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Ripe Fruit Detection and Classification using Machine Learning

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ABSTRACT

One of the most important sectors in any country is the agricultural sector. However, in some countries, farmers and fishermen have limited technology compared to other developed countries. One of the effects of limited technology is the low quality of crops, fruits, and vegetables. This is because the quality of the products is only assessed depending on external factors like appearance, shape, color, and texture, which can be prone to human error. Determining the quality and ripeness level of fruit requires consistency, which can be hard and tedious for humans when it becomes repetitive work. This paper aims to present various methods and approaches on how ripe fruit detection and classification can be made easier and more convenient using machine learning and machine vision algorithms. Furthermore, this study presents systems that can be utilized in pre and post-harvest analysis. This paper aims to provide solutions using computer applications to help farmers have lesser manual labor yet more accurate data and results in the evaluation of crops.

Key words : Machine Learning, Classification Engineering, Convolution, Neural Networks.

1. INTRODUCTION

The attempts of imitating the abilities of the human brain are the bases of several applications such as object detection, face recognition, autonomous vehicles, image processing, and robotics. Moreover, numerous studies and experiments have also been attempting to provide convenience in the quality assessment of the food industry using computer applications.

Classification of various kinds of fruits and even vegetables is not a simple task due to several similarities in shape, size, and color [1]. Typically, fruits, vegetables, and crops, before harvested and released to the market are examined by an expert or trained personnel. Some factors considered by these people in the quality assessment are the color and texture of the products. However, manual checking and classification give rise to several possible human errors. For a classification to be successful, the people trained to examine the products are required to have consistent recognition and analysis which may be hard or tedious when it becomes repetitive.

Nowadays, several research studies that focus on the agriculture industry are providing various methods for the detection and classification of fruits and vegetables. Most of these methods are based on computer vision both for the processing and harvesting analysis of the products. Computer Vision refers to the analysis of visual information with the use of different kinds of images. Developments in image processing techniques have contributed on the improvement of the computer vision procedures as well. Despite the advancements of technology in the agricultural industry, the classification of fruits and vegetables continues to have complex challenges such as the wide variety, irregularity, and inconsistency in shape, color, and texture [2]. The fruit classification process is shown in Figure 1.

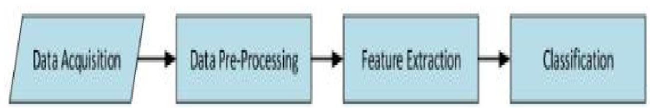

Figure 1: Fruit Classification Process Distribution

Recent studies suggest that the detection of ethylene levels in fruits can help in classifying whether the fruits are ripe or not. Ethylene is a type of plant hormone discovered during the early years of the 20^{th} century. It was observed that gases composed of ethylene had effects on the growth of plants. Furthermore, ethylene is also considered in the majority of the plant development fields such as fruit ripening, root elongation, seed germination, and flower development. The ethylene level can determine whether a fruit is ripe and ready to be harvested or not [3].

Most of the existing agricultural technologies are utilizing machine learning algorithms. Examples of the applications of machine learning are crop yield prediction and intelligent irrigation systems. Machine learning techniques are classified into two types: supervised and unsupervised learning. Examples of supervised machine learning algorithms are Naïve Bayes (NB), Discriminant Analysis (DA), Support Vector Machines (SVM), and K-Nearest Neighbor (KNN).

On the other hand, K-Means Clustering, Gaussian Mixture Models (GMMs), and Fuzzy Clustering are types of unsupervised machine learning algorithms [4].

2. LITERATURE REVIEW

According to one study, the quality of watermelons is only evaluated by assessing factors such as appearance, texture, and flavor. Nevertheless, the sole examination of these factors is not sufficient and reliable enough to indicate the overall ripeness and quality of watermelons since the determination of these qualities is prone to human mistakes. This study proposes a simple and economical method of watermelon ripeness detection and analysis using wavelet multi-resolution decomposition or WMRD. Two samples, one for ripe watermelons and one for unripe watermelons, are determined by the multi-scale decomposition of the acoustic signals of the watermelon for a particular coefficient. To provide an estimation of the degree of separation of the two samples, a discrimination index is also presented to identify the WMRD coefficient that works best. By implementing the presented method, the accuracy rates of obtained in tests and pieces of training can get as far as 91.76% and 91.67%, respectively [5].

Ethylene is an invisible and odorless substance released by fruits once they have already ripened. The amount of ethylene emitted is indicative of the ripeness level of fruit. Numerous methods have been proposed for the detection of ethylene gas. Two of the most frequently and conveniently used techniques is the portable electronic nose or PEN and the electronic olfactory system or EOS835. These methods are composed of a set of metal oxide sensors and can detect several gases at the same time. One of the best features of these methods is its commercial availability. Non-dispersive infrared spectroscopy or NDIR is also another approach used in ethylene gas detection. This system has a selective feature in measuring mixtures of substances and gases. For powerful ethylene gas detection with a lower range of ppmv, gas chromatographic systems are utilized. One study focuses on the use of gas chromatographic systems since the ethylene level must be measured in a selective manner having a resolution of 50ppbv. Measurements and values of ethylene gas in synthetic air having 400ppbv and 35ppbv concentrations were presented first in the paper. Eventually, ethylene in the air was measured by the researchers from the ripening bananas placed on a storage box having 306ppbv. The study shows and demonstrates that the procedure is also possible for micro gas chromatographic systems which is a Control System [6].

One of the most globally traded fruits and leading export products in the Philippines is banana. However, a known challenge for the product is the high percentage of postharvest loss caused by various reasons like fruit diseases, fruit immaturity, over-ripeness, physical, and chemical damages. A study conducted by Aquino-Nuevo and Apaga in 2010 presented that no standards concerning size and quality are followed for the classification of bananas as well as the other harvested products. Having no standards is alarming for errors in the classification of bananas and other products may occur and contribute to higher postharvest losses, which can eventually lead to a decrease in production profit. Several studies have also focused on fruit sorting. Most of them used and presented fruits like apples, mangoes, oranges, and lemons. The fruits were individually sorted by using machine learning algorithms. However, fruits similar to bananas and grapes are required to be grouped in bunches or tiers, hence, external characteristics of the fruit are more difficult to detect and examine by using simple machine learning. This study by Tuan-Tang Le, et.al. presents a deep learning sorting process of clustered bananas having only one image feature. Previous implementations of deep learning, a field of convolutional neural network or CNN which is also known as masked region-based convolutional neural networks or Mask R-CNN provide unique features and applications through object detection simultaneous generation of masks. Using Mask R-CNN, the detection of bananas provides a prediction of the class of the banana while simultaneously creates masks wherein the fruit is moved apart from the background. In the experiments and tests conducted in the study, an actual dataset was utilized having banana bunches as bases. The proposed system separates the normal tiers from the abnormal tiers. The deep learning classification method that was presented in this study had a successful implementation in banana bunches and was proven to be also effective for other horticultural products and crops that are clustered. The common deep learning diagram that shows the several phases is shown in Figure 2.

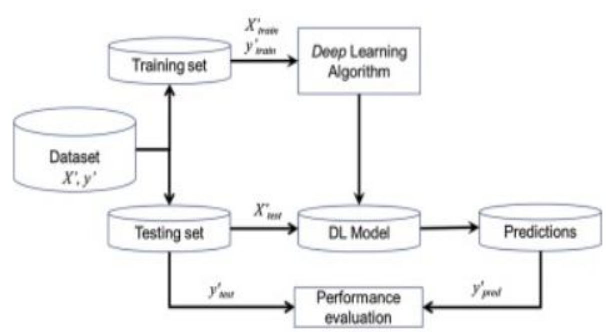

Figure 2: Common deep learning diagram containing three phases: training, testing, evaluating [7].

It has been proven and demonstrated by several studies that deep learning offers excellent features and capabilities in understanding and learning image processes which is popular and commonly used in object detection. This paper utilizes the Mask Region-based Convolutional Neural Network or Mask-RCNN to boost the performance of machine vision in the detection of fruits in a strawberry-harvesting robot. The backbone network used was Resnet50, along with the Feature Pyramid Network or FPN that served as the structure for feature extraction. To produce region proposals for the feature maps, and end-to-end training was conducted for the Regional Proposal Network or RPN. According to the experimental results of a hundred test images, the accuracy of detection reached a rate of 95.78% and a 95.41% recall rate. In comparison to conventional techniques, the presented method in this study shows a more robust environment, which is suitable and effective for hidden and clustered fruits. The summary of the R-CNN process is shown in Figure 3.

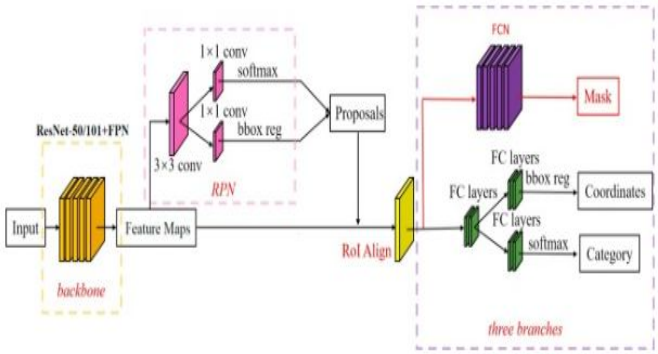

Figure 3: Summary of the Mask R-CNN Process [8].

3. THEORETICAL CONSIDERATION

Physical appearance is one of the most essential characteristics of a fruit that is indicative of its ripeness state and quality. The color and texture of fruits change throughout their maturity. However, assessment and checking of these factors even by trained personnel are still prone to inconsistencies and human error. Recent studies involve the use of machine learning in detecting and classifying objects [9].

A common pipeline of machine learning is illustrated in Fig.2. Machine learning composes of two primary parts: the training and testing phases. For the phase of training, a training dataset is utilized to generate a model with a machine learning technique. Some of the most widely known models for these are support vector machines or SVMs, random forest, and neural networks. Training verification is typically done to make sure that the process done to the model is generalized. The trained model is then examined in the test phase whether it has the capability of dataset prediction with the use of input variables. The train and test datasets have several similarities. Frequently, the test dataset is the outcome of separating the initial dataset. The performed prediction in the testing phase if often compared to the performed training process for further evaluation [10,11,12].

Deep learning or deep convolutional neural network has become a popular and widely used technique in the field of computer vision because of its ability to combine classification and extraction tasks. With the use of deep CNN, a system can do a prediction on the ripening state of a specific fruit. The rise of deep learning algorithms resulted in the incorporation of two components in the method of image processing which are dataset classification and feature extraction. Deep and other kinds of convolutional neural networks have recently been widely used in food and agriculture technology. Since the year 2015, several studies have been implemented for these industries in which the main applications were object detection and classification. The main advantage of convolutional neural networks over artificial neural networks is that they can execute both feature selection and extraction and can combine large values of parameters [13].

4. DESIGN CONSIDERATION

Images are important components in machine learning algorithms as well as in several applications like feature extraction, object detection, and object classification. One study focused on the proposal of a fruit detection method that uses machine vision. From an illumination-compensated image, a modified green and red chromatic diagram was produced. Illustrated below is an overview of the procedure proposed in this study, which can also be applied in the detection and classification of other kinds of fruits that will focus on the process of image processing, enhancement, and illumination. The fruit used in this study is citrus. The proposed detection method diagram is shown in Figure 4.

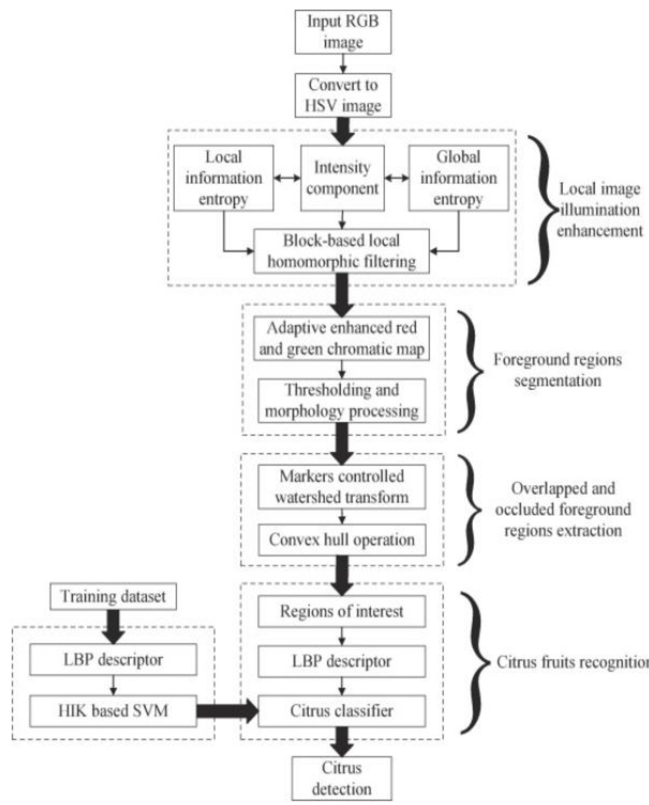

Figure 4: Diagram of Proposed Detection Method [14].

Another study emphasized the utilization of Red-Green-Blue (RGB) Depth images in fruit maturity detection and classification. Passion fruit was the fruit used in this study. For the acquiring of images, a Kinect V2.0 device was employed, and a total of 4000 images were obtained. The device contained infrared depth and an RGB camera. The figures below illustrate the setup of the Kinect V2.0 device. The sample prototype and Kinect device is shown in Figure 5.

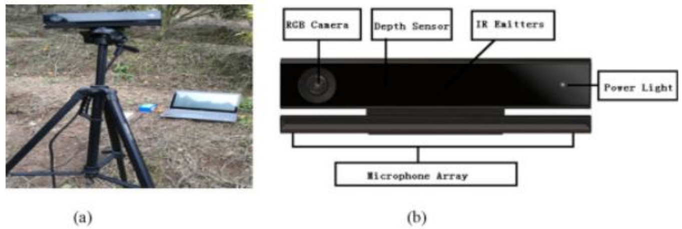

Figure 5: (a) Prototype, (b) Kinect V2.0 device

The images captured eventually underwent training and testing phases. Below is an example of an RGB image. The initial RGB images are shown in Figure 6.

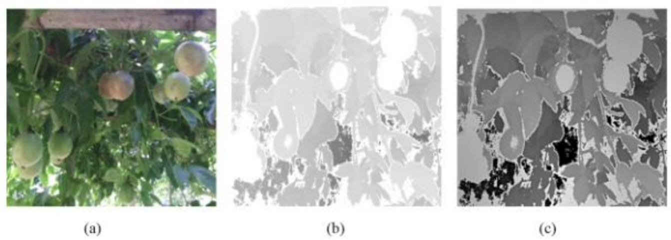

Figure 6: (a) Initial RGB image, (b) Depth Image, (c) Pre-processed depth image [15].

Another method that is widely used in fruit detection and classification is the Faster R-CNN. A diagram of an example implementation is illustrated below. The faster R-CNN Diagram for implementation is shown in Figure 7.

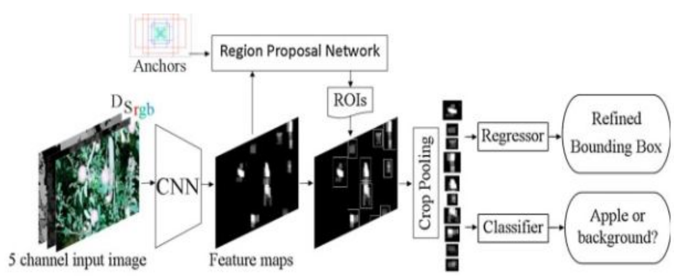

Figure 7: Faster R-CNN Implementation Diagram [16].

There may be numerous possible techniques to be used in fruit detection. However, these techniques still follow a general process for fruit detection. Below is a block diagram overview showing the general sensors, classification methods and processes involved in fruit detection. The fruit selection detection process is shown in Figure 8.

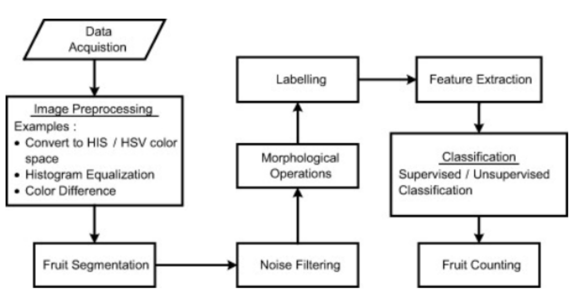

Figure 8: Fruit Detection process block diagram [17].

5. CONCLUSION

The classification of ripe fruits and the evaluation of their quality before the release in the market is commonly a human activity. However, recent studies show that having physical characteristics like shape, color, and texture as the only bases of quality assessment may be prone to human error since these factors require consistency during the examination. Several studies have proposed and presented various methods for more accurate fruit detection and classification. Programs can be created to simulate its algorithms like computer vision systems [18,19,20,21]. This paper was able to enumerate some of the most widely used and proven-effective methods such as deep learning, image illumination, faster-CNN, and the use of the gas chromatographic system in detecting ethylene gas.

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