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Mobile-Based Eggplant Diseases Recognition System using Image Processing Techniques

Jake Guabes Maggay
College of Information and Computing Sciences, Cagayan State University, Lasam, Cagayan, Philippines
jakegmaggay@csu.edu.ph

ABSTRACT

Agricultural inputs are very important; however, these are not always available to farmers. This study aimed to develop a mobile-based eggplant diseases recognition system using image processing techniques to provide information to the farmers with regard to the identification of eggplant diseases. Quantitative method using descriptive survey was used to gather data. Weighted mean was also used to analyze the rating on the extent of compliance of the system along with ISO/IEC 25010 Software Quality Standards. Convenience sampling was employed in selecting the participants. The study employed Scrum Methodology which takes an iterative approach to software development. It also utilized different image processing techniques and adapted the MobilenetV2 framework. The study found out that farmers encountered issues such as lack of modern agricultural inputs, capital, labor force, price fluctuations, production costs, water system, and unsupervised use of chemicals. They also encountered challenges such as the presence of insect pests and diseases, natural disaster, drought, and limited access to production inputs and equipment. Result of the system evaluation using ISO/IEC 25010 Software Quality Standards shows that the system is compliant to a great extent with overall weighted mean of 4.12. Based on the findings of the study, the developed mobile application can be of great help to the farmers in identifying the different eggplant pests and diseases as well as in providing the necessary management and control.

Key words: Convolutional Neural Network, deep learning, image augmentation, image classification, MobileNetV2

1. INTRODUCTION

Agriculture plays an important role in the country's economy. Based on World Bank data from 1960 to 2016, 21.36 percent was the average Gross Domestic Product (GDP) of the Philippines with a maximum of 31.06 percent in 1974 and a minimum of 9.65 in 2016 [1]. Asia and the Pacific is predominated with family farming as a form of agriculture [2]. Moreover, studies show that Filipino farmers represent the second poorest sector of the country. As a result, young people are discouraged to pursue career in agriculture. The farmers' average age of 57-59 years old means that they are growing old; and their children are taking different careers not related to agriculture [1]. Furthermore, World Bank data show that total number of employment in agriculture is decreasing from 31.01 percent in 2013 to 25.31 percent in 2018 [3]. With the present status of agriculture in the country, there is a need to encourage young individuals to be involved in crop production to increase and sustain food security [1]. In support to this, the Department of Agriculture (DA) tapped the Department of Education (DepEd) to revive basic gardening among the elementary school children in both public and private schools in the entire country. This initiative seeks to acquaint the young people with agriculture [4].

Eggplant *(Solanum melongena L.)* is the fifth most economically important crop after potato, pepper, tomato and tobacco having a global production around 50 million tons annually, with a net value of more than US$10 billion a year (2014 data of FAO). The top five producing countries in 2016 are China (28.4 million tons; 57% of world's total), India (13.4 million tons; 27% of world's total), Egypt (1.2 million tons), Turkey (0.82 million tons), and Iran (0.75 million tons) while Philippines ranked as the tenth eggplant producing country (0.24 million tons). In Asia and the Mediterranean, eggplant ranks among the top five most important vegetable crops [5].

Eggplant (common name) is known as aubergine or brinjal (English), *talong* (Tagalog), *tarong* (Ilocano), or *bringhinas* (Bisaya) and is the number one vegetable in the Philippines in terms of volume and production area [6]. It covers approximately 22,000 hectares, yielding an average volume of 220,000 metric tons annually which valued at about PhP2.6 billion [7]. Eggplant production in the Philippines in 2011 to 2016 is increasing with 208,000 metric tons in 2011 to 235,600 metric tons in 2016 [8]. The Ilocos Region has the highest percentage of produced eggplant with 59.8% share during the second quarter of 2018 while CALABARZON has the highest production in the third quarter with 34.0% share of the country's total eggplant production. The Cagayan

Valley Region is the second major producer of eggplant in the country with 8.9% and 11.4% share of the total eggplant production in the second and third quarter of 2018 respectively [9].

Some studies show that the general source of information of farmers is other farmers but for complex and technical matters, farmers prefer to have first-hand information from experts [10]. Extension service by the field experts which includes consultation is one of the ways being done in the Philippines to reach farmers and share new technologies and information for them to be engaged in simple farming innovations which later can increase production. Unfortunately, these field experts cannot always provide all the information needed by the farmers. Hence, lack of information to the farmers leads them to revert back to the traditional practice. This issue on information sharing especially on agricultural problems can be addressed through the application of Information and Communications Technology (ICT) [11].

The Food and Agriculture Organization of the United Nations (FAO) has been promoting the use of ICT to improve agricultural production and to enhance value chains [2]. Likewise, the DA is looking forward for Information Technology (IT) innovations that would provide farmers an access to needed information about plant pests and diseases. In addition, the Department aims to provide key infrastructure, facilities, technology, and information that will raise incomes, productivity, and competitiveness in the countryside [4]. This means that there is a need to leverage ICT-mediated knowledge sharing and extension services in the area of agriculture [11].

This study aimed to develop a mobile application to help farmers identify eggplant diseases with proper management using image processing techniques which is called "Eggplant Doctor". In addition, it uses Convolutional Neural Network (CNN) to classify the different diseases that are visible through mobile phones' camera [12]. Moreover, the mobile application serves as a tool for the extension service providers in sharing knowledge and information to the farmers particularly on eggplant diseases and treatment to increase production. It also provides Good Agricultural Practices (GAP) for the farmers for sustainable farming. In addition, it promotes effective information and knowledge transfer which can improve farm management.

2. RELATED LITERATURE

2.1 Diseases of Eggplant

The most common and destructive eggplant diseases are bacterial wilt [13] and fusarium wilt [14]. Aside from these, there are more diseases such as cercospora leaf spot [15], damping off [16], anthracnose fruit rot [17], verticillium wilt [18], phytophthora blight [19], southern blight [20], [21], phomopsis blight and fruit rot [13], little leaf and mosaic [21].

Among the mentioned eggplant diseases, only the damping off and southern blight have symptoms found on stems. Other diseases can manifest symptoms on leaves and some others can manifest symptoms on both leaves and fruits. This study focused only on the detection of eggplant diseases that can be recognized or detected through leaves and fruits. Therefore, damping off and southern blight are not included in the study particularly in the detection of diseases.

It is necessary to identify the exact disease of eggplant to have proper management and control [13]. In addition, identifying the diseases and knowing the proper management and control can prevent the spread of the diseases. However, non-experts might not be able to identify the diseases correctly. As a result, the proper management and control cannot be performed. Hence, a trained or an expert individual should be responsible to do the identification tasks. This study provides a tool to help the non-expert individuals in identifying the eggplant diseases.

2.2 Image Processing

This study used different image processing techniques. Image processing is defined as "every possible action performed on an image and it can be as simple as cropping an image, increasing contrast or scaling" [22]. It focuses on digital image which involved different steps [23]. Output of the different steps can be an image or an image attribute. Image acquisition, image enhancement, image restoration, color image processing, wavelets and multi-resolution processing, compression, and morphological processing generally produce image as the output while feature extraction [24], segmentation [25, representation and description, and object recognition generally produce image attributes as output [26]. Image processing is also done for storage, transmission, and representation for machine learning purposes [27]. However, this study does not use all the techniques; it selected the most appropriate technique that will result to a higher prediction accuracy in detecting eggplant diseases.

2.3 Related Works

In the study of Alamdar, et al. [28], they reduced the size of the images into 128 x 128 pixels while Verma, et al. [27] resized the images into 200 x 250 pixels during segmentation process to have better results during experiments and to reduce the running time; while all images used in the study of Bhange & Hingoliwala [29] were resized to 300 x 300 pixels. Also, Sladojevic, et al. [30] resized the images to 256 x 256 pixels for the purpose of training. Another study applied the same preprocessing technique however, they have reduced images to 16 x 20 sq. cm. which saves 30% of disk storage space and increased CPU processing speed to 1.4 times [31]. The segmented images were used or feature extraction [28], [27].

Sabrol, et al. [32] used different methods before the recognition and classification of plant diseases. They acquired images using digital devices which is similar with the study of Singh, et al. [33] and they conducted image pre-processing techniques such as smoothing, enhancement and filtering. They also conducted color space conversion, image segmentation using color, thresholding and Otsu method. After segmentation, they had extracted the color and texture features of the image. However, there are multiple classification techniques presented in their study.

In the study of Pujari, et al. [34], they detected the disease for analysis at early stage before it damages the whole leaf and eventually the whole plant. As a result of their study, they have found that using neuro-kNN (k-Nearest Neuron) as classifier method reveals a higher accuracy of 91.54% as compared to 84.11% accuracy in using the ANN.

Another study conducted by Tete, et al. [35] used segmentation such as thresholding algorithm, K-means cluster algorithm and classification technique based on Artificial Neural Networks particularly the feed forward back propagation algorithms. In their study, they acquired images using a digital camera which are in the form of RGB (Red, Green, and Blue) color. After acquiring images, they performed pre-processing technique such as cropping to get the interested region, image enhancement to increase the contrast of the image, and color conversion of RGB to gray images. However, this study does not convert the images to grayscale because the RGB which are the three (3) dimensions of an image are important features of the images for classification. It is also required in the MobileNetV2 that images should have 224 x 224 x 3 dimension. Moreover, they also segmented the images through thresholding [35], [37] to segregate objects by transforming grayscale images into binary images. Likewise, K-means algorithm was also used in their study to measure distance of elements. After segmentation, feature extraction using color, texture, and edges was also used in their study. Lastly, they used ANN to classify images [35]. Some of the image processing techniques used in the foregoing literature were also applied and explored in this study to recognize the different eggplant diseases.

3. OBJECTIVES OF THE STUDY

This study aimed to develop a mobile-based eggplant diseases recognition system using image processing techniques to provide information and expertise to the farmers with regard to the recognition of eggplant diseases. Specifically, it aimed to:

1. identify the issues and challenges encountered by the farmers in farming eggplant;
2. determine the best practices of the farmer participants in controlling insect pests and diseases;
3. determine the image processing techniques in recognizing eggplant diseases;
4. develop the features of the application to identify eggplant diseases;
5. evaluate the extent of compliance of the developed system to the standards of ISO/IEC 25010 Systems and software Quality Requirements and Evaluation (SQuaRE) in terms of Functional Suitability, Performance Efficiency, Compatibility, Usability, Reliability, Security, Maintainability, and Portability; and
6. identify the enhancements that can be done to improve the developed application.

4. METHODOLOGY

This study used different steps in the classification of eggplant diseases which was adopted from the study of Sabrol, et al. [32]. The first step is image acquisition, followed by pre-processing of acquired images such as cropping, resizing, and augmentation, the third step is feature extraction and the last step is image classification.

During the image acquisition, the researcher captured diseased eggplant leaves and fruits in the farms using Oppo A37 mobile phone with 8MP camera. A plant pathologist confirmed the diseases through laboratory tests. All the images had undergone pre-processing procedures such as cropping to select the most important area of the images, and resizing the images to 224 x 224 pixels based on the required dimensions of the image input of the adopted MobileNetV2. After the images had been resized and enhanced, image augmentation was also performed to enhance the datasets for training purposes.

Feature extraction was also performed on images of diseased leaves and fruits of eggplant to get the prominent features. The individual pixel of a color image was broken into red, green, and blue values which were arranged in sequential order. Therefore, the dimension of the images used in the study was *224* by *224* by *3* matrixes. After extracting the features of the different images of eggplant leaves and fruits, classification was performed applying the Artificial Neural Network (ANN) based on back propagation algorithm being implemented in the MobileNetV2 framework.

In the development of the mobile-based system, the study employed Scrum Methodology [38]. As mentioned by Flora, et al. [39], “this development methodology helps companies build the right product and empowers teams to continuously redesign their release to optimize its value throughout development”. In this methodology, changes in the requirements are to be expected and welcomed [40] which was also happened during the development life cycle of the system. Additionally, this study adopted the Scrum Methodology wherein software is incrementally developed, creating different versions [41] where work is performed in iterations or cycle [42].

As part of the development cycle, product backlog was set which covers the different features of the system. Planning was the first step during the system development. As mentioned by Dora & Dubey [43], this step aims to know the requirements of the system based on the needs of the users. During this step, the researcher conducted an interview with the farmers regarding their knowledge on eggplant diseases as well as their management and control. Likewise, the researcher identified and analyzed the requirements of each feature to be developed. After planning the needs of the system, system design particularly the system process and interface were created. During the design phase of the system's features, the user-interface of the mobile-based system was also determined as part of the design (Figure 1).

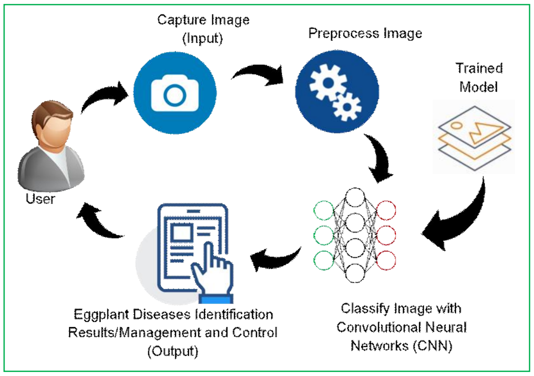

Figure 1: System Architecture

Upon completion of the design, the development of each feature started. Dora & Dubey [43] also mentioned that development is use to convert the design into code using programming language while testing is use to evaluate the actual result and the expected result. In this phase, the researcher transformed the design into a system's working feature. Prior to this activity, images of eggplant leaves and fruits were captured and processed using different techniques such as cropping, resizing, and image augmentation.

After performing the different image processing techniques, the next process was transfer learning using the adopted MobileNetV2 framework. During the training, combination of multiple augmented images were used to create different models. The created models were subjected for prediction accuracy test which served as the basis in choosing the model for implementation. Likewise, the chosen model was integrated in the mobile application during the development of the classifier module. Testing each module of the mobile application was also performed repeatedly to ensure that there are no major errors prior to the release of the Mobile-Based Eggplant Diseases Recognition System.

After the development, system evaluation was conducted. This study employed a quantitative method using descriptive survey research design in collecting and analyzing the data associated with the proposed system along with ISO/IEC 25010 Software Quality Standards conducted by the ten (10) IT Experts. Likewise, interview guide was also used to gather the issues and challenges encountered by the five (5) farmers as well as their best practices in eggplant farming. Convenience sampling was used in selecting the participants of study.

Weighted mean was used to analyze the rating of the IT experts on the extent of compliance of the developed mobile application in accordance with ISO/IEC 25010 software quality standards. A 5-point scale was used to measure the compliance of the developed system ranging from "Very Great Extent" (5) to "Very Low Extent" (1) as shown in Table 1.

Table 1: The 5-Point Scale and its Descriptive Interpretation and Scale Range

Scale Range	Weight	Descriptive Interpretation
4.20 – 5.00	5	Very Great Extent
3.40 – 4.19	4	Great Extent
2.60 – 3.39	3	Moderate Extent
1.80 – 2.59	2	Low Extent
1.00 – 1.79	1	Very Low Extent

5. RESULTS AND DISCUSSION

5.1. Issues and Challenges Encountered by the Farmers

The farmers encountered many issues on eggplant farming such as lack of modern agricultural inputs which include varietal selection and the use of recommended and approved chemicals. In addition, issues such as capital for fertilizers and farm maintenance, price fluctuations due to environmental calamities, production costs especially in purchasing for FDA-approved chemicals, water system during dry season, unavailability of labor force, and lack of knowledge in the use of chemicals were also encountered by the farmers. Likewise, farmers encountered challenges such as presence of insect pests and diseases in the farm, natural disaster which severely damaged plants, drought which reduces yields, and limited access to production inputs and equipment because of their geographical location.

5.2 Best Practices of the Farmer Participants in Controlling Insect Pests and Diseases

The farmers use fertilizers to provide necessary nutrients for the plants. They apply fertilizers during transplant, vegetative stage, and during matured or fruiting stage. They also spray insecticides such as Solomon, DuPont Lanate SP and DuPont Prevathon to prevent insect pests in attacking the eggplants one week before harvesting the fruits. Likewise, they cut shoots of eggplants that are damaged with shoot borer to prevent the spread of the insects. They also use Megatonic Foliar Fertilizer by spraying it to the plants to increase the yield of the plants. This chemical has been tested by the farmers to increase the number of buds which will produce more flowers and fruits.

According to the farmers, weed-free eggplant farms produce more fruits. In removing the weeds, farmers manually uproot weeds around the plants. However, if the plants are fully grown, farmers prefer to spray weed killer like ClearOut Plus to control them. Some of the farmers observed that planting corn as alternative to eggplant can prevent the occurrence of wilt diseases.

5.3 Image Processing Techniques in Recognizing Eggplant Diseases

As mentioned by Chitradevi & Srimathi [37], there are various image processing techniques such as image acquisition, image pre-processing, image enhancement, feature extraction and image classification. In order to recognize the different diseases of eggplant, this study performed similar techniques. Image pre-processing techniques include cropping and resizing of images. Moreover, image enhancement applying image augmentation was also performed which includes the two label preserving transformations [44] such as flipping and rotating. Other non-label preserving transformations such as sharpening, adjustment of brightness, contrast, Gaussian blur, and saturation were also performed.

This study used a mobile phone's camera to capture images of eggplant leaves and fruits that are infected with diseases or damaged by insects. However, due to the unavailability of the different diseases and other insects of eggplant, the researcher collected images from the internet. As a result, 1,710 images were captured from the farms while 792 images were downloaded from the internet with a total of 2,465 images.

Pre-processing techniques such as cropping was also performed to get the desired area of the images and resizing them to 224 x 224 as input size of the MobileNetV2. Aside from these, image augmentation was also performed to the captured images. The first two augmentation techniques performed were flipping and rotating. After flipping and rotating the images, the remaining augmentation techniques such as adjustment of brightness, contrast, color saturation, sharpness and Gaussian blur were performed to the original, flipped and rotated images. After performing all the image augmentation techniques, the number of images largely increased from 2,465 to 180,036 images. However, it was found out that adjustment of contrast, sharpening, and adjustment of saturation of the datasets does not increase the prediction accuracy of the system in recognizing eggplant pests and diseases based on the tests conducted.

Similar with the study of Feng, et al. [45], this study adopted the MobileNetV2 model which is considered as the backbone for feature extraction. Feng, et al. [45] described MobileNetV2 as a lightweight deep neural network for mobile embedded terminals. Meanwhile, this study emphasized the extraction process of the MobileNetV2 in extracting the features of each input during the training or "transfer learning" [46] process using the augmented images. Lu [46] also mentioned that the Convolutional Neural Network (CNN) has integrated the feature extraction layers and classifier in a unified Deep Neural Network and is being implemented in the MobileNetV2.

During the transfer learning process, various models were created from the combination of the different augmented images. In addition, experiments were conducted to test the prediction accuracy of each model using 10 different sample images. Table 2 shows the models with the corresponding datasets used and the average rank of predictions.

Based on the test, Model 9 obtained the highest rank in terms of prediction accuracy with an average of 1.1. It was found out that prediction accuracy increases if more augmentation techniques will be performed before feeding the images to the MobileNetV2 framework. As an example, when Model 2, 3 and 6 were trained individually, they only obtained an average of 1.9, 1.7 and 1.9 respectively, but when they were combined, the prediction accuracy had increased having an obtained average of 1.4 (Model 8). Multiple augmentation techniques can be combined, however, the appearance of the images slightly changed by some techniques such as contrast enhancement, sharpening, and saturation especially on the datasets of normal and spider mites-damaged leaves. Based on the overall result of the prediction accuracy tests, Model 9 was chosen and used as the model for the Mobile-Based Eggplant Diseases Recognition System.

Table 2: List of Used Datasets in Each Model

Models	**Images or Datasets Used**	**Rank**
Model 1	Original, Flipped, Rotated	1.8
Model 2	Original, Flipped, Rotated, Brightness-Enhanced	1.9
Model 3	Original, Flipped, Rotated, Contrast-Enhanced	1.7
Model 4	Original, Flipped, Rotated, Sharpened	1.4
Model 5	Original, Flipped, Rotated, Gaussian Blurred	1.4
Model 6	Original, Flipped, Rotated, Saturation-Enhanced	1.9
Model 7	Original, Flipped, Rotated, Sharpened, Gaussian Blurred	1.3
Model 8	Original, Flipped, Rotated, Brightness-Enhanced, Contrast-Enhanced, Saturation-Enhanced	1.4
Model 9	Original, Flipped, Rotated, Brightness-Enhanced, Gaussian Blurred	1.1
Model 10	Original, Flipped, Rotated, Brightness-Enhanced, Saturation-Enhanced, Sharpened, Gaussian Blurred	1.3
Model 11	Original and All Augmented Images	1.2

5.4 The Developed Mobile Application

The main focus of the study is to recognize the different diseases of eggplant. However, during the conduct of the study, the diseases are not present in the farms. During the farm visit, the researcher observed that there are various insects present in the farms such as shoot and fruit borer, leafhopper, mealybugs, spider mites, spotted beetles, and flea beetles. Because of the existence of the different insects, the researcher included the different insects to be recognized by the mobile application aside from the different eggplant diseases.

The developed mobile application or "mobile app" or simply "app" [47] has a home screen and contains a menu on the upper right corner of the screen which is use to display the purpose of the app and the best practices in farming eggplant. It also contains a button that will open the mobile phone's camera (Figure 2).

Meanwhile, the camera icon at the bottom of the screen initializes the camera and eventually starts the first step in recognizing eggplant pests and diseases. Upon pressing the camera icon in the main screen, the mobile phone's camera becomes ready to capture image. After the image has been captured, the user has the option to reject or accept the captured image. Likewise, the user has the option to crop the desired portion of the captured image to be used for recognition.

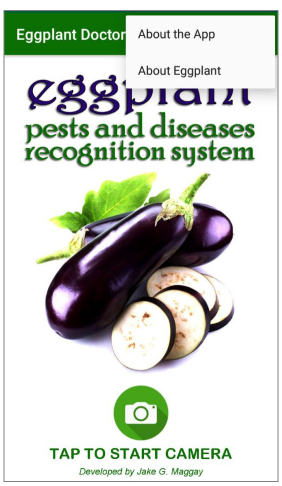

Figure 2: Mobile App's Home Screen

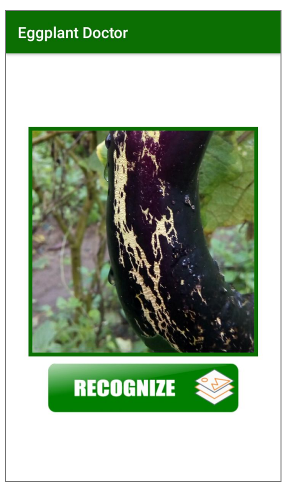

Figure 3: Mobile App's Classifier

The developed mobile app has the capability to classify image as part of the process to recognize and predict eggplant pests and diseases. The mobile app's classifier extracts the feature of the captured image and matches the extracted feature to the trained classification model. The user needs to click the "RECOGNIZE" button to start the classification process and display the top five (5) predictions (Figure 3).

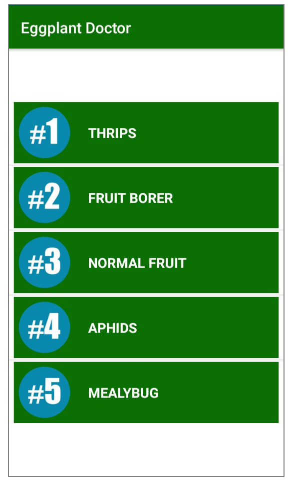

Figure 4: Top Five Prediction Sample

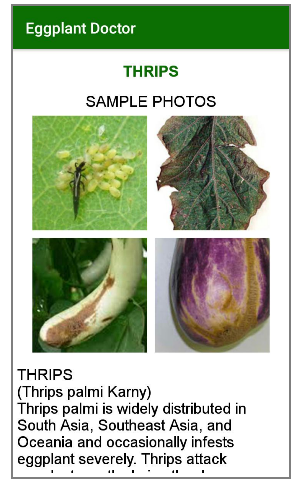

Figure 5: Sample Details of Prediction

The system ranks and displays the top five (5) predictions from first to fifth rank based on the confidence level of the classifier (Figure 4). The user may click each prediction to confirm if the appearance of the infected part of the plant is similar with the sample images being displayed in the app. Aside from the images, the app also displays the description of the predicted pest or disease as well as its management and control (Figure 5).

5.5 The Extent of Compliance of the Developed System in Accordance with ISO/IEC 25010 Systems and software Quality Requirements and Evaluation (SQuaRE)

The goal of ISO/IEC 25010 is to describe and evaluate software quality [48]. The developed Mobile Application was subjected for evaluation by IT Experts using ISO/IEC 25010 SQuaRE with various characteristics such as Functional Suitability, Performance Efficiency, Compatibility, Usability, Reliability, Security, Maintainability, and Portability. Each characteristic is composed of multiple sub-characteristics that provide consistent terminology for specifying, measuring and evaluating system and software product quality [39].

Table 3: Overall Extent of Compliance of the Developed Mobile Application in Accordance with ISO/IEC 25010 SQuaRE

Criteria	Mean	Description
Functional Suitability	4.07	Great Extent
Performance Efficiency	4.33	Very Great Extent
Compatibility	4.00	Great Extent
Usability	4.17	Great Extent
Reliability	4.03	Great Extent
Security	4.00	Great Extent
Maintainability	4.18	Great Extent
Portability	4.19	Great Extent
Overall Weighted Mean	**4.12**	**Great Extent**

Table 3 shows the overall result of the system evaluation in compliance with ISO/IEC 25010 SQuaRE. The result shows that the system is compliant to a "Great Extent" with respect to ISO/IEC 25010 SQuaRE having an overall weighted mean of 4.12.

5.6 Enhancements to Improve the Mobile Application

Based on the evaluation of the system by the IT Experts from the different institutions or affiliations, the following are the enhancements that can be done to improve the existing features of the developed system: (1) There should be more images of eggplant with diseases as training datasets to improve the prediction accuracy; (2) A users' manual should be integrated to guide users in the proper use of the system especially in cropping the relevant area of the images for the system to provide more accurate prediction; (3) Translation of the text to Filipino, Ilocano and other dialects so that anyone can understand the description of the pests and diseases, and the recommendations being provided by the system; (4) Aside from eggplant, other high-value crops may be included; and (5) Version for iOS Mobile Phone should be developed to address compatibility issues.

6. CONCLUSION

Image processing techniques such as cropping, resizing, adjustment of brightness and blurriness increase the prediction accuracy in identifying eggplant pests and diseases. Conversely, the developed mobile application can be of great help to the farmers in identifying the different eggplant pests and diseases as well as in providing the necessary management and control. Likewise, the mobile application could also help the extension service providers in providing relevant information related to eggplant farming and Good Agricultural Practices to the farmers. Generally, when the information provided by the system will be followed and applied by the farmers, it could help them monitor and manage eggplant farms.

7. RECOMMENDATIONS

The Department of Agriculture (DA) may consider providing continuous intervention and monitoring especially on the best practices of eggplant farming. They may also provide a way to reach the farmers to disseminate proper, safe and sustainable pest and disease management practices to eggplant farmers. The farmers may consider using the mobile application to help monitor and manage eggplant farms. Aside from the farmers, the app may also be adopted by individuals who are engaged in backyard gardening. It may also be adopted by the DA especially for extension service providers. For future studies, more images of the different insect pests and diseases could be provided to increase the prediction accuracy of the system. All other pests and diseases of eggplant may also be included as long as images are available. Moreover, other high-value crops could also be integrated into a single mobile application.

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