MANGGASORT: A MOBILE APPLICATION FOR CARABAO MANGO QUALITY AND MATURITY LEVEL CLASSIFICATION USING CONVOLUTIONAL NEURAL NETWORK

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In Partial Fulfillment of the Requirements for the Degree
Bachelor of Science in Computer Science

by

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May 2018

AUTHORIZATION

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SIGNATURE

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G.L.E.D and J.E.M.I

CERTIFICATE OF ORIGINALITY

This is to certify that the research work presented in this thesis, ManggaSort: A Mobile Application for Carabao Mango Quality and Maturity Level Classification Using Convolutional Neural Network for the degree in Bachelor of Science in Computer Science at the Polytechnic University of the Philippines embodies the result of original and scholarly work carried out by the undersigned. This thesis does not contain words or ideas taken from published sources or written works that have been accepted as basis for the award of a degree from any other higher education institution, except where proper referencing and acknowledgment were made.

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ABSTRACT

Title	:	ManggaSort: A Mobile Application for Carabao Mango Quality and Maturity Level Classification Using Convolutional Neural Networks
Researcher	:	Gilly Lea E. Damandaman; John Edwin M. Ibe
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Philippines is one of the top producers of Carabao mangoes worldwide. Quality and maturity assessment of the mangoes is an important process in the production of the fruit. Manual classification of mangoes requires intensive efforts and large amount of time. Thus, the researchers conducted this study in able to produce a high accuracy rate system that will identify the maturity and quality of a Carabao mango.

In this study, the researchers developed a mobile application that classifies the maturity and quality of the Carabao mangoes in just a snap of the mobile camera. The system utilized Convolutional Neural Network (CNN) algorithm for the classification of the mangoes.

This study used 50 samples of Carabao mangoes for the testing of the system. Each of the mangoes were scanned using the mobile camera of the application. The result produced a 94% accuracy rate for the classification of the maturity, 92% for the quality and 93% accuracy rate for the overall system performance. The results of this study shows that CNN has provided an accurate classification of quality and maturity level of Carabao mangoes thus is an effective algorithm that can be utilized in other classification problems.

Keywords: Polytechnic University of the Philippines, Bachelor of Science in Computer Science, Convolutional Neural Network; Quality; Maturity; Classification

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Acronyms:

CNN	Convolutional Neural Network
NN	Neural Network
ANN	Artificial Neural Network

Chapter 1

THE PROBLEM AND ITS SETTING

Introduction

Philippines is primarily an agricultural country. The country's economy revolves around agriculture which consists of farming, fishery, livestock and forestry. The country produces about 650,000 metric tons to 750,000 metric tons of mangoes yearly. With the large volume of mango productions, the country became one of the top ten producers of mangoes in the world. According to Invest Philippines (2017), mango, aside from being the country's national fruit, is among the top agricultural export and the third most important fruit crop of the country in terms of volume and value. There are many varieties of mango in the country but Carabao mango is named to be one of the best varieties in the world and is also known for its international trade as the "Philippines' Super Mango".

Figure 1. Image of Carabao Mango

Quality assessment of mango is essential in meeting the market requirements. The sorting and grading of mango according to maturity level and quality are currently being performed manually before the transportation (Afrisal et al., 2013). The sorting of mangoes is completely dependent on the human visual and judgement because the sorting process relies on the inspection of the mangoes' physical features. Being one of the largest producer of mango worldwide, the manual inspection of the mangoes is labor intensive, time consuming and poses problems in terms of consistency and accuracy due to judgement by different human (Septiana, Soesanti, Setiawan, 2016).

Consistency is important in the process of sorting mangoes for the product to be marketable and be ready for transportation (Ganiron, 2014). As mentioned earlier, the manual inspection of the fruit produces problems of inaccuracy and inconsistencies in the sorting of mangoes. To deal with this problem, this study proposed to automate the process of classifying the maturity and quality of Carabao mangoes. According to Jarimopas and Jaisin (2014), automatic sorting and grading systems results to high accuracy, uniformity and faster processing speed in the sorting of tamarind wherein the features of the tamarind is also visually examined by the computer.

There are a lot of methods that can be used in quality control to replace the manual process and to reduce the risk of inaccuracies and inconsistencies. Different techniques for the automation of mango classification have been studied through the years and each studies yielded to different results in terms of accuracy rates. The researchers of this study proposed the utilization of Convolutional Neural Networks for the development of a mobile application that can be used for the automated classification of the maturity level and quality of the Carabao mangoes.

Convolutional Neural Networks (CNN) is a deep feed-forward type of Artificial Neural Networks (ANN) that was proven to be very effective and is commonly used in areas such as image recognition and classification. The feature extraction will be done by the first layer of the CNN through applying filters to the image. The features that was extracted will serve as the training data for the neural network. According to Naik and Patel (2017), CNN which is a deep learning algorithm has proven to be a good technique for solutions in problems like fruit recognition, because of its ability to automatically extract the features of the images. Nevertheless, there are currently few studies that uses this method. For this reason, the researchers chose to use CNN for the classification of quality and maturity level of Carabao mangoes.

Statement of the Problem

The objective of the study is to design a system that will classify the maturity level and quality of the Carabao mango using convolutional neural network. At the end of this study, the following questions should be answered:

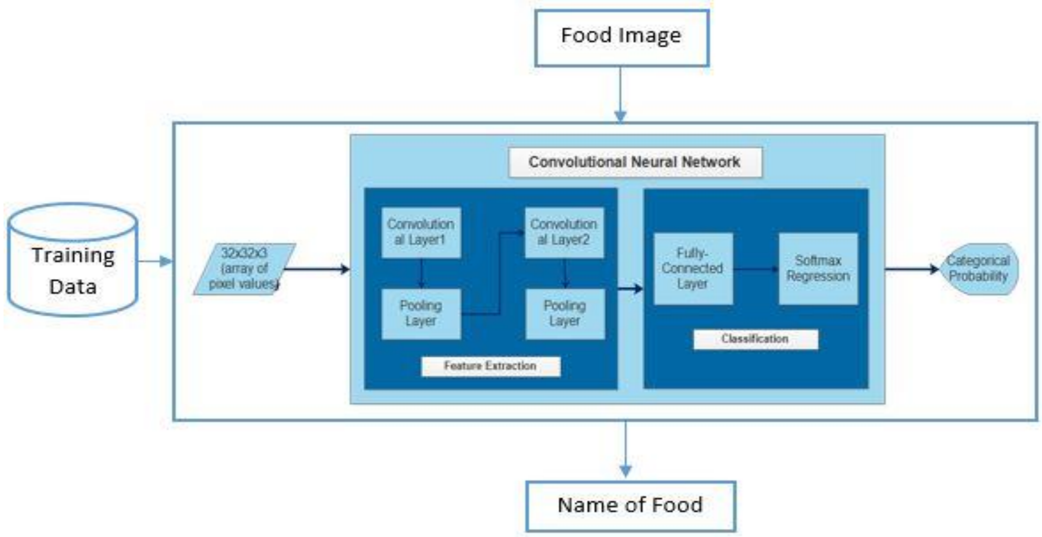
1. What is the accuracy rate of the system using Convolutional Neural Network in classifying the maturity level of Carabao mango based on:
   a. Ripe
   b. Unripe
   c. Overripe
2. What is the accuracy rate of the system using Convolutional Neural Network in classifying the quality of Carabao mango based on:
   a. Good Quality
   b. Defective

Theoretical/Conceptual Framework

Theoretical Framework

Figure 2 shows the architecture of a Food Image Recognition that uses Convolutional Neural Network (CNN). CNN has been used in many image processing task such as recognition and classification. The architecture starts with an input of food image and proceeds to the CNN Model which has been pre-trained using training data with thousands of food images. The network accepts the pixel values of the food image and applies a series of convolution on it. The first layer of the CNN is the convolutional layer. This layer starts with a filter for instance in size of 2x2x3. The filter convolves around the 32x32x3 input image starting from the top and produce a feature map. The feature map contains the important information of that certain input image such as straight edges, curves and simple colors.

Figure 2. Architecture of Food Image Recognition using CNN (2016)



To obtain high level features, series of convolutions is applied. The second convolution layer takes the output of the first convolutional layer (feature map) and convolve filters around it until the high level features are obtained. The next layer is the pooling layer which takes feature maps as its input. Pooling layer is periodically inserted in between convolutional layer and performs down-sampling to progressively reduce the amount of parameters or the size of the image while retaining the important features of it. Next layer is the fully connected layer. Neurons in the fully connected layer have full connections to all feature maps in the previous layer. Their feature map can be computed with a matrix multiplication followed by a bias offset. It is also in this layer where the classification happens. All the learned features will be compared to the training data used for the network and the result will be fed to the softmax function to compute the probability that the input image belongs to a certain class. From this, the result with the highest probability will be the final output of the system or the name of the food recognized. (Zhang, et al., 2015).

Conceptual Framework.

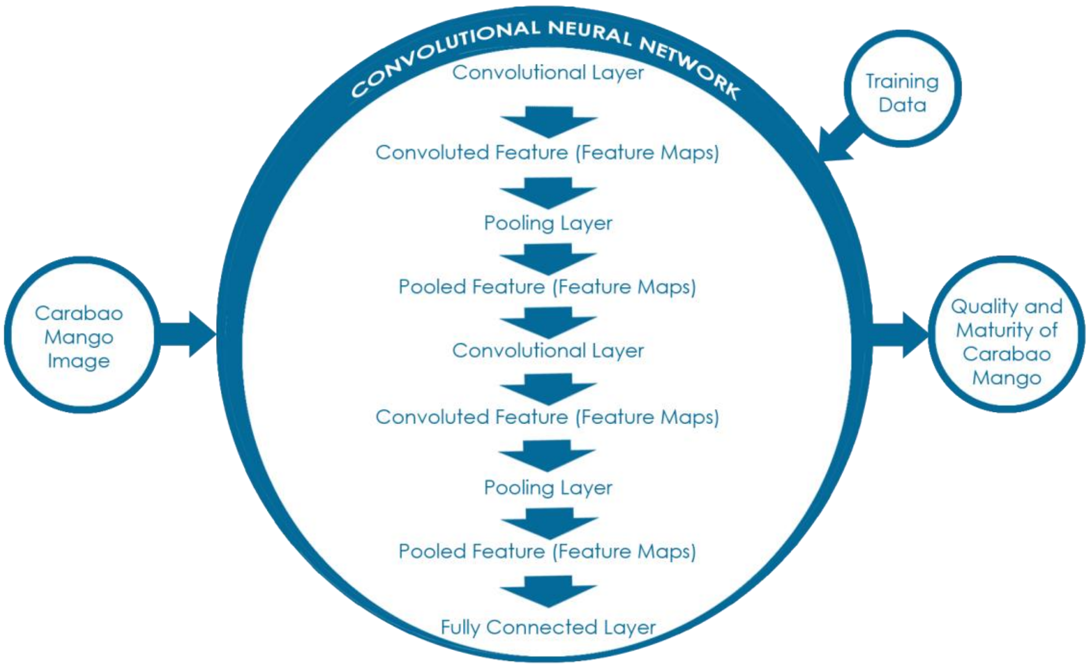
Figure 3. Conceptual Framework of the Study

Figure 3 shows the conceptual framework of the study wherein the input is the system developed by the study which is the Carabao Mango Quality and Maturity Level Classifier. The process includes the development and implementation of the system and the expected output of the study is the system's accuracy and reliability rate in classifying the quality and maturity level of the Carabao mango.

Figure 4. Illustrates the conceptual framework of the system. The framework of the system starts with an input of the Carabao mango image. The image passes through the CNN model. In the model, the image went through a series of convolutional, pooling (down sampling) and different kernel sizes to get the desired output. The model produced a probability distribution of classes that best describes the quality and maturity level of the mango based on the image. The classes were the product of the trained data. The classes comprises of the maturity such as unripe, ripe, and overripe and the quality of the mango

such as good quality and defective. The output of the system will be the quality and maturity level of the Carabao mango.

Figure 4. Conceptual framework of the System



Significance of the Study

The researchers believes that this study will have a contribution in Carabao mango production and farming in the Philippines as well as on the following:

Carabao Mango Farmers – farmers who cater Carabao mango would greatly benefit from this study. The current manual and labor intensive way of classifying the maturity level and quality of Carabao mango will be automated with the benefit of this study.

Carabao Mango Farm Owners – accurate classification of the mango maturity level and quality will also contribute to the production of mangoes in a farm as well as the export productions which will benefit the owners of mango farms.

Carabao Mango Distributors – mango distributors have wide knowledge about the quality and the maturity of the mango they are distributing since they work closely with Carabao mango farmers. This study will be significant to the Carabao mango distributors since they will be able to check and sort the mangoes before they sell the product.

Carabao Mango Consumers – some consumers have little knowledge in determining the quality of the mango they are buying. Through this study, the consumers will be able to check the quality of the mangoes before buying the product using their mobile phones.

Future Researchers - this study will also benefit the future researchers who intends to study other techniques for the automation of mango sorting.

Scope and Limitation of the Study

This study is limited only on the maturity level and quality classification of Carabao mangoes. The study focused mainly on the following maturity levels of the mango:

1. Unripe
2. Ripe
3. Overripe

The classification of the quality of the mango was also limited to the following:

1. Good Quality
2. Defective

The mangoes to be captured by the application must be harvested mangoes and without leaves for better classification. Mobile cameras will be the tool used in capturing the mangoes. In order to process and recognize the image more efficiently, these are the factors to be considered:

1. Image quality (At least 8 megapixels).

2. View/angle of the object in the image (side view of the mango).
3. Mangoes should be captured with proper lighting.

Operational Terms

Accuracy Rate - The degree of being free from mistakes and errors; the quality of being true, correct or exact.

Artificial Neural Networks - A computational networks consisting mainly of massively parallel processing units that interact with each other through weighted interconnections.

Carabao Mango - A type of mango that is commonly found in the Philippines. Also known as Philippines' super mango. When ripe, the flesh is golden yellow, very tender with delicate, aromatic non-turpentine flavor, exquisite sub-acid taste.

Computer Vision - Is concerned with the automatic extraction, analysis and understanding of useful information from a single image or a sequence of images.

Convolutional Neural Network - Is a class of deep, feed-forward artificial neural network that comprises of a network of learning units called neurons. These neurons learn how to convert input signal into corresponding output signals, forming the basis of automated recognition.

Dark Spot - A foreign substance on the surface of the mango fruit that is usually caused by insects or mishandling during the harvest time.

Defective - Mango with dark spots and do not qualify to the standard mango size.

Feature Extraction - Starts with an initial set of measured data and builds derived values called as features.

Feature - It is a distinctive attribute or characteristic of the mango.

Good Quality - Mango free from dark spots and qualifies the standard size.

Grading - Mango sorting base on quality and maturity.

Image Processing - Is particularly attractive to experience algorithms and methods since one immediately sees what is done by displaying results via images and graphing image-derived quantitative information.

Mature - Mango with the shade of color green and yellow.

Maturity Level - Whether a mango is ripe, unripe, or overripe.

Quality - The degree of excellence. In terms of mango, quality is measured by either good or defective.

Sorting - To arrange systematically in groups or separate groups according to its similar feature like type, class and quality.

Chapter 2

REVIEW OF LITERATURE AND STUDIES

Related Literature and Studies

Related Literature

According to Ivanova (2016), technological advances have contributed in the way farmers gather and evaluate the products. According to her, the condition or quality scoring in agriculture has been shown to be a subjective process that is prone to discrepancies of different observers and of observations of the same subject by the same observer. The use of computer vision in the field of agriculture resulted to a maintained accuracy and lasting records, and the measurements are objective because no human influence is intervening with the process. For these reasons, computer vision has become significant in terms of precision agriculture.

According to RSIP Vision (2016), computer vision techniques such as image processing has been widely used for precise agriculture. It discussed that image processing is presently being used in studies and projects related to agriculture. The use of image processing has resulted to increased yields, reduced spraying of the products, more efficient growth methods and increased profits for the farmers. One of the breakthrough developments in agricultural farming is the grading and sorting of fruits and vegetables using computer vision. The use of computer vision for this process has resulted to a fast and accurate grading and sorting of agricultural product. According to the article, the automation of the process benefitted the farmers because of its ability to effective detect existing features and defects in the product. By using automated detection of features and defects, the productivity of a farm increases because of the faster time of performance.

According to The Express Tribune (2016), there was a farm that installed automated grading machine to ensure the mango quality. The machine provides the facility with all the requirements such as hot water, dying and cooling treatments to the fruit to ensure a good quality mango. This automated machine has reportedly increased the production of quality mangoes by the farm. Another proof that automation has a good effect in agricultural farming.

The following related literatures discussed are all relevant to the study for the reason that they are all about the use of automation in agricultural farming. This study is all about automating the process of grading and classifying the maturity level of the Carabao mango. The topic at hand was driven by the literatures that discusses the advantages of using computer techniques for agriculture.

Related Studies

Dara and Devolli (2016) studied about the application of Artificial Neural Network (ANN) techniques in visual sorting of apples. The objective of their study is to sort the apple fruits into size group such as small, medium and large by utilizing image processing and ANN techniques. The authors of the study concluded that using ANNs techniques in the sorting of apply resulted to high speed and high accuracy of the process.

In 2015, Sonali, Pooja, Rohini and Ranpise developed a fruit quality assessment and classification using image processing. Identifying the maturity level and quality of the product with high accuracy is the main goal of the study. The features of the fruit such as the color, shape and size were fed into the system for the classification. In the end of the study, the authors were able to classify various fruits. The author of the study believed that new computer techniques can be helpful for the farmers in the agriculture field in the assessment of the fruits.

According to Nandi, Tudu and Koley (2014), machine vision techniques is a good technique for automatic mango fruit sorting. The author sorted and graded the maturity level and size of the mango fruit. The size of the mango is calculated from the binary image of the fruit. The features of the mango such as the color is used in the image processing for the classification of the maturity level. Fuzzy logic algorithm is used for the automatic sorting and grading of the mango fruit. The result of using fuzzy logic for the automated mango fruit sorting and grading is close to the result from the manual sorting conducted by the experts, and the authors believed that it could be an alternative for the manual sorting of mangoes.

Zhang, Wang, Ji and Phillips (2014) studied the use of computer vision in fruit classification. The purpose of their study is to recognize the type of fruits using Fitness-scaled chaotic artificial bee colony (FSCABC) algorithm and feed forward neural network (FNN). The authors extracted the color histogram, texture and shape features from the images of the fruits to compose the feature space that will be used for the classification of the fruit. In the end of their study, they concluded that FSCABC and FNN produces higher accuracy rate than using genetic algorithm and FNN.

Another study was conducted by Zawbaa, Abbass, Hazman and Hassenian (2014) about the automatic fruit image recognition. The study focuses on the classification and identification of the fruit types based on the shape and color features extracted from the fruit image. The authors used K-Nearest Neighborhood algorithm and support vector machine algorithm for the classification of the different kinds of fruits. The result of their study was able to automatically recognize the fruit name of the fruit image with high degree of accuracy.

The use of computer technologies has been widespread in the field of agriculture. According to Gomes and Leta (2012), visual inspection systems have been implemented in agriculture as a replacement for the manual inspection of product quality. There have been studies about the use of computer vision for the essential processes in agriculture such as the sorting and classification of agricultural products. According to Arakeri and Lakshmana (2016), manual fruit grading is inefficient, labor intensive and prone to error. In their study, they discussed that automated grading system is useful in agriculture as it can speed up the time of processing and minimize the inaccuracies in the grading. Fruit grading system for quality evaluation of tomato is the focus of their study. Image processing is the technique they used for the analysis of the defects and ripeness of the tomato. The authors were successful in evaluating the quality of the tomato.

According to Pabico, De Grano and Zarsuela (2012), Artificial Neural Network (ANN) can be used for natural food classifier. The author were able develop an automated classification of tomato ripeness and acceptability of eggs. By the utilization of ANN, the authors concluded that automated grading of tomato and eggs can be an alternative for the present manual grading of the products.

Another study was conducted by De Grano and Pabico (2007). The study is about the classification of tomato maturity using image analysis and neural networks. The color of the tomato is the characteristic they used to assess the ripeness and the degree of maturity of the tomato. Feed forward back propagation training algorithm was used for their study. In conclusion, the authors believe that the manual grading of tomato can be replaced by automatic grading using neural networks and image processing.

In 2006, a fruit grading and sorting using machine vision was studied by Reyes. The color, size and shape are considered for the sorting and grading of the products. Colors were extracted for the classification of the product according to its proper grade. The author was able to use machine vision technology for the automated sorting and grading of fruits which aims to improve productivity and reduce manual labor.

In 2002, Njoroge, Ninomiya, Konto and Toita studied automated fruit grading system using image processing. They utilized engineering designs and image processing techniques to grade the fruits. The grading of the fruit is done by external fruit inspection through the processing of the color from the image of the subject.

In 2014, Szegedy et. al. use CNN in their entry entitled GoogleNet in the ImageNet Large Scale Visual Recognition Challenge (ILSVRC). ILSVRC is an annual visual recognition challenge. The task is to be able to classify 1.2M labeled images with 1k classes by making 5 guesses on the given image. Their entry got the first place with the error rate of 6.67%.

The following studies reviewed in this section are all relevant to the topic being studied in this paper. This study uses computer vision and techniques similar with the relevant studies discussed. The related studies utilized similar concepts like the utilization of computer technologies for grading and classification of food products. The concepts of following studies served as a foundation for the development of this study.

Synthesis of the Reviewed Literature and Studies

The researchers relate and differentiate the present study to different studies based on the concepts that applies to this study. The proponents of this study believe that each and every literature and studies stated in this research is similar on the present study.

In summary of the studies discussed in this chapter, the proponents learned that Convolutional Neural (CNN) is commonly used in image processing task such image recognition and classification. CNN is a type of ANN that transforms the original image layer by layer from the original pixel values to the final class scores.

The table below shows the gathered differences between CNN and ANN in Fruit Classification based on the related studies.

Table 1

Difference between CNN and ANN in Fruit Classification

Convolutional Neural Network	**Artificial Neural Network**
Deep Learning	Machine Learning
The network can properly extract the important features of the fruit without the need of other feature extraction methods like image processing.	Needs the use of feature extraction methods before feeding into the network, which can result to inconsistencies and inaccuracies in the extracted features.

ANN is a Machine Learning while CNN is Deep Learning. Another difference of CNN and ANN when it comes to fruit classification is that in CNN, the network is modeled to extract the important features of the fruit without the need of using image processing techniques. Whereas in ANN, the network requires that the features must already be extracted before being fed in the model which means that other feature extraction methods must be used to the image. Additionally, using only one feature extraction technique is not enough to accurately extract all the important features of a fruit. Features are the key to a better classification and CNN has been applied in several studies that successfully extracted and recognized features.

CNN has a number of remarkable studies related to classification and feature extraction problems which resulted to high accuracy rates and better results when dealing with feature extractions. The proponents aimed to classify the quality and maturity level of Carabao mangoes with high accuracy, which is the reason for the use of CNN in this study.

Although there are a lot of existing studies about the classifier of quality and maturity of fruits, this study remains unique because it focuses on the classification of quality and maturity level of Carabao mango. Presently, there are no existing mobile classifier system of Carabao mango and the development of a high accuracy rate mobile application for the classification of the quality and maturity level of Carabao mango using CNN is the main focus of this study.

Chapter 3

METHODOLOGY

Research Design

The researchers of this study used the Experimental type of research design. This study is focused on the development of a tool for the quality and maturity assessment of a Carabao mango. The system examined the features of the Carabao mango that is associated with the maturity and quality. From the assessment, the system produced the maturity level and quality of the subject. The type of experimental research for this study is Post-test Only Design where the treatment, which is the system, was applied to the Carabao mango then the result of the treatment, such as the accuracy rate of the system, was compared to the present manual assessment of mangoes.

Sources of Data

Population

The population frame of this study consisted of harvested Carabao mangoes. The Carabao mangoes may be unripe, ripe overripe, and defective or in good quality.

Respondents

The respondents of this study must be familiar about the quality and maturity of Carabao mangoes as to improve the accuracy of the system. The respondents comprised of Carabao mango farmers, farm owners, and consumers or distributors of Carabao mangoes.

Sampling Technique

Random sampling is used in the selection of samples from the population. The researchers chose the samples according to the following criteria:

a. Harvested Carabao mangoes.

b. Carabao mangoes that are being prepared for exportation.

c. Carabao mangoes that are being prepared for or in market selling.

Instrumentation

Software/Hardware Tools

System Architecture

Figure 5. System Architecture of the Study

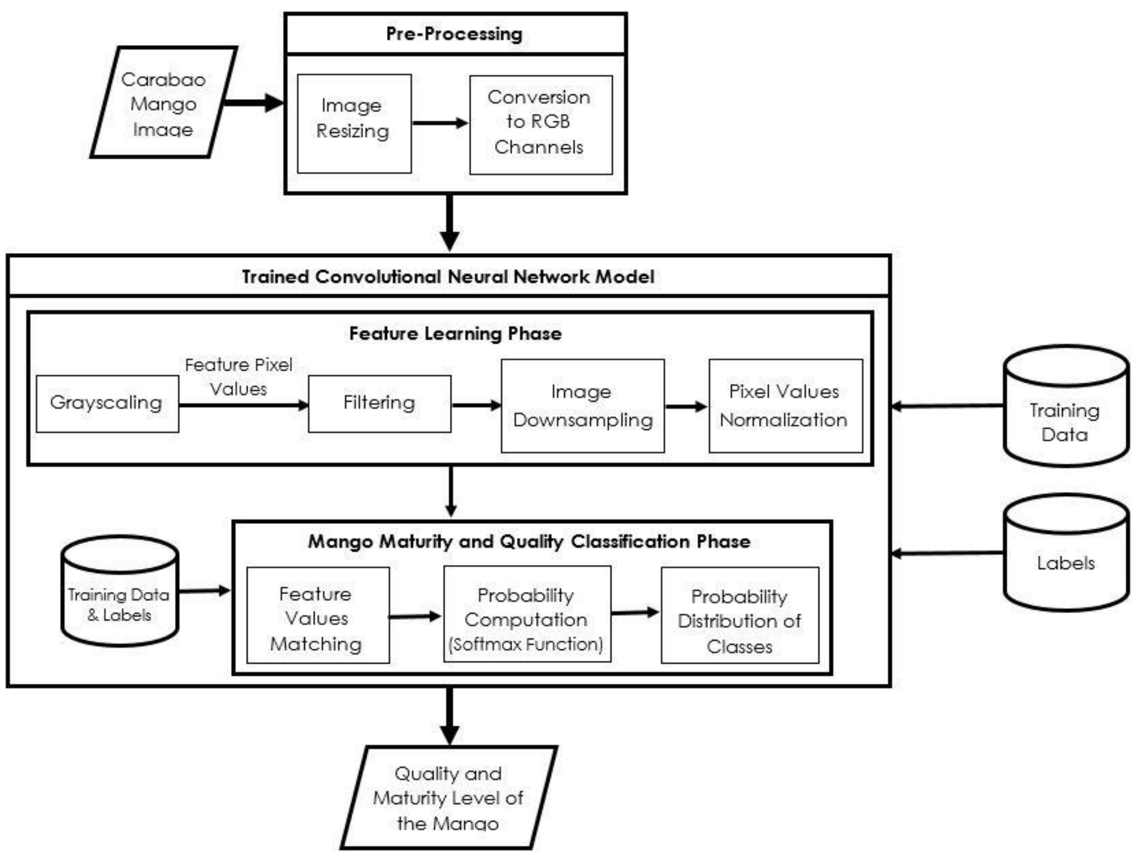


Figure 5 shows the system architecture of the Carabao mango quality and maturity level classifier using Convolutional Neural Network (CNN). CNN is a type of deep neural network that has the ability to learn to sort images into categories. The architecture starts with an input the Carabao mango image. From the input, the image will undergo a pre-processing which includes the resizing of the image and the conversion of the image to Red, Green and Blue channels. After the pre-processing, the image will go through the trained CNN model wherein the first part is the Feature Learning Phase. In the Feature Learning Phase, the first process is Converting to Grayscale where the RGB channels of the image will be converted into grayscale. After converting to grayscale, the model will get the part of the pixels with a higher or non-negative values. The pixel with higher or non-negative values are known as the feature pixel values. From these, the pixels will undergo through Filtering wherein each part of the feature pixel values will be multiplied to the equivalent pixels in the image. After filtering, the image will go through the Image Downsampling. In downsampling, the image will be checked per window of pixels and the maximum value will be left to represent the entire window. Through this, the size of the image will be reduced and the important features of the image will be focused. Next is the Pixel Values Normalization in which all the pixels with negative values will be replaced with zeroes in order to normalize the values of the pixels.

After the learning the features of the image, the input will go through the Classification phase, the last part of the CNN model, where the training data will be used to compare or match the extracted features in the input image. By matching the structures to the training data, the model will be able to get the pre-normalized values of the probabilities. The pre-normalized values will be used to the Probability Computation which consist of the Softmax Function wherein Softmax Function will be applied to the output scores from the Feature Values Matching for the calculation of the actual probabilities associated with each classes. The Probability Distribution is the actual distribution of votes to the classes of quality and maturity levels in every match of the features in the input image and the training data or the normalized probabilities. After that, the model will have values of probability for each classes. From this, the quality and the maturity label with the highest probability will be the final output of the application. After going through a series of processes, the application will be able to output the quality and maturity levels of the mango. Below is the pseudocode of the system:

Phase 1 Preprocessing Phase

Initialize desired width and height of the input image and its number of channels

Input Carabao Mango Image
Resize input image to given desired width and height
Convert input image that has given number of channels per pixel
Output pixel values of the converted input image
End

Phase 2 Feature Learning Phase

Load and Initialize pre-trained model with its filters,
sizes and shapes of filters, number of strides.

Load and Initialize model to an object
Convert returned pixel values of the output image from preprocessing phase into grayscale
Load filters from object of the model to an object

Convolve the object of filters around the gray scaled input image and
map the products of pixel values to an array of integers which we call a feature maps

for current = filter to number of filters do

```
  for counter = 0 to height of image - height of filter do
          for walker = 0 to width of image - width of filter do
                  Multiply the values in the filter with the original pixel values of the
image
                  Map the products of pixel values to array
                  walker = walker + number of strides of the current filter
          end
          counter = counter + height of filter + number of strides
  current = current + 1
  end
end
```

Output feature maps

Reduce the spatial size of the feature maps after convolving the filters to image to reduce the number of parameters and computation in network, and hence to also control overfitting and map the maximum pixel values from each pooling unit to an array if integers which we also call as feature maps.

```
 for current = filter to number of filters do
  for counter = 0 to height of image - height of filter do
          for walker = 0 to width of image - width of filter do
                  Get the maximum pixel value from pooling units
                  Map the maximum pixel value to array
                  walker = walker + number of strides of the current filter
          end
          counter = counter + height of filter + number of strides
  end
  current = current + 1
end
```

Output feature maps

Normalization of pixel values of feature maps after pooling of image by replacing negative pixel values to zero.

for current = 0 to number of feature maps do
for counter = 0 to number of columns in feature maps - 1 do
for walker = 0 to number of rows in feature maps - 1 do
if pixel value from column index as counter and row index as walker of the array of integers of current feature map < 0
Assign element from feature map with column index as counter and row index as walker to 0
end
walker = walker + 1
end
counter = counter + 1
end
current = current + 1
end

Output pixel values of high level features of the image
End

Phase 3 Mango Maturity and Quality Classification Phase

Get input volume or the output feature maps after feature learning and outputs an N dimensional vector where N is the number of classes.

Compare or Match the high-level features to each class and compute its scores
Apply SoftMax function to the scores for the normalization of the probability of each class
Output an N dimensional vector where N is the number of classes. Each number in this N dimensional vector represents the probability of a certain class.
Distribute probabilities to each class.
Output index of highest probability in this N dimensional vectors. Each index represents a class with labels.
End

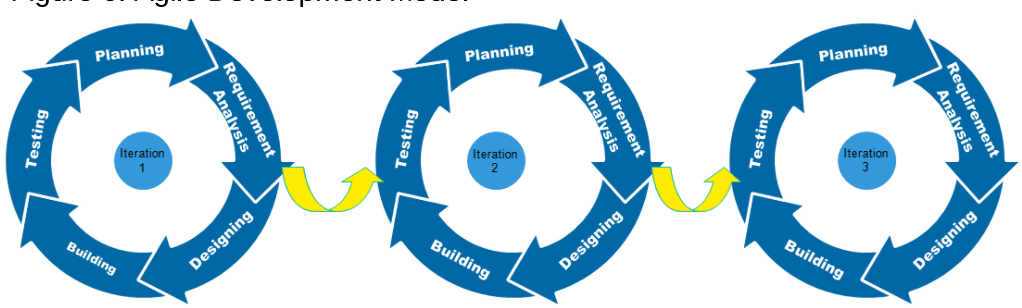
Phase 4 Display Quality and Maturity Level of the input Carabao mango image

Get label of the class that corresponds to the output index.
Display output label of the class. (For maturity level, it consists of unripe, ripe and overripe class and for quality, it consists of good and defective class).

Development Details

The researchers developed the Carabao mango quality and maturity level classification system using Android programming language in Android Studio version 2.3. The researchers used OpenCV (Open Source Computer Vision) for blurring, sharpening, edge detection, and other image processing functions for the preprocessing of the Carabao mango images. OpenCV is a library that consists of programming functions related to computer vision and machine learning. For building the Convolutional Neural Network (CNN) model and training the data, TensorFlow Library and Keras are used. TensorFlow is a machine learning library that is usually used for applications of deep learning like CNN. Whereas Keras is an API built on TensorFlow that can be used to quickly build and test a neural network model. There are a number of training data used in the development in order to achieve high accuracy rate of the system.

Figure 6. Agile Development Model



The researchers used the Agile Development Model in the development of the classifier mobile application. Incremental and rapid cycle for the development of the system was utilized for this study wherein the system is tested frequently after every release of iterations or version in order to minimize the risk of major failures in the future.

Research Instrument

The researchers used an experiment paper to gather data from the samples with the help of experts in Carabao mangoes. The experiment paper was given to the expert in the field in order to gather knowledge for the improvement of the accuracy and reliability rate of the system. Appendix A shows the experiment paper used for this study.

Data Generation

The data needed in this study is a multiple image of the Carabao mango, defective or in good quality with three maturity levels, unripe, ripe and overripe. Convolutional Neural Network requires thousands of images for the training therefore the researchers used 1000 images of harvested Carabao mango as training data. Below are the narrative step-by-step actions for data acquisition.

Preliminaries

The procedures to acquire valid data are as follows:

1. Choosing of mango farm in the Philippines that caters Carabao mango for export and local markets is used as a source of mango images for the data set of this study.

2. Mango image acquisition or using digital camera or mobile phone in capturing harvested Carabao mango individually.
    a. Image quality (At least 8 megapixels).
    b. View/angle of the object in the image (side or top view, fit to screen).
    c. Image size/dimension (500x500 and up).
    d. Plain background color (White or Black).
    e. Image captured with proper lighting.
3. Choosing of a manual mango grading expert who will help in labelling the mangoes with their corresponding maturity level and quality and will then be used as training data. The labeling task is performed by manual mango graders who are expert in the maturity level and quality assessment.

Experimentation

The researchers conducted various experimentation procedures in order to formulate the result and conclusions for the study. These procedures are the following:

1. Labeling of the mangoes with the three levels of maturity such as the unripe, ripe and overripe and the two classifications of quality such as the defective and good quality.
2. Gathering of mango images for the testing of the system in which the expert conducted the manual assessment for the maturity level and quality of the mango individually.
3. Feeding of the images to the system for the automatic maturity and quality classification.
4. Answering of the experiment paper with the help of the Carabao mango expert. The manual classification was compared to the automated classification of the system. This served as the basis for the accuracy of the system's output.

Data Analysis

The main objective of the study is to know the accuracy rate of the proposed method in classifying the maturity level and quality of Carabao Mango. The following formula is used in the computation of accuracy:

$$Accuracy = \frac{T}{N}\ X\ 100\%$$

Classification Accuracy Formula

Where:

T **–** Number of cases correctly classified by the system.

N **–** Total number of sample cases.

Above is the Classification Accuracy Formula. Accuracy of the classification system is obtained by dividing T by N and multiplying the result by 100. T refers to the number of cases which are correctly classified by the system whereas N is the total number of sample cases regardless of being correctly or incorrectly classified. By using the formula stated above, the researchers were able to determine the accuracy rate of the system in classifying the quality and maturity level of the Carabao mangoes.

Chapter 4

RESULTS AND DISCUSSION

The main objective of this study is to develop and analyze the accuracy rate of a mobile application that classifies the maturity and quality level of the Carabao mangoes. In this chapter, experimentations were already carried out and the results were already analyzed by the researchers. This chapter presents the discussion about the results gathered by the proponents with the help of the expert.

The first problem stated in chapter 1 aims to find the accuracy rate of the system in classifying the maturity level of the Carabao mango. The researchers used the experiment paper to gather the data needed for the computation of the accurateness of the system in categorizing the maturity.

Appendix A shows the result of the experimentation for 50 samples of Carabao Mangoes. The researchers recorded the maturity that the expert and the system has classified. The experiment paper consisted of the maturity level classification from the expert and the system as well as the column whether the system produced similar result with the expert. If both the classifications are the same, the output of the system is considered as correct, however if the printed result of the system does not match with the classification of the expert, then the result of the system is considered to be incorrect. The result of the assessment of the expert and the application were compared to compute for the accuracy.

For the maturity classification experiment, as shown in Table 2, the samples consisted of 12 samples of unripe, 25 samples of ripe and 13 cases of overripe mangoes. In the identification of unripe, only 11 out of 12 samples were correctly classified as unripe. On the other hand, all the samples of ripe mangoes were properly assessed and for the overripe cases, only 11 out of the 13 samples were identified as overripe.

Table 2

Summary and Accuracy Rates of the Maturity Classification

MATURITY LEVEL	TOTAL	CORRECT	ACCURACY
Unripe	12	11	91.67%
Ripe	25	25	100%
Overripe	13	11	84.62%
Overall	50	47	94%

Overall, a total of 47 out of 50 samples were correctly classified whereas only 3 out of the 50 samples were incorrectly categorized. The results in Table 2 shows that the correctly assessed cases are higher than the incorrect cases. Thus, the accuracy rate of the maturity classification for unripe resulted to 91.67%. 100% accurateness for the classification of ripe mangoes, 84.62% for the overripe mangoes and an overall accuracy rate of 94% for the maturity level classification.

The second research question stated in the first chapter of this study aims to determine the accuracy rate of the system in classifying the quality of the mangoes. In determining the accuracy rate of the classification of quality, the researchers used the data from the experiment paper. Same with the maturity level, the researches recorded the assessment of the expert, the system, and the outcome whether the system was able to correctly or incorrectly identify the quality. Appendix A presents the results of the experimentation conducted in order to compute for the accuracy rate of the classification of the quality in Carabao mangoes.

Table 3

Summary and Accuracy Rates of the Quality Classification

QUALITY	TOTAL	CORRECT	ACCURACY
Good	31	30	96.77%
Defective	19	16	84.21%
Overall	50	46	92%

Table 3 shows the summary of the results of the classification of good and defective qualities. In the experiment conducted for the quality assessment, 31 samples of good quality mangoes and 19 samples for the mangoes that are defective were used. The result of the experiment shows that only 30 mangoes were correctly classified as good quality whereas only 16 defective mangoes were properly identified. With this data, the accuracy of the quality classifications were calculated by the researchers resulting to 96.77% for the good quality fruits, and 84.21% for the defective ones.

The results from Table 3 shows that there are more cases of incorrect assessments for the defective mangoes. In total, 46 out of 50 samples of mangoes were correctly identified while only 4 mangoes were incorrectly categorized. With this, the researchers were able to compute for the overall accuracy of the quality classification, which gives a result of 92%.

With the results gathered, the researchers observed that the system can correctly classify ripe mangoes that are defective and good quality as well as the unripe and good quality. However, it has difficulty in the classification of unripe when the mango is defective.

The system classifies the unripe mangoes as overripe when the mango is defective because the images of unripe and defective are not entirely unripe or already contains dark yellowish colors, similar with the colors of overripe mangoes. In addition, most cases of the defectiveness occur in the ripe and overripe stages resulting to insufficient training data for the unripe and defective cases. Because of this, the system has difficulty in properly classifying the unripe and defective mangoes.

Furthermore, the researchers also observed that in some cases, the system cannot properly assess the overripe mangoes. The proponents examined the incorrect cases of overripe mangoes and realized that the system has difficulty in distinguishing the ripe and overripe cases when some parts of the mango are still not totally overripe. Some overripe mangoes still have spots that are not entirely overripe, because of this, its color has a combination of the colors of ripe and overripe mangoes, resulting to the ambiguity in the assessment of the system.

After experimenting, analyzing the results gathered and computing the accuracy of the system's maturity and quality classification, the researchers were able to calculate the overall accuracy rate of the system which resulted to 93%.

Chapter 5

SUMMARY OF FINDINGS, CONCLUSIONS, AND RECOMMENDATIONS

This chapter presents the summary of all the findings of the study from the actual data through experimentation. The results of the experimentation are discussed and is further interpreted to come up with a conclusion. Recommendations for future work is also stated based on the results and problem encountered throughout the study.

Summary of Findings

This study aimed to develop and determine the accuracy rate of a Carabao Mango Quality and Maturity Level Classifier using Convolutional Neural Network". By this, the study aimed to answer the statement of the problems stated in Chapter 1 such as: (1) What is the accuracy rate of using Convolutional Neural Network in classifying the maturity level of Carabao mango based on: (a) Ripe (b) Unripe (c) Overripe and (2) What is the accuracy rate of using Convolutional Neural Network in classifying the quality of Carabao mango based on: (a) Good Quality (b) Defective?

In able to answer the research questions of this study, the researchers conducted experimentations and analysis on the results gathered. With the help of the expert, the proponents tested the system on 50 samples of Carabao mangoes, which were chosen randomly based on the criteria stated in the sources of data. The results were recorded and used for the calculation of the overall accuracy rate of the system in the classification of the maturity level and quality.

Based on the experiments carried out by the researchers on the evaluation of the respondents, our study entitled "ManggaSort: A Mobile Application for Carabao Mango Quality and Maturity Level Classification Using Convolutional Neural Networks" has obtained a high accuracy. In the classification of Carabao Mango's maturity level, the researchers calculated the accuracy rate for the assessment of each maturity levels. For the classification of unripe mangoes, the system gives a 91.67% accuracy rate. 100% for the ripe mangoes and 84.62% for the assessment of overripe mangoes. In total, the maturity classification yields a result of 94% accuracy rate.

For the assessment of the quality, the overall accuracy resulted to 92%. In the classification of good quality mangoes, the system gives a result of 96.77% and only 84.21% for the defective mangoes.

All in all, the overall system performance has produced an accuracy rate of 93% for the quality and maturity level classification of Carabao mangoes.

Conclusions

This study is aimed at determining the accuracy rate of the classification for quality and maturity level of Carabao mangoes with the use of CNN. Through careful experiment and analysis conducted by the researchers from the implementation of the study, the researchers observed that the quality and amount of training data greatly affects the performance of the system. In this study, the researchers gathered great amount of high resolution images of training data for the system to produce better classification.

During the experimentation and analysis of the data gathered, the researchers observed that the system was able to properly identify the maturity and quality of the ripe mangoes in good and defective qualities. In terms of unripe, the system properly identified the unripe and good quality but has difficulty in classifying the unripe and defective mangoes since there are only few training data for unripe and defective mangoes. In addition, the researchers found out that defective cases of mangoes mostly occur in ripe and overripe stages. For the overripe, the system was able to properly assess the overripe mangoes in defective and good quality, although in some cases, it incorrectly classified overripe mangoes as ripe.

The study resulted with a high accuracy of 94% for the assessment of maturity, 92% for the quality classification and an overall accuracy rate of 93%. With this, the researches came up with the conclusion that CNN is an effective algorithm to be used in Carabao mango quality and maturity classification in order to achieve high accuracy rate.

Recommendations

Based on the findings and conclusions of the study, the following are the researcher's recommendation for further enhancement of the system's performance and for the future studies in the field of deep learning and fruit classification:

1. Add an adaptive color feature extraction techniques that can be used to improve the classification of the maturity level of a carabao mango particularly in presence of dark spots.
2. Consider another technique for better classification of carabao mango quality.
3. Try applying this research to other object classification like food classification and grocery item classification.

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APPENDICES

Appendix A: Instrument

Directions: *Write down the quality and maturity level of the carabao mango. Then scan the mango in the system for the automated classification. Write the result of the system in the columns provided.*

Carabao Mango	Maturity	System Output Maturity	Correctly Classified	Incorrectly Classified	Quality	System Output Quality	Correctly Classified	Incorrectly Classified
Mango 1	Ripe	Ripe	✓		Defective	Defective	✓	
Mango 2	Ripe	Ripe	✓		Defective	Defective	✓	
Mango 3	Ripe	Ripe	✓		Defective	Defective	✓	
Mango 4	Ripe	Ripe	✓		Good	Good	✓	
Mango 5	Ripe	Ripe	✓		Good	Good	✓	
Mango 6	Ripe	Ripe	✓		Good	Good	✓	
Mango 7	Ripe	Ripe	✓		Good	Good	✓	
Mango 8	Ripe	Ripe	✓		Good	Good	✓	
Mango 9	Ripe	Ripe	✓		Good	Good	✓	
Mango 10	Ripe	Ripe	✓		Good	Good	✓	
Mango 11	Ripe	Ripe	✓		Good	Good	✓	
Mango 12	Ripe	Ripe	✓		Good	Good	✓	
Mango 13	Ripe	Ripe	✓		Good	Good	✓	
Mango 14	Unripe	Unripe	✓		Good	Good	✓	
Mango 15	Unripe	Unripe	✓		Good	Good	✓	
Mango 16	Unripe	Unripe	✓		Good	Good	✓	
Mango 17	Unripe	Unripe	✓		Good	Good	✓	
Mango 18	Unripe	Unripe	✓		Good	Good	✓	
Mango 19	Unripe	Unripe	✓		Defective	Good		✓
Mango 20	Unripe	Unripe	✓		Good	Good	✓	
Mango 21	Unripe	Unripe	✓		Good	Good	✓	
Mango 22	Unripe	Unripe	✓		Good	Good	✓	
Mango 23	Unripe	Unripe	✓		Good	Good	✓	
Mango 24	Ripe	Ripe	✓		Good	Good	✓	
Mango 25	Ripe	Ripe	✓		Good	Good	✓	
Mango 26	Ripe	Ripe	✓		Good	Good	✓	
Mango 27	Ripe	Ripe	✓		Good	Good	✓	
Mango 28	Overripe	Ripe		✓	Good	Defective		✓
Mango 29	Ripe	Ripe	✓		Good	Good	✓	
Mango 30	Ripe	Ripe	✓		Good	Good	✓	
Mango 31	Ripe	Ripe	✓		Good	Good	✓	
Mango 32	Ripe	Ripe	✓		Good	Good	✓	
Mango 33	Ripe	Ripe	✓		Good	Good	✓	
Mango 34	Overripe	Ripe		✓	Defective	Good		✓
Mango 35	Ripe	Ripe	✓		Good	Good	✓	
Mango 36	Ripe	Ripe	✓		Good	Good	✓	
Mango 37	Ripe	Ripe	✓		Defective	Defective	✓	
Mango 38	Overripe	Overripe	✓		Defective	Defective	✓	
Mango 39	Overripe	Overripe	✓		Defective	Defective	✓	
Mango 40	Overripe	Overripe	✓		Defective	Defective	✓	
Mango 41	Overripe	Overripe	✓		Defective	Defective	✓	
Mango 42	Overripe	Overripe	✓		Defective	Defective	✓	
Mango 43	Overripe	Overripe	✓		Defective	Defective	✓	
Mango 44	Overripe	Overripe	✓		Defective	Defective	✓	
Mango 45	Unripe	Overripe		✓	Defective	Defective	✓	
Mango 46	Overripe	Overripe	✓		Defective	Defective	✓	
Mango 47	Overripe	Overripe	✓		Defective	Defective	✓	
Mango 48	Unripe	Unripe	✓		Defective	Good		✓
Mango 49	Overripe	Overripe	✓		Defective	Defective	✓	
Mango 50	Overripe	Overripe	✓		Defective	Defective	✓	
TOTAL			47	3			46	4

Appendix B: Correspondents

Polytechnic University of the Philippines
College of Computer and Information Sciences
Department of Computer Science
Sta. Mesa, Manila

September 8, 2017

Dear Sir/Madam:

We are students of Bachelor of Science in Computer Science under the Department of Computer Science of Polytechnic University of the Philippines currently researching for our research paper, Carabao Mango Quality and Maturity Level Classifier Using Convolutional Neural Network. It is an automated tool that will classify the quality and maturity level of the Carabao mango. We are in awe of your expertise on the field of mango farming, and we are taking the opportunity to ask for advice regarding the classification of the quality and maturity level of Carabao mangoes.

We would like to request a brief informational interview with you in person depending on your availability and if you would let us, we are humbly asking to record the conversation for educational purposes. We would also greatly appreciate your suggestions for our study.
You can contact us at 0945 334 3581. Thank you for your kind consideration.

Sincerely,

John Edwin Ibe
Researcher

Gilly Lea Damandaman
Researcher

Noted by:

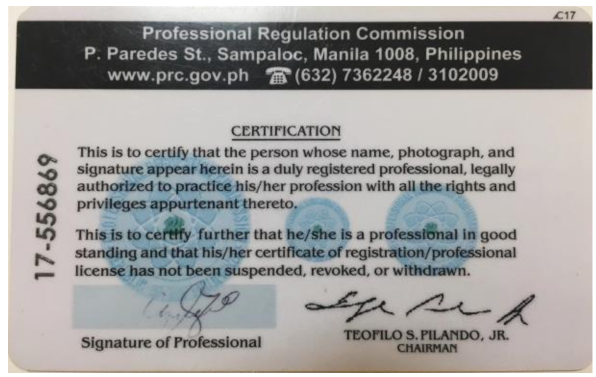
Melvin Roxas
Chairperson
Department of Computer Science

Gisela May Albano
Dean
College of Computer and Information Sciences

Appendix C: Certification of Editing

This is to certify that the thesis work entitled "ManggaSort: A Mobile Application for Carabao Mango Quality and Maturity Level Classification Using Convolutional Neural Network" by Gilly Lea E. Damandaman and John Edwin M. Ibe was proofread and edited by the undersigned.

This Certification is being issued for whatever legal purpose it may serve.



Signed:

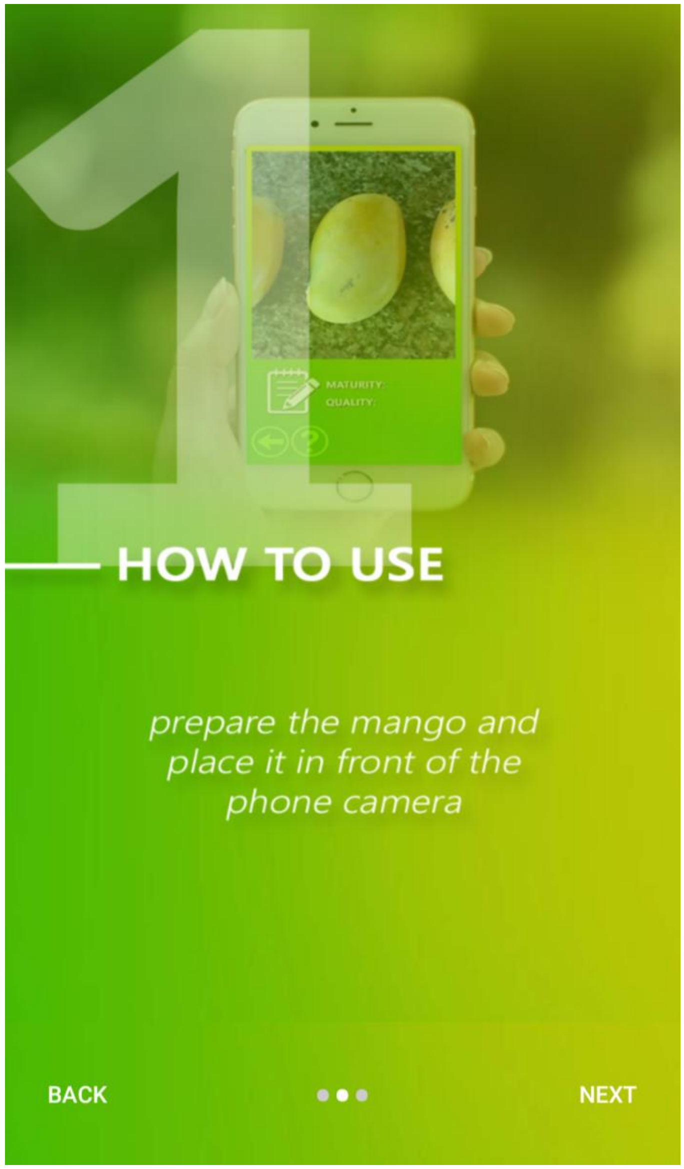
_______Xyrenne P. Tan______

(Signature over Printed Name)

Appendix D: Screenshots of the Prototype

START-UP PAGE – this contains the title, logo and tag-line of the system. This page also contains the button NEXT.

NEXT – once the NEXT button is tapped, the screen will display the HOW TO USE PAGE of the system.



HOW-TO-USE PAGE 1 – contains the directions on how to use the system. The first HOW TO USE PAGE displays the first step in using the system.

BACK – this button will return the user back to the START UP PAGE.

NEXT – this button will display the second step on how to use the system.

HOW-TO-USE PAGE 2 – contains the second and last direction on how to use the application. This also contains the BACK button and START button.

BACK – this button will redisplay the HOW-TO-USE PAGE 1 which shows the first step on how to use the application.

START – this button will show the HOME PAGE of the system.

HOME PAGE – this page displays the camera to be used for the classification of the mangoes as well as the results which contains the quality and maturity of the scanned mango.

Appendix E: Resume/CV of the Researchers

Gilly Lea E. Damandaman

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Contact Number: 09157722949
E-mail Address: gillylead@gmail.com

PERSONAL INFORMATION:

Nickname:	Gilly
Birthday:	November 27, 1995
Birthplace:	Negros Occidental
Age:	22
Nationality:	Filipino
Civil Status:	Single
Language/s Spoken:	English, Filipino

EDUCATIONAL BACKGROUND:

TERTIARY:	POLYTECHNIC UNIVERSITY OF THE PHILIPPINES Bachelor of Science in Computer Science Major in Computer Science Research Sta. Mesa, Manila 2014 – Present
SECONDARY:	THE SISTERS OF MARY SCHOOL INC. JP Rizal Street, Talisay City, Cebu 2009 – 2013

JOB EXPERIENCES/INTERNSHIP:

WEB DEVELOPER - TRAINEE
Information Technology (IT) Department
SME Soft Inc.
April – May 2017

John Edwin M. Ibe

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E-mail Address: johnedwinmahoribe@gmail.com

PERSONAL INFORMATION:

Nickname:	John/Edwin
Birthday:	February 23, 1996
Birthplace:	Moncada, Tarlac City
Age:	22
Nationality:	Filipino
Civil Status:	Single
Language/s Spoken:	English, Filipino

CERTIFICATION/S:

IT PASSPORT CERTIFIED
Philippine National IT Standards (PHILNITS) Foundation Inc.

EDUCATIONAL BACKGROUND:

TERTIARY:	POLYTECHNIC UNIVERSITY OF THE PHILIPPINES Bachelor of Science in Computer Science Major in Computer Science Research Sta. Mesa, Manila 2014 – Present
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