDORSE** the said thesis manuscript to the English Editor/Grammarian for **English Grammar Editing.**

Dr. Ma. Beth S. Concepcion
Technical Editor's Name & Signature

Date: May 9, 2023

Group Members:

1. Khrysma Dei Caldina
2. Clarence Gealon
3. Alyza Marie Tarrazona
4. Clarnick Yap
5. Paola Bianca Zarriz

Note: *This form should be accomplished and signed if the corrections and changes made by the Technical Editor have been implemented and a new copy of the document have been printed for checking and submission to the next editor.*

Appendix E

Letter to the English Editor

	ENGLISH EDITOR/GRAMMARIAN'S ENDORSEMENT FORM (For Thesis Manuscript)	Document No.	**WVSU-ICT-SOI-03-F12**
		Issue No.	**1**
		Revision No.	**0**
	WEST VISAYAS STATE UNIVERSITY	Date of Effectivity:	**April 27, 2018**
		Issued by:	**CICT**
		Page No.	**Page 1 of 1**

Respectfully endorsed to the **Thesis Format Editor**, the attached manuscript of the thesis entitled:

Insect Pest Identification App with Prescribe Pesticide on Rice fields Using SSD Mobilenet Model on Deep Learning

Said manuscript was presented to me for English grammar editing, corrections has been made and the proponents whose names are listed hereunder implemented said corrections and changes in the revised manuscript.

Now therefore, I hereby **ENDORSE** the said thesis manuscript for **Thesis Format Editing**.

ESPERVAL CEZHAR H. CADIAO
English Editor/Grammarian's Name and Signature

Date: May 11, 2023

Group Members:
1.Khrysma Dei Caldina
2.Clarence Gealon
3. Alyza Marie Tarrazona
4. Clarnick Yap
5. Paola Bianca Zarriz

Note: *This form should be accomplished and signed if the corrections and changes made by the English Editor have been implemented and a new copy of the document have been printed for checking and submission to the next editor.*

Appendix F

Letter to the Format Editor

	THESIS FORMAT EDITOR'S ENDORSEMENT FORM (For Thesis Manuscript)	Document No.	WVSU-ICT-SOI-03-F13
		Issue No.	1
		Revision No.	0
	WEST VISAYAS STATE UNIVERSITY	Date of Effectivity:	April 27, 2018
		Issued by:	CICT
		Page No.	Page 1 of 1

Respectfully endorsed to the **Thesis Coordinator**, the attached manuscript of the thesis entitled:

Insect Pest Identification App with Prescribe Pesticide on Rice fields Using SSD Mobilenet Model on Deep Learning

Said manuscript was presented to me and has checked the preliminaries, thesis document convention and end matters, made some corrections which was implemented by the proponents whose names are listed hereunder.

Now therefore, I hereby **ENDORSE** said manuscript to the Thesis Coordinator for appropriate action.

Dr. Regin A. Cabacas
Thesis Format Editor's Name and Signature

Date: May 25, 2023

Group Members:
1.Khrysma Dei Caldina
2.Clarence Gealon
3. Alyza Marie Tarrazona
4. Clarnick Yap
5. Paola Bianca Zarriz

Note: *This form should be accomplished and signed if the corrections and changes made by the Thesis Format Editor have been implemented and the four (4) new copies have been printed ready for bookbinding.*

Appendix G

Letter to the Certification for Bookbinding

	CERTIFICATION FOR BOOKBINDING (For Thesis Manuscript)	Document No.	WVSU-ICT-SOI-03-F14
		Issue No.	1
		Revision No.	0
	WEST VISAYAS STATE UNIVERSITY	Date of Effectivity:	April 27, 2018
		Issued by:	CICT
		Page No.	Page 1 of 1

This certifies that the attached manuscript of the thesis entitled:

Insect Pest Identification App with Prescribe Pesticide on Rice fields Using SSD Mobilenet Model on Deep Learning

Is now ready for bookbinding. Said manuscript was presented to me and has checked the preliminaries, thesis document convention and end matters, made some corrections which was implemented by the proponents whose names are listed hereunder.

Now therefore, I hereby **ENDORSE** said manuscript for **BOOKBINDING**.

Dr. Regin A. Cabacas
Thesis Coordinator's Name and Signature

Date: ____________________

Group Members:
1.Khrysma Dei Caldina
2.Clarence Gealon
3. Alyza Marie Tarrazona
4. Clarnick Yap
5. Paola Bianca Zarriz

Note: *This form should be accomplished and signed if the corrections and changes made by the Thesis Format Editor have been implemented and the four (4) new copies have been printed ready for bookbinding.*

Appendix H

Gantt Chart

Thesis Progress Report

Group 5

Project Start Date	1/29/2022 (Saturday)	Display Week	2
Project Lead	Alyza Marie Tarrazona		

WBS	TASK	ASSIGNED	START	END	DAYS	% DONE
1	**Introduction**			-		
1.1	Background of the Study	Paola & Clarnick	Sat 1/29/22	Wed 2/02/22	5	100%
1.2	Theoritical Framework	Khrysma	Fri 2/11/22	Wed 2/16/22	6	100%
1.3	Objectives of the Study	Clarnick	Wed 2/09/22	Sun 2/13/22	5	100%
1.4	Significance of the Study	Paola	Tue 2/01/22	Mon 2/07/22	7	100%
1.5	Definition of the Terms	Clarnick	Wed 2/02/22	Sat 2/05/22	4	100%
1.6	Delimitation of the Study	Clarence	Thu 2/03/22	Thu 2/10/22	8	100%
2	**Review of Related Studies**			-		
2	Review of Existing and Related Studies	Alyza	Fri 2/11/22	Thu 2/17/22	7	100%
3	**Research Design and Methodology**			-		
3.1	Description of the Proposed Study	Alyza	Mon 2/21/22	Wed 3/02/22	10	100%
3.2	Proposed System	Clarence	Mon 3/21/22	Wed 3/30/22	10	100%
3.3	Assumptions and Preconditions	Khrysma	Mon 3/21/22	Sat 3/26/22	6	100%
3.4	Methods and Proposed Enhancements	Paola	Sun 3/20/22	Tue 3/29/22	10	100%
3.5	Components and Design			-		
3.5.1	System Architecture	Clarnick	Thu 3/24/22	Fri 4/01/22	9	100%
3.5.3	Procedural Design	Clarnick	Tue 4/26/22	Thu 5/05/22	10	100%
3.5.4	Input-Process-Output	Alyza	Sat 4/09/22	Fri 4/15/22	7	100%
3.5.5	Object-Oriented Design	Paola	Sun 3/27/22	Wed 3/30/22	4	100%
3.5.6	Use Case Diagram	Paola	Fri 4/01/22	Thu 4/07/22	7	100%
3.5.7	Process Design	Paola	Fri 4/01/22	Thu 4/07/22	7	100%
3.5.8	SDLC	Khrysma	Fri 4/08/22	Thu 4/14/22	7	100%
1	**Result and Discussion**			-		
.1	Implementation	Clarnick	Tue 5/10/22	Thu 5/19/22	10	100%
.1	Results Interpretation and Analysis	Paola	Sat 5/07/22	Mon 5/16/22	10	100%
.1	System Evaluation Results	Clarnick	Sat 5/21/22	Mon 5/30/22	10	100%
5	**Summary, Conclusions, and Recommendations**					
5.1	Summary of the Proposed Study Design and Implementation	Clarnick	Thu 6/02/22	Sat 6/11/22	10	100%
5.2	Summary of Findings	Paola	Sat 06/18/22	Mon 6/27/22	10	100%
5.3	Conclusions	Paola	Sat 7/02/22	Mon 7/11/22	10	100%
5.4	Recommendations	Clarnick	Tue 7/12/22	Thu 7/21/22	10	100%

Appendix I

Source Code

pestLib.xml

```
<?xml version="1.0" encoding="utf-8"?>
<resources>
     <string name="source_link">
         Knowledge                 Bank:                  <a
href="http://www.knowledgebank.irri.org/step-by-step-
production/growth/pests-and-
diseases/insects">www.knowledgebank.irri.org.</a>
    </string>
    -------------------------------------------------<!--
Brown Planthopper-->----------------------------------------
------------
    <string name="bph_name">Brown Planthopper</string>
    <string name="bph_sci_name">Nilaparvata lugens</string>
    <string name="bph_does">
        High population of planthoppers cause leaves to
initially turn orange-yellow before becoming brown and dry
and this is a
        condition called hopperburn that kills the plant.
        \n
        \nBPH can also transmit Rice Ragged Stunt and Rice
Grassy Stunt diseases. Neither disease can be cured.
    </string>
    <string name="bph_why_where">
       Planthoppers can be a problem in rainfed and in
irrigated wetland environments.
        It also occurs in areas with continuous submerged
        conditions in the field, high shade, and humidity.
        \n
        \nClosed canopy of the rice plants, densely seeded
crops, excessive use of nitrogen,
        and early season insecticide spraying also favors
insect development.
    </string>
    <string name="bph_identify"><![CDATA[
        Check for the presence of insect:
        \n
```

```
        \n-crescent-shaped white eggs inserted into the
midrib or leaf sheath
        \n-white to brown nymphs
        \n-brown or white adults feeding near the base of
tillers


        \n
        \nCheck the field for:
        \n
        \n-hopperburn or yellowing, browning and drying of
plant
        \n-ovipositional marks exposing the plant to fungal
and bacterial infections
        \n-presence of honeydew and sooty molds in the bases
of areas infected
        \n-plants with ragged stunt or grassy stunt virus
disease
        \n
        \nHopperburn is similar to the feeding damage or
"bugburn" caused by the rice black bug.
        To confirm hopperburn caused by planthoppers,
        check for the presence of sooty molds at the base of
the plant.
    ]]></string>
    <string name="bph_pesticide">
        ACE ASSAULT 50 SC
        \nACE CARTAP 50 SP
        \nAGCHEM FIPRONIL 5 SC
        \nTORPEDO 5 EC
        \nKNOCK OUT 5 EC
    </string>
    <string name="bph_active_ing">
        PHENTHOATE
      \nPHENTHOATE+BPMC
       \nCYPERMETHRIN
    </string>

    <string name="bph_important">
        The feeding damage caused by planthoppers results in
the yellowing of the plants. At high population density,
        hopperburn or complete drying of the plants is
observed. At this level, crop loss may be 100%.
        In field conditions, plants nearing maturity can have
hopperburns if infested with about 400-500 BPH nymphs.
```

```
    </string>
    <string name="bph_mngmnt"><![CDATA[
        Outbreaks result from pesticides destroying natural
enemies (BPH eggs hatch unchecked, and surviving
        BPH quickly build-up populations to
            damaging levels), or when longwinged planthoppers
are being carried in by the wind.
        \n
        \nTo prevent outbreaks of planthopper:
        \n
        \n1. Remove weeds from the field and surrounding
areas.

        \n2. Avoid indiscriminate use of insecticide, which
destroys natural enemies.
        \n3. Use a resistant variety. Contact your local
agriculture office for an up-to-date list of available
varieties.
        \n4. Critical numbers: At a density of 1 BPH/stem or
less there is still time to act in case the numbers increase.
        \n5. Look for BPH daily in the seedbed, or weekly in
the field, on stems and the water surface. Check each side of
            the seed bed (or direct-seeded fields). For older
rice plants, grasp the plant, bend it over slightly, and
gently
            tap it near the base to see if planthoppers fall
onto the water surface. For transplanted rice look at bases
of 10
            to 20 hills as you cross the field diagonally.
There is no need to scout for BPH or WBPH beyond the milk
stage.
        \n6. Use light traps (e.g., an electric bulb or
kerosene lamp near a light colored wall or over a pan of
water) at night
            when rice is prone to planthopper attack. Do not
place lights near seedbeds or fields. If the light trap is
inundated
            with hundreds of BPH, it\'s a signal to check
your seedbed or field immediately; then scout every day for
the next
            few weeks. If farmers monitor on a daily basis
anyway, then a light trap is unnecessary.
        \n
        \nTo control planthoppers:
        \n
```

```
        \nMechanical & physical measures
        \n
        \n-Flood the seedbed, for a day, so that only the
tips of seedlings are exposed will control BPH.
        \n-Sweep small seedbeds with a net to remove some BPH
(but not eggs), particularly from dry seed beds. At high BPH
densities,
            sweeping will not remove sufficient numbers of
BPH from the base of the plant.
        \n
        \nBiological control
        \n
        \n-If natural enemies out-number BPH the risk of
hopperburn is low. Even rice already damaged by hopperburn
should
            not be treated with insecticides if natural
enemies out-number BPH. Natural enemies of BPH include water
striders,
            mirid bugs, spiders, and various egg parasitoids.
        \n
        \nChemical control
        \n
        \nOnly apply insecticides to the seedbed, for BPH or
WBPH, if all of these conditions are met:
        \n


        \n-an average of more than one planthopper per stem,
        \n-on average, more planthoppers than natural
enemies,
        \n-flooding the seedbed is not an option.
    ]]></string>
<!--<string name="bph_hyperlink">
        Source:
        <a
href="http://www.knowledgebank.irri.org/training/fact-
sheets/pest-management/insects/item/planthopper">
            knowledgebank.irri.org
        </a>
    </string>-->
--------------------------------------------------<!--Green
Leaf Hopper-->-------------------------------------------------
------
    <string name="glh_name">Green Leafhopper</string>
```

```
    <string                  name="glh_sci_name">Nephotettix
virescens</string>
    <string name="glh_does">
       Green leafhoppers are the most common leafhoppers in
rice fields and are primarily critical because they spread
        the viral disease tungro. Both nymphs and adults feed
by extracting plant sap with their needle-shaped mouthparts.
    </string>
    <string name="glh_why_where">
        Staggered planting encourages population growth of
GLH.
        \n
        \nGreen leafhoppers are common in rainfed and
irrigated wetland environments. They are not prevalent in
upland rice.
            Both the nymphs and adults feed on the dorsal
surface of the leaf blades rather than the ventral surface.
        They prefer to feed on the lateral leaves rather than
the leaf sheaths and the middle leaves.
        They also prefer rice plants that have been
fertilized with large amount of nitrogen.
    </string>
    <string name="glh_important">
        Green leafhoppers are important pests. They are
vectors of viral diseases such as tungro, yellow dwarf,
        yellow-orange leaf, transitory yellowing, and dwarf.
    </string>
    <string name="glh_identify">
        Rice fields infested by GLH can have tungro, yellow
dwarf, yellow-orange leaf, and transitory yellowing diseases.
        \n
        \nSymptoms include:
        \n
        \n-stunted plants and reduced vigor
        \nreduced number of productive tillers
        \n-withering or complete plant drying
        \n
        \nTungro infected crops may sometimes be confused
with nitrogen deficiency or iron toxicity or acid soils.
        To confirm the cause of the problem, check for virus
infected plants in the fields, and the presence of the insect:
        \n
        \n-white or pale-yellow eggs inside leaf sheaths or
midribs
```

```
        \nyellow or pale green nymphs with or without black
markings
        \npale green adults with or without black markings
feeding on upper parts of the crop
    </string>
    <string name="glh_pesticide">
        ACE CARTAP 50 SP
        \nPERMECHEM 10 EC
        \nPHENTO-M 50 EC
        \nCARDAN 50 SP
        \nSTRENGTH 40 SP
    </string>
    <string name="glh_active_ing">
       LAMBDA-CYHALOTHRIN
        \nCYPERMETHRIN
        \nPHENTHOATE
    </string>

    <string name="glh_mngmnt"><![CDATA[
        1. Use GLH-resistant and tungro-resistant varieties.
Contact your local agriculture office for an up-to-date
            list of available varieties.
        \n2. Reduce the number of rice crops to two per year
and synchronized crop establishment across farms reduces
        leafhoppers and other insect vectors.
        \n3. Transplant older seedlings (>3 weeks) to reduce
viral disease susceptibility transmitted by leafhoppers.
        \n4. Plant early within a given planting period,
particularly in the dry season to reduce the risk of insect-
vector disease.
        \n5. Avoid planting during the peak of GLH activity
(shown by historical records) to avoid infestation. Light
traps can be
        used to show GLH numbers.
        \n6. Apply nitrogen as needed (e.g., using the Leaf
Color Chart) to avoid contributing to population outbreaks by
applying
        too much nitrogen, or hindering
            plant recovery from planthopper damage by
applying insufficient nitrogen.
        \n7. Control weeds in the field and on the bunds to
remove the preferred grassy hosts of GLH and promotes crop
vigor.
```

```
        \n8. Perform crop rotation with a non-rice crop
during the dry season to decrease alternate hosts for
diseases.
        \n9. Intercrop upland rice with soybean to reduce the
incidence of leafhoppers on rice.
        \n
        \nIn areas without tungro source, insecticides are
not needed, avoid spraying of insecticide (it is often unable
        to prevent or reduce tungro infections).
        \n
        \nEncourage biological control agents: small wasps
(parasitize the eggs), mirid bug; strepsipterans, small
wasps,
        pipunculid flies, and nematodes (parasitize both the
nymphs and adults), aquatic veliid bugs, nabid bugs, empid
        flies, damselflies, dragonflies, and spiders, fungal
pathogen (attacks both nymph and adult).
    ]]></string>
<!-- <string name="glh_hyperlink">
        Source:
        <a
href="http://www.knowledgebank.irri.org/training/fact-
sheets/pest-management/insects">
                    knowledgebank.irri.org
        </a>
    </string>-->
```

Main_activity.kt

```
     private val takePicturePreview =
registerForActivityResult
(ActivityResultContracts.TakePicturePreview()) { bitmap ->

        if(bitmap != null){
            captured_Image.setImageBitmap(bitmap)
            outputGenerator(bitmap)
        }
    }


    Private valon Result=
registerForActivityResult(ActivityResultContracts.StartActi
vityForResult()){ result->
```

```
        Log.i("TAG", "this is the result: ${result.data}
${result.resultCode}")
        onResultReceived(GALLERY_REQUEST_CODE, result)
    }

    private fun onResultReceived(requestCode:Int, result:
ActivityResult?){


        when(requestCode){
            GALLERY_REQUEST_CODE->{
                if(result?.resultCode==
Activity.RESULT_OK){
                    result.data?.data?.let{uri->
                        Log.i("Tag", "onResultReceived:
$uri")
                        val bitmap=
BitmapFactory.decodeStream(contentResolver.openInputStream(
uri))

captured_Image.setImageBitmap(bitmap)
                        outputGenerator(bitmap)
                    }
                }
                else{
                    Log.e("Tag", "onActivityResult:error in
selecting image")
                }
            }
        }
    }
```

Training the model using Google Colab

```
# Start to train the model
# Run the command below from the
content/models/research/object_detection directory
"""
PIPELINE_CONFIG_PATH=path/to/pipeline.config
MODEL_DIR=path to training checkpoints directory
NUM_TRAIN_STEPS=50000
SAMPLE_1_OF_N_EVAL_EXAMPLES=1
```

```
python model_main_tf2.py -- \
  --model_dir=$MODEL_DIR  --num_train_steps=$NUM_TRAIN_STEPS
\
  --
sample_1_of_n_eval_examples=$SAMPLE_1_OF_N_EVAL_EXAMPLES \
  --pipeline_config_path=$PIPELINE_CONFIG_PATH \
  --alsologtostderr
"""

!python                 model_main_tf2.py                 --
pipeline_config_path=/mydrive/TestTrain/data/ssd_mobilenet_
v2_fpnlite_640x640_coco17_tpu-8.config                    --
model_dir=/mydrive/TestTrain/training --alsologtostderr
```

Appendix J

Evaluation Letter for Department of Agriculture – Region VI

West Visayas State University
COLLEGE OF INFORMATION AND COMMUNICATIONS TECHNOLOGY
La Paz, Iloilo City

Regional Crop Protection Center
Department of Agriculture - Western Visayas
WESVIARC Compound, Hamungaya, Buntatala, Jaro Iloilo City

DEPARTMENT OF AGRICULTURE
RECORDS UNIT
RECEIVED
17 NOV 2022

17 November 2022

To
ENG. REMELYN R. RECOTER, MNSA, CESO III
Regional Executive Director

Attention: **RYAN V. RASGO**
Center Chief

Subject: Request for Thesis Respondents for Evaluation of our Mobile Application

Ma'am/Sir,

With all due respect, we are Khrysma Dei Caldina, Alyza Marie Tarrazona, Clarnick Yap, Clarence Gealon, and Paola Bianca Zarriz, third-year Bachelor of Science in Information Technology (BSIT) students from the College of Information and Communications Technology at West Visayas State University - Main Campus.

It is with the utmost modesty that we notify you that we are working on a thesis entitled **"Insect Pests Identification App with Prescribe Pesticide in Rice Fields using Mobilenet Single Shot Detector Model on Deep Learning"**. We are writing this letter to seek your department's approval to lend a portion of your time for us to test and evaluate our mobile app.

Specifically, we would like to request the following information;
1. Authorize at least five (5) D.A. officials to test and evaluate our mobile application.
2. Verify the validity of the information in the mobile app, including the insect names and pesticides.

We sincerely ask that you grant our request so we can test our mobile app when and where it is most convenient for you.

West Visayas State University
COLLEGE OF INFORMATION AND COMMUNICATIONS TECHNOLOGY
La Paz, Iloilo City

We can assure you that the information will be solely used in thesis purposes only. Your promptness in this regard will be highly appreciated. Thank you!

Yours truly,

ALYZA MARIE YARRAZONA
Lead Researcher

KHRYSMA DEI C. CALDINA
Member

CLARENCE T. GEALON
Member

CLARNICK B. YAP
Member

PAOLA BIANCA S. ZARRIZ
Member

Noted:

NIKIE JO DEOCAMPO
Research Adviser

John Cristopher Mateo
Research Adviser

Appendix K

Survey Evaluation form for DA

West Visayas State University
COLLEGE OF INFORMATION AND COMMUNICATIONS TECHNOLOGY
La Paz, Iloilo City

Insect Pest Identification App with Prescribe Pesticide in Rice fields Using SSD Mobilenet Model on Deep Learning
(*Inspestor Mobile App*)

Name (Optional): **Date:**

Age: **Job Position:**

Type of Respondent:

Signature:

Directions: Just put check onto the desired rating below aligned to its characteristics.

Scale	Descriptive	Rating Qualitative Description
5	Excellent	The performance of the app always exceeds the required output
4	Very Satisfactory	The performance of the app meets and often exceed the required output
3	Satisfactory	The performance of the app meets the required output
2	Fair	The performance of the app needs some development to meet the required output
1	Poor	The app fails to meet the required output

	5 (Excellent)	4 (Very Satisfactory)	3 (Satisfactory)	2 (Fair)	1 (Poor)
1. The app can accurately detect the six types of insect pest.					
2. The app's camera used in capturing insect pests is functioning well.					
3. The app features load quickly when navigated.					
4. Information about insect pests and recommended pesticides					

are reliable and adequately provided.					
5. The app is compatible on my android device.					
6. The app detects insect pests faster and suggests appropriate pesticides.					
7. The mobile application's loading speed meets my needs.					
8. The app is not complicated to use.					
9. The app's features like menus, buttons, etc. are user-friendly.					
10. The app's interface is clean, simple and consistent.					
11. Graphics, media elements, & content are clear and appealing.					
12. Background and text size are pleasing, compatible and easy to read.					
13. The organization of contents and pages are precise and well organized.					
14. Colors are used in an effective way.					
15. I am satisfied with the look and feel of the app.					
16. The app is suitable to the target audience.					
17. This app will greatly aid farmers in rice production.					
18. Incorrect use of keys/commands does not cause program to abort.					
19. Aside from farmers, the app is also useful to other common users.					
20. The organization of content are precise and well presented.					

Feedbacks or any recommendations:

Appendix L

Consultation Log for External Sources

	INVITATION LETTER FOR ADVISER	Document No.	**WVSU-ICT-SOI-03-F03**
		Issue No.	**1**
		Revision No.	**0**
	WEST VISAYAS STATE UNIVERSITY	Date of Effectivity:	**April 27, 2018**
		Issued by:	CICT
		Page No.	**Page 121 of 143**

Academic Year

Insect Pest Identification with Prescribe Pesticide on Rice fields Using SSD MobileNet Model on Deep Learning	
Group Members:	
1. Khrysma Dei Caldina	4. Clarnick Yap
2. Clarence Gealon	5. Paola Bianca Zarriz
3. Alyza Marie Tarrazona	6.

Date	Attendance	Comments/Suggestions/Instructions	Signature
02/21/22	Ryan Rasgo	Discussion and gave advice on the different insect pests and pesticides	
03/15/22	Ryan Rasgo	Confirmation of proper name for each image of the captured insect pest: 1. Rice Grain Bug 2. Green Leafhopper 3. Rice Bug 4. Brown Planthopper 5. Rice Black Bug 6. Leaffolder	
04/18/22	Ryan Rasgo	Validated list of three active ingredients as the generic name of pesticides based on the FPA lists of Pesticides on each insect pest	

06/28/22	Karl Patrick Arabang	Making of Test Scenarios and discussion of test steps	
11/04/22	Karl Patrick Arabang	Checking of Test Scenarios while using the Mobile app	
11/04/22	Ryan Rasgo	Evaluation and testing of Mobile Application together with DA technical staffs.	
11/17/22	Ryan Rasgo	Reevaluating our mobile application and testing the new training model of our system through detecting our sample insect pests along with the DA technical staffs	
11/17/22	Karl Patrick Arabang	Evaluation and testing of mobile application based on ISO 25010	
11/22/22	Mr. Noel V. Negre	Providing FPA Pesticide registered products last February 20, 2022	

Adviser: Nikie Jo Deocampo
John Cristopher Mateo

Consultation Schedule: 10:00 AM – 10:30 AM

Appendix M
Validation Letter for FPA

West Visayas State University
COLLEGE OF INFORMATION AND COMMUNICATIONS TECHNOLOGY
La Paz, Iloilo City

Letter of Validation for the Fertilizer and Pesticide Authority – Western Visayas

West Visayas State University

COLLEGE OF INFORMATION AND COMMUICATIONS TECHNOLOGY

La Paz, Iloilo City

LETTER OF VALIDATION

Date:

To obtain data on recommended pesticide for each type of insect pest that is prescribed to be administered in rice fields that will be used in our research "Insect Pest Identification App with Prescribe Pesticide on Rice fields Using SSD Mobilenet Model on Deep Learning", the researchers contacted the Fertilizer and Pesticide Authority (FPA) – Western Visayas via email. The FPA granted our request and provided us with a link on the FPA Pesticide registered products that we can download and use it in our study. This letter ultimately serves as certification that the information provided in our application about insect pests and their corresponding recommended pesticides are valid and true.

The Researchers,

ALYZA MARIE TARRAZONA
Lead Researcher

KHRYSMA DEI C. CALDINA
Member

CLARENCE T. GEALON
Member

CLARNICK B. YAP
Member

PAOLA BIANCA S. ZARRIZ
Member

Recommended for Approval:

MR. NOEL V. NEGRE
Regional Officer, FPA Region VI

Appendix N
Consultation Letter for Buga Farmers Association

July 4, 2022

NESTOR CABALFIN
President, Buga Farmers Association
Buga, Leon, Iloilo

Good day!

We, the 3rd year student of Bachelor of Science in Information Technology, are currently conducting a research study entitled, **"Insect Pest Identification with Prescribe Pesticide in Rice fields Using SSD Mobilenet Model on Deep Learning,"** as part of our academic thesis requirements.

In this light, we humbly request your permission to conduct a survey with the members of Buga Farmers Association. The respondents will be farmers with android cellphones as needed for our survey.

Your kind consideration and positive response is deeply acknowledged in the fulfillment of this academic endeavor.

Thank you!

Respectfully yours,

ALYZA MARIE TARRAZONA
Lead Researcher

KHRYSMA DEI CALDINA
Member

CLARENCE GEALON
Member

PAOLA BIANCA ZARRIS
Member

CLARNICK YAP
Member

Receive and Approved by:

NESTOR CABALFIN
President, Buga Farmers Association
Buga, Leon, Iloilo

Appendix O
Survey Evaluation Form for Farmers

West Visayas State University
COLLEGE OF INFORMATION AND COMMUNICATIONS TECHNOLOGY
La Paz, Iloilo City

Insect Pest Identification App with Prescribe Pesticide in Rice fields Using SSD Mobilenet Model on Deep Learning
(*Inspestor Mobile App*)

Name (Optional): **Date:**

Age:

Type of Respondent:

Signature:

Directions: Just put check onto the desired rating below aligned to its characteristics.

(Ibutang lang ang tsek sa gusto nga rating sa nahiuyonan nga mga kinaiya.)

Scale	Descriptive	Rating Qualitative Description
5	Excellent	The performance of the app always exceeds the required output
4	Very Satisfactory	The performance of the app meets and often exceed the required output
3	Satisfactory	The performance of the app meets the required output
2	Fair	The performance of the app needs some development to meet the required output
1	Poor	The app fails to meet the required output

	5 (Excellent)	4 (Very Satisfactory)	3 (Satisfactory)	2 (Fair)	1 (Poor)
1. The app can accurately detect the six types of insect pest. *(Ang app makadetect insekto sang anum nga peste nga insekto.)*					
2. The app's camera used in capturing insect pests is functioning well. *(Ang camera sang app nga gigamit sa pagkuha*					

sang larogway sang mga peste nga insekto ga function tig insakto.)					
3. The app features load quickly when navigated. (Ang features sang app dasig lng mag proseso kng pagamitun)					
4. Information about insect pests and recommended pesticides are reliable and adequately provided. *(Ang impormasyon bahin sa mga peste nga insekto kag ginarekomendar nga pestisidyo masaligan kag igo nga ginhatag.)*					
5. The app is compatible on my android device. *(Ang app tugma sa akong cellphone.)*					
6. The app detects insect pests faster and suggests appropriate pesticides. *(Ang app dasig nga makadetect sang mga peste nga insekto kag garekomendar sang sakto nga pestisidyo.)*					
7. The mobile application's loading speed meets my needs. *(Ang kadasigun sa pagproseso sang*					

aplikasyon nalab-ot sa akong panginahanglan.)					
8. The app is not complicated to use. (Ang app dili komplikado kng paggamitun.)					
9. The app's features like menus, buttons, etc. are user-friendly. *(Ang mga feature sa app parehus sa mga menu, pirinduton, kag iban pa dali lng kung pagamitun.)*					
10. The app's interface is clean, simple and consistent. *(Ang hitsura sang app limpyo, simple kag pare-pareho tulukon.)*					
11. Graphics, media elements, & content are clear and appealing. *(Klaro intindihon ang mga graphic, element sa media, kag mga unod nga impormasyon sang app.)*					
12. Background and text size are pleasing, compatible and easy to read. *(Ang background kag ang kadaku-on sang teksto manami tulukon, nagakaangay, kag dali basahon.)*					
13. The organization of contents and pages are precise and well organized.					

(Maayo ang pagkay-o kag pagpasunod sang mga nasulod nga mga konteksto.)					
14. Colors are used in an effective way. *(Epiktibo kag manami sa mata ang paggamit sang mga kolor.)*					
15. I am satisfied with the look and feel of the app. *(Nanami-an ako sa bilog nga hitsura sang app.)*					
16. The app is suitable to the target audience. *(Ang app naga-angay san na-target nga mga manug-gamit.)*					
17. This app will greatly aid farmers in rice production. *(Dako ang mabulig sang app sa produksyon sang paray.)*					
18. Incorrect use of keys/commands does not cause program to abort. *(Ang sala nga paggamit sang mga pirindutan indi rason para mapatay ang app.)*					
19. Aside from farmers, the app is also useful to other common users. *(Ini nga app, indi lamang mapuslan sang mga mangunguma kundi mangin mapuslanon man sa iban nga mga tawo nga gusto maggamit.)*					
20. The organization of content are precise and well presented. *(Maayo ang pag-pasunod kag pagpresentar sang nga unod nga impormasyon.)*					

Feedbacks or any recommendations

Appendix P
Letter for Data Gathering

West Visayas State University
COLLEGE OF INFORMATION AND COMMUNICATIONS TECHNOLOGY
La Paz, Iloilo City

Insect Pest Identification App with Prescribe Pesticide in Rice fields Using SSD MobileNet Model on Deep Learning
(*Inspestor Mobile App*)

Date:

Dear Respondent,

Greetings!

We are presently conducting a study entitled "**INSECT PEST IDENTIFICATION APP WITH PRESCRIBE PESTICIDE IN RICE FIELDS USING SSD MOBILENET MODEL ON DEEP LEARNING**", as a requirement of the course CIT 215 (Thesis Writing for IT 1).

In light of this, we respectfully request your participation in our research. We hope that you can assist us by providing sincere and accurate responses to the survey. Your response(s) will be treated with confidentiality and will be used solely for academic purposes.

Thank you very much.

Very truly yours,

ALYZA MARIE TARRAZONA
Lead Researcher

KHRYSMA DEI C. CALDINA
Member

CLARENCE T. GEALON
Member

CLARNICK B. YAP
Member

PAOLA BIANCA S. ZARRIZ
Member

Noted:

NIKIE JO DEOCAMPO
Research Adviser

JOHN CRISTOPHER MATEO
Research Adviser

Appendix Q

Software Quality Evaluation Form for IT Expert

SO/IEC 25010: SOFTWARE QUALITY EVALUATION

1 response

Name (Last Name, First Name)

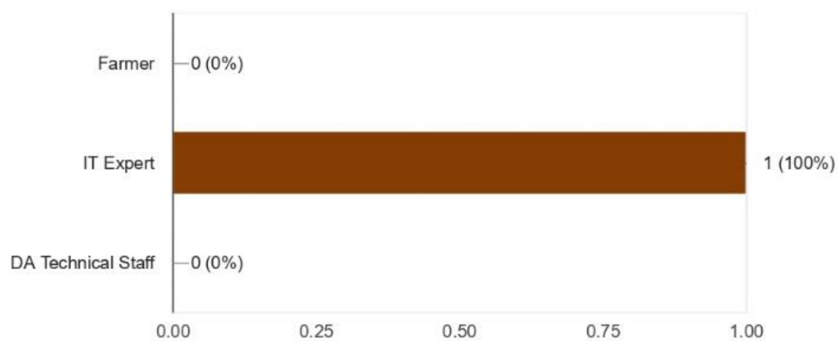
1 response

Arabang, Karl Patrick

Type of Respondent

Copy

1 response



Email

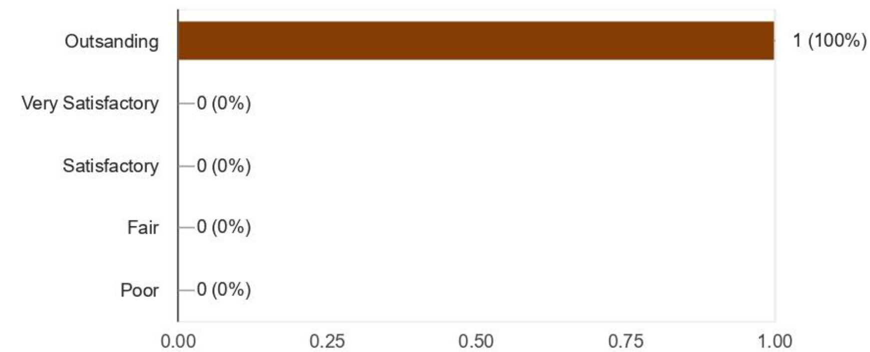
1 response

karl@abakadastudios.com

Functional Correctness

Copy

1 response



Time Behavior

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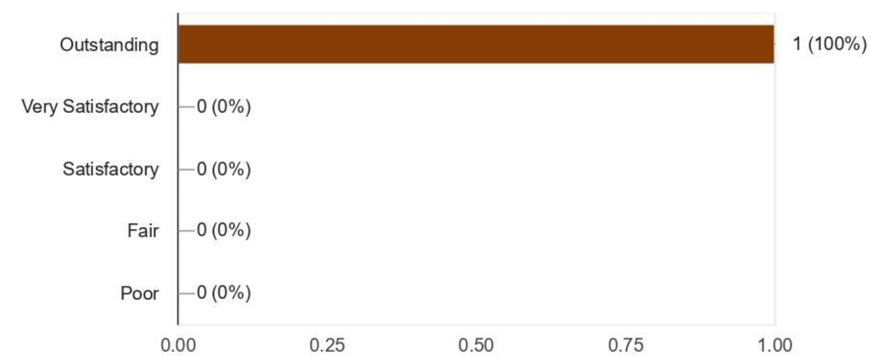
1 response



Resource Utilization

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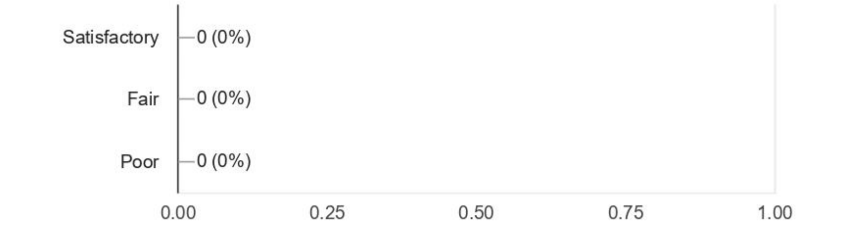
1 response



Co-existence

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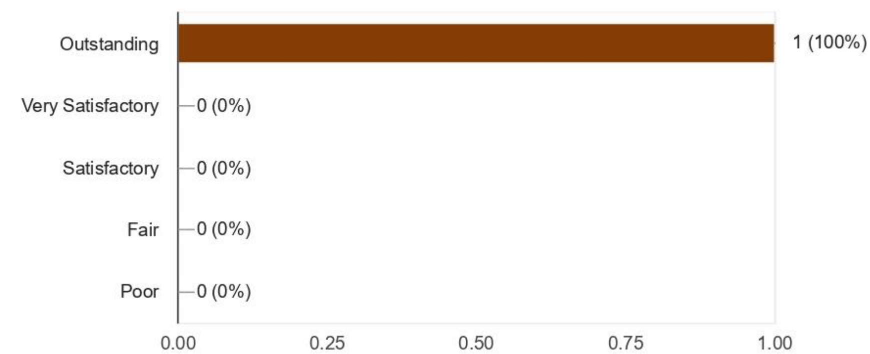
1 response



Operability

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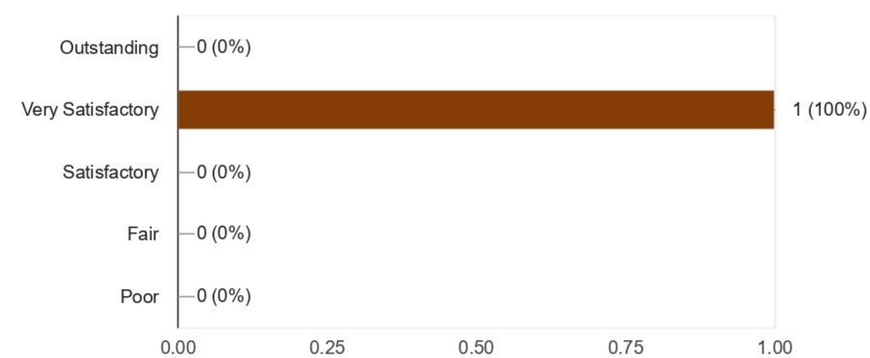
1 response



User Interface Aesthetics

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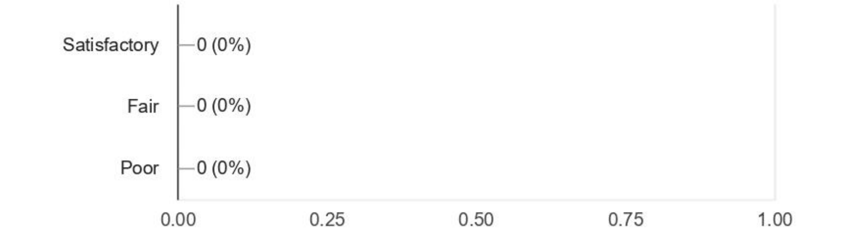
1 response



Fault Tolerance

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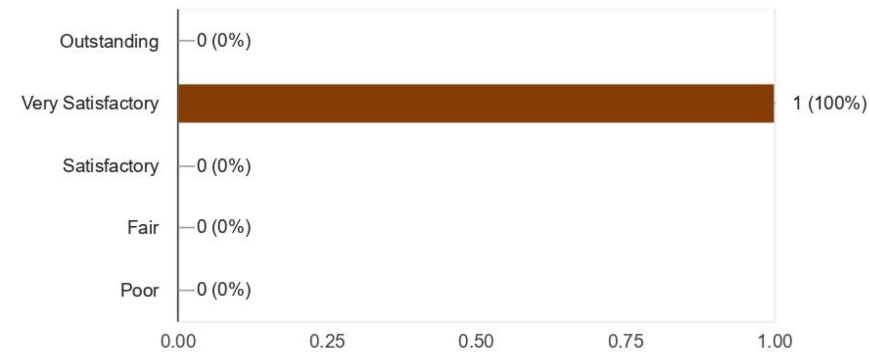
1 response



Reusability

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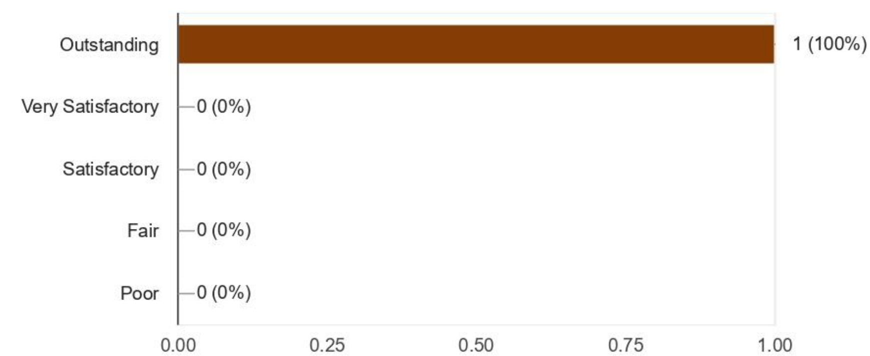
1 response



Analysability

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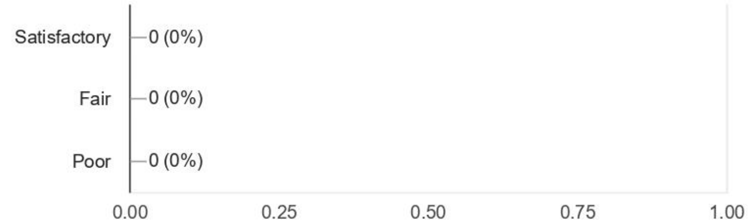
1 response



Any comments, recommendations or suggestions?

1 response

The App itself is easy to use and very useful since it does not need the Internet to be able to perform its functionalities, Items that were considered as very satisfactory may have room for more improvement.

Appendix R

Validation Letter for ISO Evaluator

West Visayas State University
COLLEGE OF INFORMATION AND COMMUNICATIONS TECHNOLOGY
La Paz, Iloilo City

Letter of Validation for IT Expert

West Visayas State University
COLLEGE OF INFORMATION AND COMMUICATIONS TECHNOLOGY
La Paz, Iloilo City
LETTER OF VALIDATION

Date:

The researchers are undertaking research entitled "Insect Pest Identification App with Prescribe Pesticide in Rice fields Using SSD MobileNet Model on Deep Learning". In accordance with this, IT expert is required to lend their expert opinion in validating our android application's accuracy and performance based on ISO 25010. Our IT specialist, Mr. Karl Patrick Arabang, provided his professional discretion in evaluating our application's quality performance. After several online consultations, Mr. Arabang offered suggestions and ideas on how to improve our mobile application's performance based on our current training model. He also provided documents in making test scenarios to help us test our mobile application. Attached herewith are the materials produced upon consultation with him including the form for the survey, signed letter as our IT expert and the log form with suggestions and comments during our consultation. This letter ultimately serves as certification that the app's quality performance is validated.

The Researchers,

ALYZA MARIE TARRAZONA
Lead Researcher

KHRYSMA DEI C. CALDINA
Member

CLARENCE J. GEALON
Member

CLARNICK B. YAP
Member

PAOLA BIANCA S. ZARRIZ
Member

Recommended for Approval:

MR. KARL PATRICK ARABANG
IT Expert

Appendix S

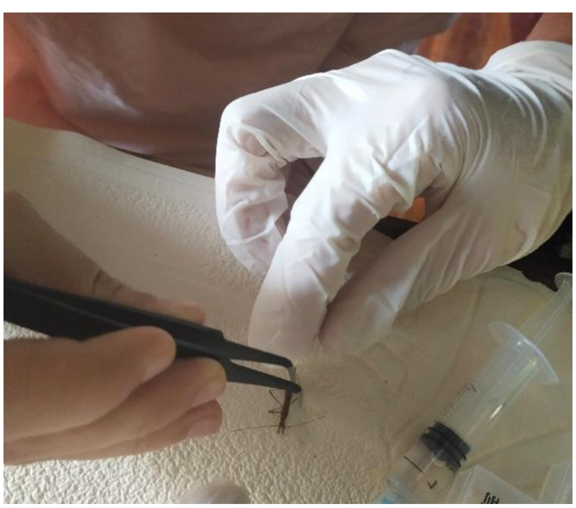
Documentation

A. Data Gathering






B. Sorting and Preserving the Insects



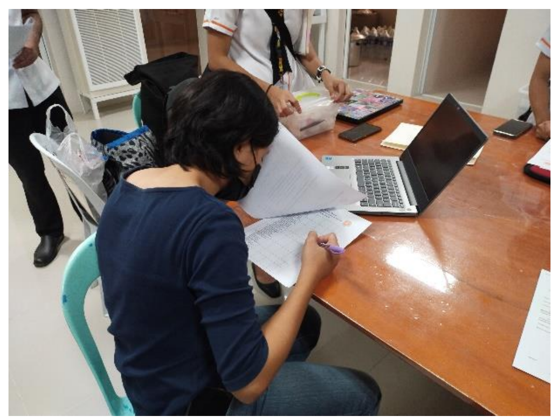
C. Conducting System Testing and Evaluation with the Farmers



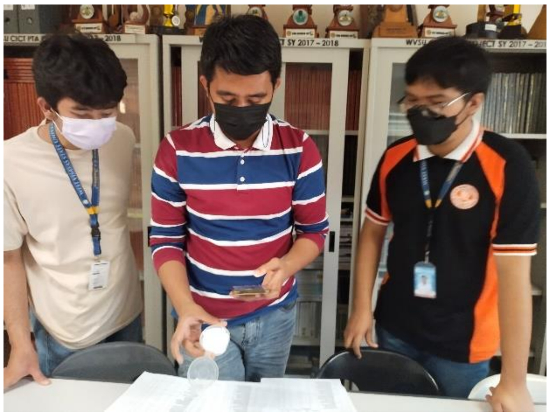


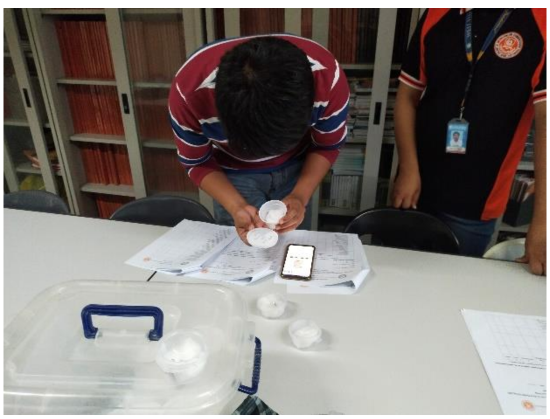

D. Conducting System Testing/Evaluation with the DA Staffs and FPA



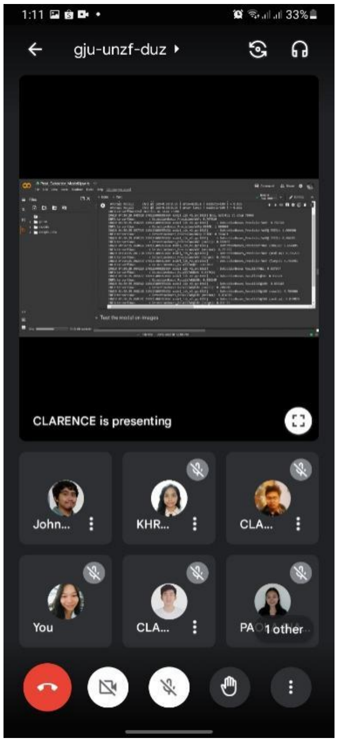



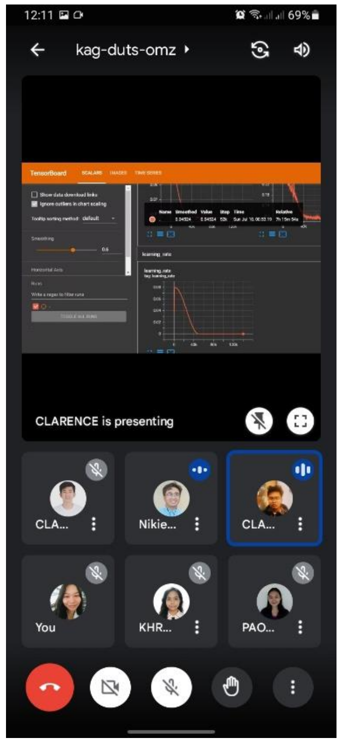
E. Testing the Application Together with Thesis Adviser

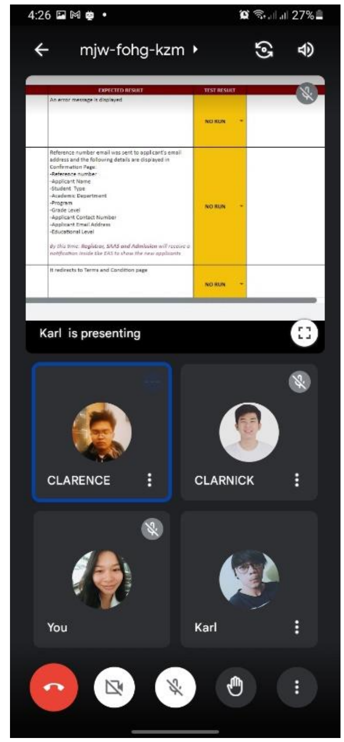


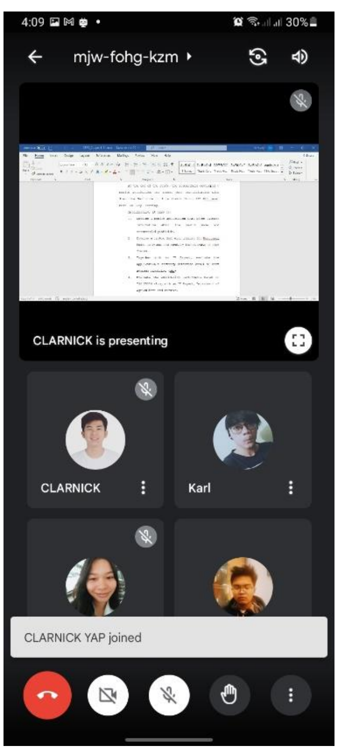


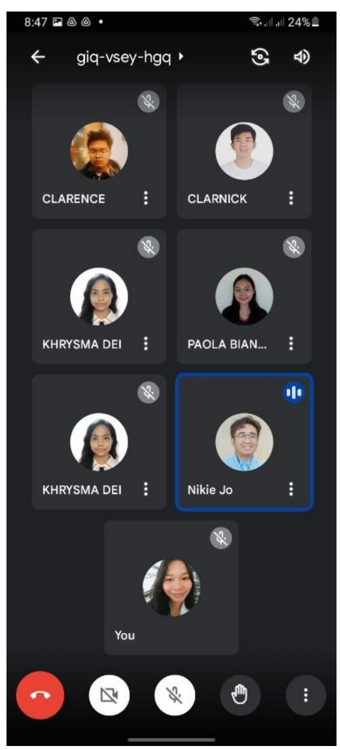
F. Screenshots of Online Meeting

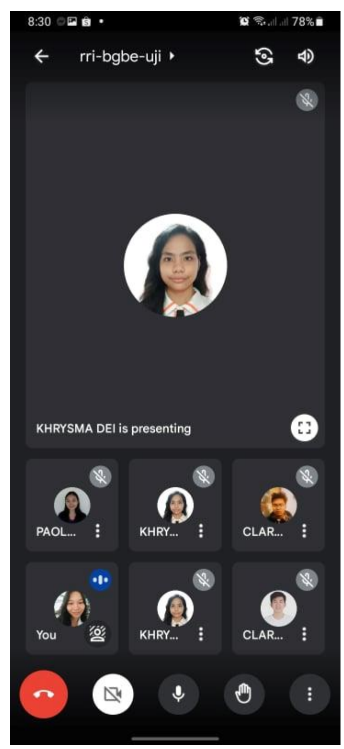












Disclaimer

In part fulfillment of the requirements for the degree, Bachelor of Science in Information Technology, this software project and its corresponding documentation, titled "Insect Pest identification App with Prescribed Pesticide in Rice Fields using Single Shot Detector MobileNet Model on Deep Learning," are submitted to the College of Information and Communications Technology, West Visayas State University. It is the product of our own work, with the exception of the text indicated.

We hereby grant the College of Information and Communications Technology permission to freely use, publish in local or international journals/conferences, reproduce, or distribute publicly the printed and electronic versions of this software project and its associated documentation, in whole or in part, as long as we are credited.

Caldina, Khrysma Dei C.

Gealon, Clarence T.

Tarrazona, Alyza Marie

Yap, Clarnick B.

Zarriz, Paola Bianca S.

June 2023