**RESEARCH ARTICLE**

# Determining 'Carabao' Mango Ripeness Stages Using Three Image Processing Algorithms

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## Abstract

Harvested mangoes are commonly classified or sorted manually. This method is tedious, time consuming, inaccurate and prone to errors. Human inspection is also subjective and factors like visual stress and tiredness may arise that can result in the inconsistencies in judgment. The use of a chroma meter is reliable but the equipment is expensive. This study explored the use of three digital image processing algorithms to determine harvested 'Carabao' mango ripeness stages. Canny edge detection, Sobel edge detection, and Laplacian of Gaussian detection algorithms were used to extract a mango image from its original image. The mean red, green, and blue (RGB) values of the detected images were converted to L*a*b* color values which were used to identify the ripeness level of the mango image based on the standard generated from gathered data of 'Carabao' mangoes. The standard generated was also based on the mango peel color index scale from University of the Philippines Los Baños Postharvest Horticulture Training and Research Center (PHTRC). The algorithms' performance had an overall accuracy of 80.5% for canny edge detection algorithm and L*a*b* color extraction using neural networks; 63.88% for Sobel edge detection algorithm and L*a*b* color extraction using rgb2lab function in MATLAB software; and 17.33% Laplacian of Gaussian detection and L*a*b* color extraction using OpenCV. Overall, the implementation of Canny edge detection algorithm for image processing and L*a*b* color extraction using neural networks performed best among the algorithms used in classifying 'Carabao' mango ripeness stages. To improve the performances of the algorithms, it is recommended to improve the quality of the sample images by controlling the light, exposure, and camera to be used, matching it with more chroma meter sample points on the 'Carabao' mango to attain a better color average of the sample mango.

**Keywords:** 'Carabao' mango • image processing • L*a*b* color values • neural networks

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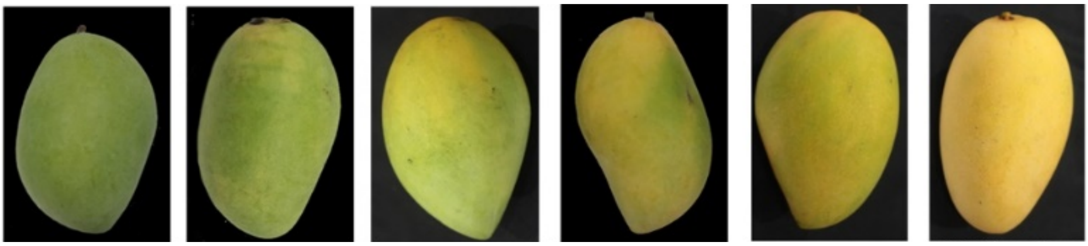
## Introduction

Mango (*Mangifera indica* L.) is the third most important fruit crop in the Philippines, behind only to banana and pineapple based on export volume of the country (PSA 2019b). The ‘Carabao’ variety, also known as ‘Super Manila’ mango is the most popular variety with its distinct unique taste (DA 2013). According to Philippine Statistics Authority, it also comprised 81.4% of the total mango production of the country from March 2018 to March 2019 (PSA 2019a). Mangoes only have a 0.6% share in total agro-based products for export, but despite this small percentage, the Philippines remains as one of the top exporters of mangoes to countries such as Belgium, France, Germany, Ireland, the Netherlands, New Zealand, Switzerland, and the United Kingdom.

The acceptance of exported mangoes in these countries largely depends on the excellent eating quality of ‘Carabao’ mango. One of the components in judging the quality of fruits is based on its appearance. It is the first thing that will catch consumers’ attention and affect their decision in choosing what to buy (FAO 2017). Appearance includes the color, size, shape, wholeness, presence of defects, finish or gloss, and consistency (Barrett et al. 2010). Out of these factors, skin or peel color is commonly used because as a fruit changes in skin color, it also indicates the ripeness and maturity of fruit and thus can be considered as a quality index (Ahmad and Siddiqui 2015). The maturity level of fruits and vegetables is an important factor to determine its storage method and storage life that will be the basis of its overall quality when marketed (Dhatt and Mahajan 2007). For the mangoes to be exported, it is important to harvest it in their right maturity. If it is picked early, it will not ripen properly whereas late picking will have a greater possibility for the fruit to be spoiled faster as a result of softening and the development of various diseases (NDA 2000).

Another factor is knowing the ripeness stage of the mango. Fruits undergo the process of ripening which is characterized by a decrease in flesh firmness and increased juiciness, starch conversion into sugars, increase in soluble solid contents, increase in aroma, and changing flesh color from greenish yellow to golden yellow and changing skin color from green to yellow (National Mango Board 2016). Changes in the skin color is one of the most commonly used maturity index, but it is not reliable enough because it varies between cultivars. On the other hand, changes in flesh color are consistent in almost all cultivars making it a reliable index of maturity and ripeness (Kader 2008).

It is helpful to determine the proper and optimal strategy in sorting and handling fruit after harvest to acquire the best quality for the market (Slaughter 2009). Sorting is a postharvest practice that classifies produce into various qualities and is important for the classification and uniformity of the product. Current practices include having mangoes manually sorted. Manual sorting can be tedious, time consuming, inaccurate, and prone to human errors (Nandi et al. 2014). Human inspection is subjective and varies from observer to observer and whose consistency of judgment may be affected by stress and fatigue. Discussing on color context, Grais mentioned an interaction called simultaneous contrast where two colors put together side by side can affect how we see those colors. Objects surrounded by darker color appears lighter while objects surrounded by lighter colors appears darker. A peel color index (Figure 1) or a color standard is used as a tool during manual inspection to measure color objectively, but this needs expert, experienced, and well-trained workers to do the job correctly and appropriately



| 1 | 2 | 3 | 4 | 5 | 6 |
|---|---|---|---|---|---|
| Green | Breaker, trace of yellow at stem end | Turning, more green than yellow | More yellow than green | Yellow with trace of green | Fully yellow |

**FIGURE 1** Mango peel color index (lifted from UPLB-PHTRC 2014)

(Leon et al. 2009). Other methods make use of equipment such as the chroma meter, colorimeter, and spectrophotometer, which are nondestructive to the fruits, but is rather expensive.

There is an increasing demand for high quality in agricultural products, thus researchers search for new ways to improve quality, productivity and sustainability (Saxena and Armstrong 2014). Vibhute and Bodhe (2012) highlighted different applications of image processing in agriculture. Their survey stated that image processing techniques has proven to be an effective machine vision system for the agriculture domain. Under the proper algorithms, different classification accuracies vary from 85%–96%. Vibhute and Bodhe, however, shows that there are different algorithms that perform best for different agriculture classification applications, and it also depends on the limitations of image acquisition. Furthermore, the survey does not highlight any image processing classifications for mangoes.

Some studies have been conducted in different mango cultivars and other fruits to measure and assess their maturity and ripeness nondestructively using machine vision and image processing.

Raut and Bora (2016) used MATLAB software for image analysis and artificial neural network modeling to develop an automatic vision system for sorting and grading cherry and strawberry according to their maturity level. They initially acquired the image in its red, green, and blue (RGB) format then converted it to red, blue, and green channels. Next, they did feature extraction of useful information of the images followed by feature training and testing. This resulted in 63% accuracy in cherry fruit and 60% in strawberry fruit.

Syahrir et al. (2009) developed a tomato maturity estimator to take over the manual practice of tomato color grading. They used image enhancement and feature extraction techniques to highlight the important features of the image. From RGB image, they converted it to L*a*b* image to get a* value that is needed for the comparison using MATLAB functions. Their research on the tomato maturity estimator using image processing had 90% success rate in estimating tomato maturity.

Paulraj et al. (2009) developed a system that determined the ripeness of the banana fruit using a neural network model. Their system consisted of three stages, namely, the preprocessing, the feature extraction, and the ripeness classification. In preprocessing, the captured images were resized and extracted to its red, blue, and green color components. The histogram of the total pixels of each re-scaled color threshold was used in the feature extraction stage that determined the fruit ripeness. For color recognition, the neural network model resulted in a 96% ripeness recognition rate.

The applicability of machine vision and image processing in mangoes depend on characteristics of particular cultivars. Nagle et al. (2016) studied surface color determination of "all yellow" mango cultivars using computer vision system (CVS) and made use of the International Commission on Illumination (CIE) L*a*b* color space to acquire color data as it is the most commonly used color space in food research. Their results showed that CVS can be an alternative way to evaluate the degree of ripeness of the 'Nam Dokmai' and 'Maha Chanok' cultivars.

In the Philippines, Ilagan et al. (2015) used image processing in grading of 'Carabao' mango and made use of the Mandami fuzzy interference system in analyzing the blemishes and the maturity of 'Carabao' mangoes. The results showed that digital photometry using a simple digital camera and software for color analysis based on RGB, hue, saturation, and value (HSV), or L*a*b* systems, is a promising method for determining the ripeness degree of 'Carabao' mango fruits. This computer-based method is an alternative to the conventional subjective technique for evaluating mango fruit ripeness (Ilagan et. al 2015).

As a possible alternative to the use of expensive equipment for determining mango quality, this study examined the use of three digital image processing algorithms for determining harvested 'Carabao' mango ripeness stages. The study specifically aimed to (1) implement Canny edge detection, Sobel edge detection, and Laplacian of Gaussian detection algorithms to separate a captured 'Carabao' mango image from its background image, (2) convert RGB values of the extracted mango image to L*a*b* values using Artificial Neural Network models from the images extracted by the Canny edge detection Algorithm, (3) convert RGB values of the extracted mango image to L*a*b* values using rgb2lab function in MATLAB software from the images extracted by the Sobel edge detection algorithm, (4) convert RGB values of the extracted mango image to L*a*b* values using OpenCV from the images extracted by the Laplacian of Gaussian detection algorithm, (5) determine the ripeness stage of the sample 'Carabao' mangos from the extracted L*a*b* values, and (6) compare the accuracy of the L*a*b* values extracted from the three different methods, with an expert determined ripeness level of the sample 'Carabao' mangoes.

## Materials and Methods

### Requirements

The data used for this study were the training data and the testing images. These consisted of R, G, and B values and its corresponding L*, a*, and b* values. Testing images were 'Carabao' mango images taken using a camera and corresponding L*a*b* values for testing the results were extracted per mango using a CR-400 Minolta chroma meter.

Testing images featured a single mango under a clear background for better image detection. The preferred image resolution must be at least 640 × 480 pixels with the recommended setting as a plain white or black background for lesser noise and disturbances. Images were taken in a well-lit area. A Canon EOS 1100D camera (4272 by 2848 dimension, f/8 F-stop, 1/15 seconds, exposure time, ISO-400 ISO speed, and 18 mm focal length of the lens) was used. The study also tried to take 'Carabao' mango images using a mobile phone but disregarded the same as it showed very pixelated images considered of lesser quality. Compared to Ilagan et al. (2015) which used 18 mangoes, this study used 60 mangoes, 30 from the Island Garden City of Samal (IGaCOS), Davao del Norte, and 30 from Digos City, Davao del Sur,

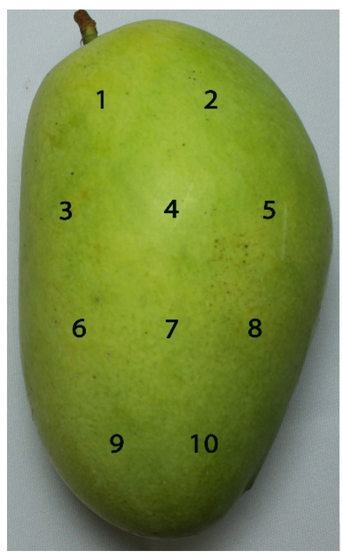



**FIGURE 2** Mango image with sample 10 testing points on a mango cheek for L*a*b* data gathering.

were used. Thirty (30) of the 60 mangoes, 15 from each location, were treated with ethephon.

In extracting L*, a*, and b* data values using the chroma meter, ten points were chosen in both cheeks of the mango. Thus, L*a*b* values per mango fruit totaled 20 points (Figure 2). The L*a*b* values of each mango were taken using a CR-400 Minolta chroma meter.

**Implementation**

The first process to determine the ripeness level of the 'Carabao' mangoes was the image processing of the images using Canny edge detection, Sobel edge detection, and Laplacian of Gaussian detection algorithms. The algorithms were coded in Java and the inputs were the images of individual 'Carabao' mangoes taken with the above-mentioned specifications. The images undergo image processing to remove the background image until only the mango will be left with black background. The reason in leaving the image in a black background was because in calculating for the average color of the mango, black pixels were not considered in calculating for the average RGB of the image by using the 'nonzeros' function in MATLAB.

After removing the background, the second process for determining 'Carabao' mango ripeness made use of the extracted RGB values from the image and then converted to L*a*b* values using neural network models from the images extracted by the Canny edge detection algorithm, rgb2lab function in MATLAB software from the images extracted by the Sobel edge detection algorithm, and OpenCV from the images extracted by the Laplacian of Gaussian detection algorithm.

*Creation of neural network model.* The neural network model for the conversion of RGB to L*a*b* values was done using MATLAB software's Neural Network Toolbox specifically using the Neural Fitting (ntstool). It is a Graphical User Interface (GUI) that automatically generates command-line scripts.

Three neural network models were created, one for each L*, a*, and b* values as output nodes. The first step was to open the GUI of neural fitting tool using the command nftool. After this, the input data which was the RGB training data and the output data (i.e., L*, a*, and b* values) were loaded. After which, the percentages for training, validation, and testing were set. For each of the models, the data for training was set to 70%, validation for 15%, and testing for 15%. For the training of each model, 8 hidden neurons were set and the default Levenberg-Marquardt (trainlm) algorithm was used. Training was followed by the evaluation of the network for each of the models. The last part was the auto-generation of MATLAB functions for each of the models.

*Creation of standards.* The standards used in this study was created using the color index of each mango with their corresponding L*, a*, and b* values obtained from the chroma meter. First, the mangoes were sorted according to the mango peel color index scale, from index 1 to 6, by experts. The average from the 20 points that were taken in each mango was calculated. To get the range of values accepted for each of the indexes, the confidence interval with a 95% level of confidence generated by the Past software was used. The range of each of the index were used as basis in determining the results or the ripeness levels of each of the processed images.

**Performance Evaluation**

A confusion matrix is a table that is often used to describe the performance of a classification model (Data School 2016) where in this study, the ability of the system to correctly identify the ripeness level of a 'Carabao' mango. The confusion matrix for multiple classes based on Manliguez (2016) was used in this study (Table 1).

**TABLE 1** Confusion matrix for multiple classes lifted from Manliguez (2016)

| | | PREDICTED | | | | | |
|---|---|---|---|---|---|---|---|
| | | 1 | 2 | 3 | 4 | 5 | 6 |
| ACTUAL | 1 | $a_{11}$ | $a_{12}$ | $a_{13}$ | $a_{14}$ | $a_{15}$ | $a_{16}$ |
| | 2 | $a_{21}$ | $a_{22}$ | $a_{23}$ | $a_{24}$ | $a_{25}$ | $a_{26}$ |
| | 3 | $a_{31}$ | $a_{32}$ | $a_{33}$ | $a_{34}$ | $a_{35}$ | $a_{36}$ |
| | 4 | $a_{41}$ | $a_{42}$ | $a_{43}$ | $a_{44}$ | $a_{45}$ | $a_{46}$ |
| | 5 | $a_{51}$ | $a_{52}$ | $a_{53}$ | $a_{54}$ | $a_{55}$ | $a_{56}$ |
| | 6 | $a_{61}$ | $a_{62}$ | $a_{63}$ | $a_{64}$ | $a_{65}$ | $a_{66}$ |

In evaluating the performance in determining ripeness stages, the following are computed:

- The true positive (TP) rate is when the actual result matched the predicted result. TP can be seen diagonally indicated in red marks (Table 1).

- Total false negative (TFN) of each ripeness category is the sum of values in the corresponding row, excluding TP (Eq. 1).

$$TFN_i = \sum_{j=1}^{n} a_{ji} \quad (1)$$

*where*
$i$ : represents each of the classes
$n$ : total number of classes

- Total false positive (TFP) of each ripeness category is the sum of values in the corresponding column, excluding TP (Eq. 2).

$$TFP_i = \sum_{j=1}^{n} a_{ji} \quad (2)$$

- Total true negative (TTN) of each ripeness category is sum of all columns and rows excluding that ripeness category's column and row (Eq. 3).

$$TFP_i = \sum_{j=1}^{n} a_{ji} \quad (3)$$

- Precision refers to the relevance of the result (Eq. 4).

$$PRECISION_i = \frac{TP_i}{TP_i + TFP_i} \quad (4)$$

- Recall corresponds to the TP rate of each ripeness category (Eq. 5).

$$RECALL_i = \frac{TP_i}{TP_i + TFN_i} \quad (5)$$

- The formula for the Overall Accuracy (Eq. 6) is as follows:

$$OVERALL\ ACCURACY = \frac{a_{11} + a_{22} + a_{33} + a_{44} + a_{55} + a_{66}}{\text{total no. of all testing images}} \quad (6)$$

**Data Gathering**

Data was gathered for two weeks from a total of 560 'Carabao' mango images that were captured, with a minimum of 30 images from each peel color category resulting to 180 images for the six peel colors in the peel color index. This constituted 32% of the total number of images taken. These were used to test the image processing and accuracy of the RGB to L*a*b* conversion algorithms (Figure 3).

## Results and Discussion

The first process was to subject the gathered mango images for the six peel colors in the peel color index to the Canny edge detection, Sobel edge detection, and Laplacian of Gaussian detection algorithms. The algorithms successfully extracted the mango image from its background to a black background (Figure 4).

After removing the background, the second process for determining 'Carabao' mango ripeness was implemented where RGB values from the image was converted to L*a*b* values. Before the conversion, the processed images of both sides of a mango was extracted to each of its individual R, G, and B channels. The mean R, G, and B from the two processed images were then computed and used as parameters in the conversion of RGB to L*a*b* values.

**Ripeness Level Identification**

To determine the ripeness level, a fixed standard was created using the gathered data of 'Carabao' mangoes using the chroma meter. To show the distribution of data, boxplots generated from the Past software was used. The standards generated from this study was based on the a* values only because if these values are compared to the b* values, only the a* has an increasing pattern (Figure 5) while the b* boxplot generated outliers showing decreased values from index 5 going to index 6 (Figure 6).

The Past software was used to get the confidence intervals of each of the index having 95% level of confidence. To avoid the unidentified images, the index 1 and 6 were set to have values up to negative and positive infinity respectively. The final resulting intervals are shown in Table 2.

**FIGURE 3** Sample mango images: side A (top) and side B (bottom).

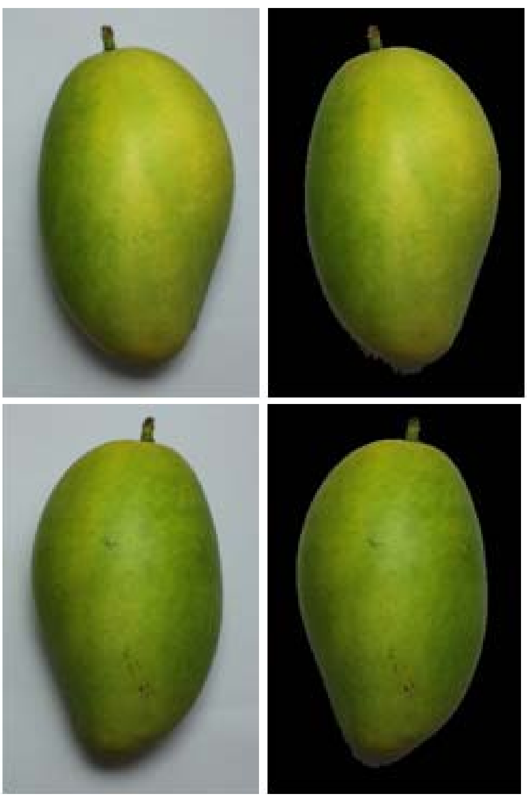


**FIGURE 4** Sample mango images before and after mango image extraction

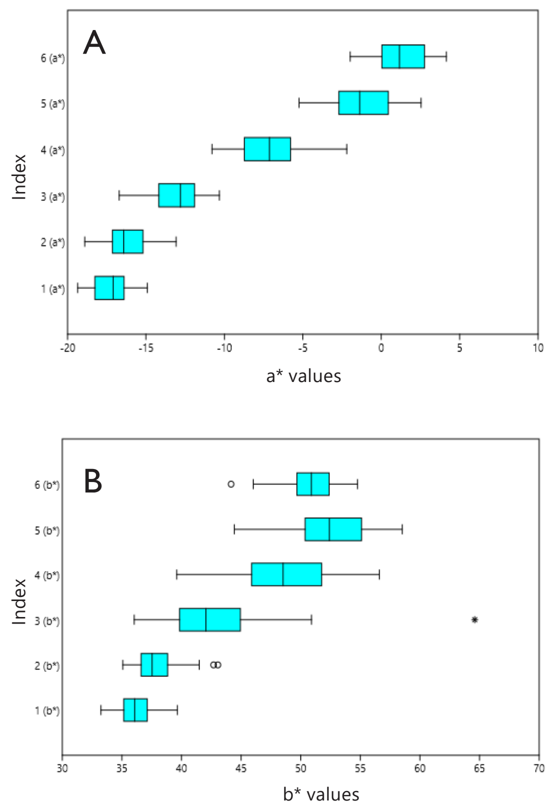



**FIGURE 5** Boxplot for a* values (A) and b* values (B) from the Past software

**TABLE 2** Final Interval Results of a* values.

| Index # | Description | [Lower Bound, Upper Bound] |
|---|---|---|
| 1 | Green | [∞, −17.054] |
| 2 | Breaker | [−17.053, −15.901] |
| 3 | Turning | [−15.900, −12.733] |
| 4 | More yellow than green | [−12.732, −6.713] |
| 5 | Yellow with trace of green | [−6.712, −0.932] |
| 6 | Fully yellow | [−0.931, ∞] |

## Evaluation of Accuracy

The confusion matrix shows the performance in determining the 'Carabao' mango ripeness stages for the 180 mango testing images (Tables 3, 4, and 5). The extracted values were compared to the fixed standard.

Recall percentages correspond to the true positive (TP) rate of each of the index or the ratio of the determined index i to the total number of images with index i.

Using the implementation of Canny edge detection algorithm for image processing and L*a*b* color extraction using neural networks, results show that index 1 had 90%, index 2 had the lowest result at 60%, index 3 had 77%, index 4 had 87%, index 5 had 70%, and index 6 had the highest result at 100%.

For the above index 2 that had the lowest TP percentage, there were a number of breaker (index 2) images that was determined as green (index 1). One factor can be that because of the determination of breaker index was based on the trace of yellow at stem end of the mango but overall, the mango has still a lot of green and just have a very small portion of yellow. Since the average color of the whole mango was calculated, those small portions of yellow will be covered by the green color (Figure 7).

Using the implementation of Sobel edge detection algorithm for image processing and L*a*b* color extraction using rgb2lab function in MATLAB software, results show that index 1 had 73.33%, index 2 had 76.66%, index 3 had 73.33%, index 4 had 40%, index 5 had the lowest result at 36.66%, and index 6 had the highest result at 83.33%.

**TABLE 3** Confusion matrix for the implementation of Canny edge detection algorithm for image processing and L*a*b* color extraction using neural networks

| | | PREDICTED | | | | | |
|---|---|---|---|---|---|---|---|
| | | 1 | 2 | 3 | 4 | 5 | 6 |
| ACTUAL | 1 | 27 | 3 | 0 | 0 | 0 | 0 |
| | 2 | 8 | 18 | 4 | 0 | 0 | 0 |
| | 3 | 0 | 2 | 23 | 5 | 0 | 0 |
| | 4 | 0 | 0 | 0 | 26 | 4 | 0 |
| | 5 | 0 | 0 | 0 | 0 | 21 | 9 |
| | 6 | 0 | 0 | 0 | 0 | 0 | 30 |

**TABLE 4** Confusion matrix for the implementation of Sobel edge detection algorithm for image processing and L*a*b* color extraction using rgb2lab function in MATLAB software

| | | PREDICTED | | | | | |
|---|---|---|---|---|---|---|---|
| | | 1 | 2 | 3 | 4 | 5 | 6 |
| ACTUAL | 1 | 22 | 8 | 0 | 0 | 0 | 0 |
| | 2 | 6 | 23 | 1 | 0 | 0 | 0 |
| | 3 | 0 | 2 | 22 | 0 | 0 | 0 |
| | 4 | 0 | 0 | 0 | 12 | 1 | 0 |
| | 5 | 0 | 0 | 0 | 17 | 11 | 2 |
| | 6 | 0 | 0 | 0 | 0 | 5 | 25 |

**TABLE 5** Confusion matrix for the implementation of Laplacian of Gaussian detection for image processing and L*a*b* color extraction using OpenCV

| | | PREDICTED | | | | | |
|---|---|---|---|---|---|---|---|
| | | 1 | 2 | 3 | 4 | 5 | 6 |
| ACTUAL | 1 | 30 | 0 | 0 | 0 | 0 | 0 |
| | 2 | 30 | 0 | 0 | 0 | 0 | 0 |
| | 3 | 30 | 0 | 0 | 0 | 0 | 0 |
| | 4 | 30 | 0 | 0 | 0 | 0 | 0 |
| | 5 | 29 | 1 | 0 | 0 | 0 | 0 |
| | 6 | 17 | 19 | 4 | 0 | 0 | 0 |

**FIGURE 7** Testing images in side A (top) and side B (bottom) with actual breaker (index 2) but predicted as green (index 1)

Using the implementation of Laplacian of Gaussian detection algorithm for image processing and L*a*b* color extraction using OpenCV, results show that index 1 had the highest result at 100% while index 2 to 6 were at 0%.

Precision, on the other hand, refers to the relevance of the results or the ratio of the correctly determined index i to the total number of images predicted in the index i regardless if correct or not (Koehrsen 2018).

Using the implementation of Canny edge detection algorithm for image processing and L*a*b* color extraction using neural networks, results show that predictions on index 1 had 81% precision, index 2 had 78%, index 3 had 85%, index 4 had 84%, index 5 had 84%, and index 6 had 77% precision (Table 6). Predictions made on turning (index 3) mangoes had the highest precision while predictions made on fully yellow (index 6) mangoes had the lowest precision.

Using the implementation of Sobel edge detection algorithm for image processing and L*a*b* color extraction using rgb2lab function in MATLAB software, results shows that predictions on index 1 had 78% precision, index 2 had 58%, index 3 had 55%, index 4 had 42%, index 5 had 64%, and index 6 had 92% (Table 7). Predictions made on fully yellow (index 6) mangoes had the highest precision while predictions made on turning (index 3) mangoes had the lowest precision.

**TABLE 6** Corresponding results and precision and recall percentages for the implementation of Canny edge detection algorithm for image processing and L*a*b* color extraction using neural networks

| Metric | Index | | | | | |
|---|---|---|---|---|---|---|
| | 1 | 2 | 3 | 4 | 5 | 6 |
| TFN | 3 | 12 | 7 | 4 | 9 | 0 |
| TFP | 8 | 5 | 4 | 5 | 4 | 9 |
| TN | 142 | 145 | 146 | 145 | 146 | 141 |
| Precision | 0.81 | 0.78 | 0.85 | 0.84 | 0.84 | 0.77 |
| Recall | 0.90 | 0.60 | 0.77 | 0.87 | 0.70 | 1.00 |

**NOTE:** TFN – true false negative; TFP – true false positive; TN – true negative

**TABLE 7** Corresponding results and precision and recall percentages for the implementation of Sobel edge detection algorithm for image processing and L*a*b* color extraction using rgb2lab function in MATLAB software

| Metric | Index | | | | | |
|---|---|---|---|---|---|---|
| | 1 | 2 | 3 | 4 | 5 | 6 |
| TFN | 8 | 7 | 8 | 18 | 18 | 5 |
| TFP | 6 | 16 | 18 | 16 | 6 | 2 |
| TN | 143 | 133 | 131 | 133 | 144 | 147 |
| Precision | 0.78 | 0.58 | 0.55 | 0.42 | 0.64 | 0.92 |
| Recall | 0.73 | 0.76 | 0.73 | 0.40 | 0.37 | 0.83 |

**NOTE:** TFN – true false negative; TFP – true false positive; TN – true negative

In calculating for the overall accuracy of the system, the sum of all the correctly predicted mangoes with respect to their true color index was divided to the total number of images (180).

The overall accuracy of Canny edge detection algorithm for image processing and L*a*b* color extraction using neural networks in determining the correct ripeness stages of 'Carabao' mangoes was only 80.5%

The overall accuracy of Sobel edge detection algorithm for image processing and L*a*b* color extraction using rgb2lab function in MATLAB software in determining the correct ripeness stages of 'Carabao' mangoes was only 63.88%

The overall accuracy of Laplacian of Gaussian detection for image processing and L*a*b* color extraction using OpenCV in determining the correct ripeness stages of 'Carabao' mangoes was only 16.77%.

## Conclusions and Recommendations

Based on the results shown on the implementation of the three image processing algorithms, the implementation of Canny edge detection algorithm for image processing and L*a*b* color extraction using neural networks performed best among the algorithms used in classifying 'Carabao' mango ripeness stages with an overall accuracy of 80.5%, though not as accurate as that of a chroma meter. The implementation of Sobel edge detection algorithm for image processing and L*a*b* color extraction using rgb2lab function in MATLAB software had an accuracy of only 63.88%, while Laplacian of Gaussian detection for image processing and L*a*b color extraction using OpenCV software had an accuracy of 16.77%. The results means that the system judgments could not accurately imitate expert judgment yet.

The performance of the implementation of Laplacian of Gaussian detection for image processing and L*a*b* color extraction using OpenCV could not produce a desired output due to compatibility reasons. The CR-400 uses as standard D50, the same illuminant as the Adobe Photoshop. On the other hand, the OpenCV has a default illuminant of D65. It was identified that the range of values it produced differed from the values produced by the chroma meter. It is recommended to ensure that the illuminants of the software to be used are the same as the illuminant of the test chroma meter.

In this study, only 10 sample points for each mango cheek were considered to obtain the average L*, a*, and b* values of a mango. More sample points in each cheek of the mango may be considered for future studies including images at the shoulder (stem end), and beak of the mango and other sides so that the whole color of a 'Carabao' mango fruit is captured. The quality of the possible input images to be used may be optimized further by controlling the light, exposure, and camera to be used. This study used Canon EOS 1100D, a high definition camera. Better image quality may lead to more accurate performances of the algorithms used. In future studies, it is recommended to explore methods that are optimized to extract images from a phone camera.

Only the ripeness level based on the six peel color scales was considered and assumed that the input images do not have diseases or must have a good quality. For future studies, it is recommended to add features like detection of peel defects and blemishes as part of the overall fruit quality. Furthermore, it is recommended to have more sample points in each cheek of the sample 'Carabao' mango. Attempts to capture images at the stem end of the mango and other sides of it aside from the front and back are recommended so the whole color of a 'Carabao' mango fruit can be retrieved.

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