Optimization of Sorting Processes of Partially Rotten Mango for Food Processing with Image Processing

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***Abstract* –This research aims to develop a method for improving the process of separating partially rotten fruit of ripe mango to the process of creating new creative Mango Stir-Fry. The partial rotten approximation process was based on image processing using Gaussian Mixture Model, HSV color model, dilation, erosion, Otsu's binarization thresholding, and image color proportions techniques for mobile application development. The results showed that the techniques presented in this study could sort and approximate partially rotten mangoes with an accuracy of 99.06%. Moreover, the developed mobile application can approximate the net weight of ripe mango pulp and the net weight of Mango Stir-Fry to be obtained. These approximation errors were 0.68% and 1.91% for the net weight of net ripe mango pulp and Mango Stir-Fry, respectively. Therefore, this work helps the cooking process to classify partially rotten ripe mangoes and estimate the volume of processed products more conveniently.**

***Keywords* – image processing, food processing, optimization, partially rotten fruit**

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1. Introduction

Fruits are an important natural food source for humans. Fruits can be eaten immediately without any processing like meat or some vegetables. Mango (Mangifera indica L.) is one of the most popularly cultivated fruits in Thailand. It can also be eaten both ripe and unripe. Further, mangoes are famous abroad in South Korea, China, Malaysia, Hong Kong, Indonesia, Russia, and the United Arab Emirates. In 2021, there were 116,850 tons of fresh or frozen mango exports, worth 3,367,228,976 baht [1]. Mangoes have a variety of nutritional values depending on the maturation of the fruit, including geographically cultivated areas [2], [3], [4] Generally, farmers allowed vendors to come and harvest their produce themselves at the farm or garden to buy mangoes directly. However, due to the epidemic of Coronavirus Disease-19 (COVID-19), people must maintain social distance to lessen the risk of infecting and transmitting the disease. Consequently, it directly affects the business in the agricultural system and products [5], causing it to be disconnected and slow down. Even the farmers are affected as well, when there were no direct buyers or vendors. Especially the elderly farmers could not collect mangoes from the trees due to the physical inability to climb the mango trees and pick mangoes from the trees, the mangoes ripened and fell to the ground. These dropped ripe mangoes lose their value and eventually become rotten, a harvest loss of up to 50% in developing countries [6].

Therefore, agricultural product processing is an appropriate approach to develop products for food preservation, such as superheated steam drying [7] and stirring. However, superheated steam drying requires specific equipment to control the steam and proper pressure. Thus, the processed ripe mango by stirring then dry in the sun or bake is a solution for this situation with low-cost requirement. For example, processing ripe mangoes that have fallen from the trees into Mango Stir-Fry is probably the ideal way to generate income at a household level for seniors. Products that have passed agricultural product processing will help extend the product life and keep it for a long time. It also increases the value instead of selling directly as a fruit. It is also an indirect benefit in helping to reduce waste from discarded or rejected fruit [7], [8]. Mango Stir-Fry is a processed product made from ripe mango pulps that are crushed or finely blended and then dried in the sun or baked. Transforming ripe mangoes into Mango Stir-Fry generally consists of ten steps, as shown in Figure 1.

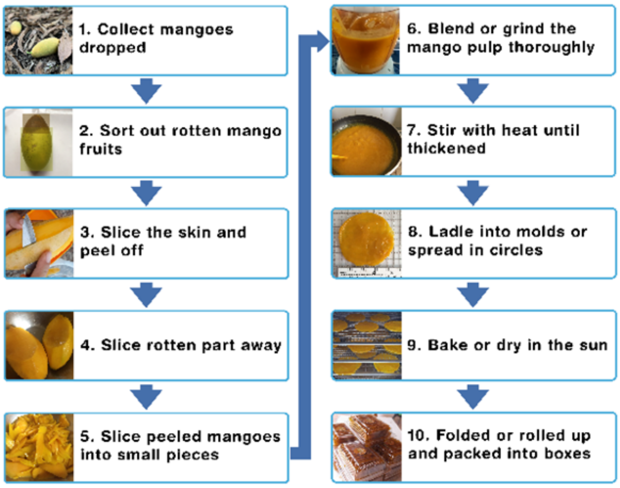

Figure 1. Mango Stir-Fry processing

The ripe mangoes without rotten parts are sorted out for sale directly. Except in cases where the fruit is too ripe or not sold in time, it may be processed into Mango Stir-Fry. The ripe, partially rotten fruit will be screened again to determine whether it can be used as raw material for processing or not. Consequently, the process of selecting which ripe mangoes can be processed or which ripened fruit has too much rotten that must be discarded is very important. Especially the cooks have to sort out the mango fruit with many rotten parts by using the naked eye to look at it and consider discarding the very rotten fruit. If there is too much spoilage, it may be part of the germs, such as fungi that affect the health of the person who eats it [9].

Most recent studies of rotten fruit classification or fruit freshness detection are based on neural networks or deep learning techniques [10], [11], [12], [13]. Convolutional Neural Network, Laplacian, Adaptive Gaussian Thresholding, and Hue Saturation Value color model were applied to classify the rotten fruit [14]. Machine learning and image processing were proposed to classify and grade apple fruit with an accuracy of 98.42% [15]. Although neural network techniques are widespread, most such techniques require many images to be machine-learned and can take a long time to process. Besides, very few studies have been found to quantify the area of fruit spoilage.

Nowadays, there are a variety of technologies that have come to help in everyday life, such as smartphones that most people have and carry with them like part of the body. It also supports installing mobile applications developed or programmed on fruit sorting machines to work as intended. Moreover, a built-in smartphone camera, combined with image processing technology, can assist fruit analysis and rotten fruit classification. It is suitable for cooks who have poor eyesight or have visual problems such as bleary-eyed. However, in the image processing of rotten parts and good parts by image color proportions directly, there may be some discrepancy because black or brown color on some peels does not represent the spoiled portion of the fruit, such as freckles or spots. These do not affect the pulp of the ripe mango under the peel. Therefore, this research aims to develop an image processing method to approximate the partially rotten of ripe mangoes and help classify which fruits can process Mango Stir-Fry.

2. Methodology

Partially rotten mango fruits are classified as to whether they can still be used as raw materials for food processing. This work applied the color pixel approximation image processing-based to classify rotten fruits. There are five main processes for improving the partially rotten fruit approximation, as shown in Figure 2.

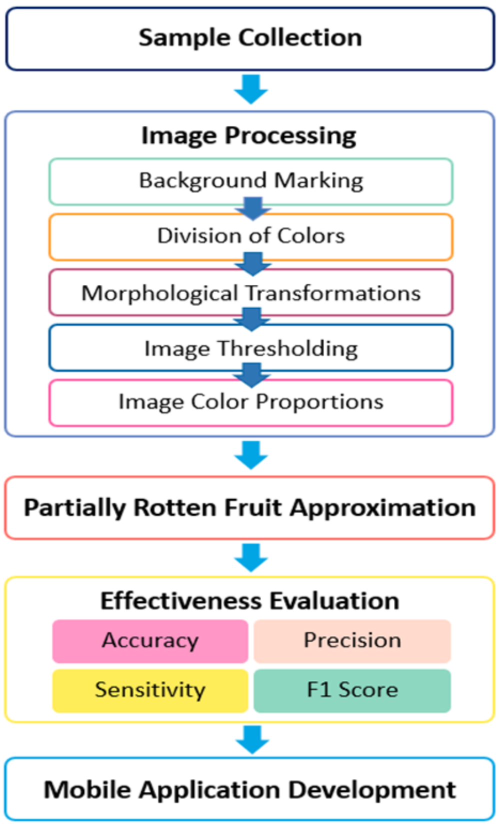

Figure 2. The research methodology framework

Sample Collection

In this process, the authors collected 320 ripe mangoes that fell then scattered on the ground under the mango trees. It has a total weight of 134.552 kg. Each ripe mango weighs between 300 g and 600 g. According to their health conditions, all ripe mangoes are divided into yellow healthy, yellow-brown healthy, and brown healthy. The mangoes with healthy yellow have 100% yellow skin. This group of mangoes is considered to be ripe mangoes of good quality. Therefore, all pulp can be processed into Mango Stir-Fry. For the yellow-brown healthy, these mangoes have the most yellow skin with few brown skins. This research found that the mangoes processed into Mango Stir-Fry have brown skin less than or equal to 35.5% of the total skin area. The brown healthy mango with a brown skin of more than 35.5% was judged unsuitable for further processing. This is because there may be some bacteria or spoilage that can affect human health. For the next process, all collected mangoes were photographed by smartphones to calculate the percentage of spoilage area. In addition, the yellow-brown healthy and brown healthy mangoes were peeled and cut to confirm the amount of spoilage in each fruit then labelled it. The number of mangoes is divided into three groups, as shown in Table 1.

Table 1. The number of mangoes grouped by the health of mango peel or skin color

Mango health	**Percentage of the brown color of mango peel**	**Number of mangoes**	**It can be processed into Mango Stir-Fry**
Yellow healthy	0%	80	Yes
Yellow-Brown healthy	≤ 35.5%	130	Yes (only the yellow part)
Brown healthy	> 35.5%	110	No

Image Processing

In the process, the images of each mango fruit taken were then subjected to image processing to analyze and calculate the rotten area of each fruit. The image processing includes background marking, division of colors, morphological transformations, image thresholding, and image color proportions, as illustrated in Figure 3.

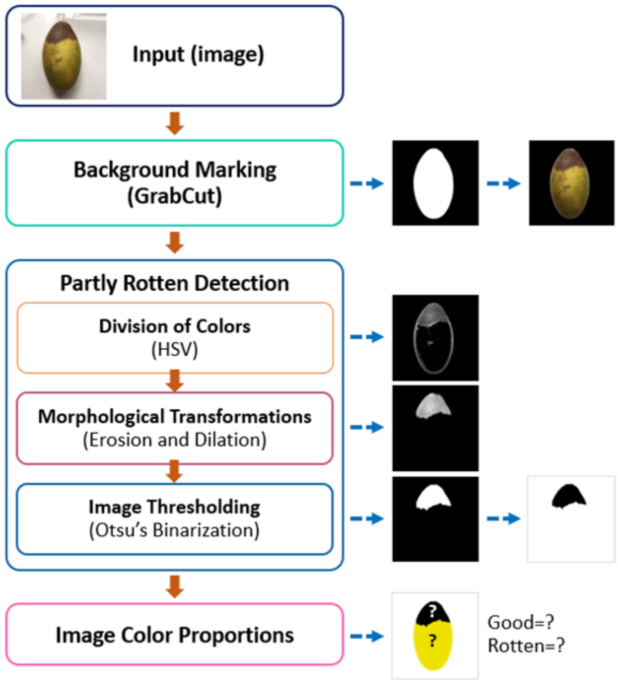

Figure 3. Image processing for a mango skin analysis to calculate the rotten ratio

Partly Rotten Detection

Each mango image taken with smartphones has background information around the mango. Thereby, it is necessary to remove the background information (background marking) from the image to leave only the mango in the image. GrabCut technique is applied to compute the edges of the mango fruit image [16], making it possible to define the background marking area more clearly by using Gaussian Mixture Model (GMM), which is the calculated probability in equation (1) [17].

$$p(x|\theta) = \sum_{i=1}^{N} \alpha_i g(x|\theta_i) \qquad (1)$$

Where N refers to the number of components in GMM, x refers to the multidimensional input sample, α_i refers to the coefficient mixing probability of the i-th component ($0 \leq \alpha_i \leq 1$and $\sum_{i=1}^{N} \alpha_i$ is 1), $g(x|\theta_i)$ refers to the Gaussian distribution density and covariance matrix of the i-th component, θ_i refers to the mean value of each component.

Division of Colors

After getting the images with only mango, these images were analyzed to find brown or black spoilage areas. An appropriate method of categorizing the skin color of ripe mangoes can be to use a yellow color representing areas where the pulp under the peel is thought to be of good quality that can be processed to Mango Stir-Fry. According to the Hue-Saturation-Value (HSV) color model, the yellow color range is around 60 degrees for the hue parameter. This process helps remove the mango skin's yellow ripeness from the image. However, this image leaves a brown or black area expected to be rotten.

Morphological Transformations

Some mangoes may have an uneven skin tone. For example, there are small brown spots as texture scattered all over the fruit skin, which is not the rotten part. Thus, the erosion technique was used to remove these tiny spots or pigments from the mango fruit on the image defined as equation (2) [18]. Then a dilation technique is used to compensate for pixels lost in the erosion process, defined as equation (3) [18].

$$I_e = \min\{I(x+a, y+b) - S(a,b)\} \qquad (2)$$

$$I_d = \max\{I(x-a, y-b) + S(a,b)\} \qquad (3)$$

Where $I(x, y)$ refers to the binary image in grey-scale at coordinate (x, y) and $S(a, b)$ refers to the structuring element with coordinate (a, b).

This work applied the kernel 3x3 pixels to both erosion and dilation. The erosion and dilation were processed alternately for fifteen cycles. Furthermore, in the end, extend the dilation process two times to help compensate for the number of rapidly changing pixels. Hence, only the areas that were thought to be rotten have appeared on the image.

Image Thresholding

The dilation process results in the expansion of color groups or clumping together on the image. Thereby, Otsu's binarization technique is used to convert similar color spaces to the same color based on the image histogram. Otsu's binarization algorithm finds the global thresholding, which minimized the weighted sum of within class variance as equation (4) [19].

$$\sigma_w^2(t) = w_1(t)\sigma_1^2(t) + w_2(t)\sigma_2^2(t) \qquad (4)$$

Where t refers to the thresholding value, $w_1(t)$ and $w_2(t)$ refer to the weights that are probabilities of two classes at threshold t and $\sigma_1^2(t)$ and $\sigma_2^2(t)$ refer to the variances of two classes.

All color spaces were conversed between white and black in this work. First, focus on turning the rotten area into white within a black background color. After that, it was inverting the color of the image results in the rotten area becoming all black pixels while the background becomes white color.

Image Color Proportions

The image resulting from the background marking process is inverted between white and black, causing the mango area to be black. After that, it turns yellow, which is like a ripe mango. When the image of the yellow mango was combined with the rotten portion obtained in the image thresholding stage, the whole mango showed the good and the rotten areas clearly. Therefore, this image can calculate the number of rotten and good area pixels. The image shows only two colors units, making it easy to count the number of pixels, as equation (5) and equation (6).

$$P_r = \sum_{x=0}^{w-1}\sum_{y=0}^{h-1} 1_{p(x,y)\ is\ black} \qquad (5)$$

$$P_g = \sum_{x=0}^{w-1}\sum_{y=0}^{h-1} 1_{p(x,y)\ is\ yellow} \qquad (6)$$

Where P_r refers to the number of pixels of the rotten area on the image, P_g refers to the number of pixels of the good area on the image, w refers to the image width (pixels), h refers to the image height (pixels) and $p(x, y)$ refers to the coordinate of a pixel on a plane x and y.

Partially Rotten Fruit Approximation

From the data collection and then dissection to check the rotten area of the mango fruit, it was found that the rotten areas expanded more than the brown color appearing on the mango skin. Most mango pulps were rotten beyond the rind in the 1.5%-29.9% range of brown skin. Thus, an additional 30% of the number of pixels counted in the image color proportions step is calculated to estimate the rotten area closer to reality. Consequently, the percentage of rotten for the whole mango fruit was approximated in equation (7).

$$\%Rotten = \frac{P_r + 0.3P_r}{P_r + P_g} \times 100\% \qquad (7)$$

Furthermore, looking for rotten parts around the mango fruit can be done by photographing other aspects of the mango fruit, such as the left side, right side, and back, combined with the front view as four sides. Suppose, let n be the number of images for a mango. Then, the percentage of rotten was approximated in equation (8).

$$\%Rotten = \frac{\sum_{i=1}^{n}\left(P_{r_i} + 0.3P_{r_i}\right)}{\sum_{i=1}^{n}\left(P_{r_i} + P_{g_i}\right)} \times 100\% \qquad (8)$$

Finally, suppose the percentage of the rotten area of mango is more significant than 35.5% (the default accepted rate by the cooks). In that case, this mango is considered unsuitable for processing into Mango Stir-Fry.

Effectiveness Evaluation

The effectiveness evaluation of the partially rotten fruit approximation is based on accuracy, precision, sensitivity, and F1 score (F-measure). Therefore, the authors actually measured the values obtained from each mango and compared them to values obtained by the partially rotten fruit approximation proposed in this work. The accuracy, precision, sensitivity, and F1 score were calculated in equation (9), equation (10), equation (11) [20], and equation (12) [21], respectively.

$$Accuracy = \frac{TP+TN}{TP+FP+TN+FN} \tag{9}$$

$$Precision = \frac{TP}{TP+FP} \tag{10}$$

$$Sensitivity = \frac{TP}{TP+FN} \tag{11}$$

$$F1\ score = \frac{2 \times Precision \times Recall}{Precision+Recall} \tag{12}$$

Where TP denotes the outcome where the approximation is correct in the positive class, TN denotes the outcome where the approximation is correct in the negative class, FP denotes the outcome where the approximation is incorrect in the positive class and FN denotes the outcome where the approximation is incorrect in the negative class.

Mobile Application Development

The authors evaluated the efficiency of the partially rotten fruit approximation then developed a mobile application running on the Android platform. This application is developed with Android Studio version 2020.3.1, based on Java language programming on Windows 64bit operating system. The mobile application features consist of taking pictures of fruits, partially rotten fruit approximation, calculating the weight of mango pulp, and calculating the weight of Mango Stir-Fry as the final result from each mango. An example screen of the application is shown in Figure 4.

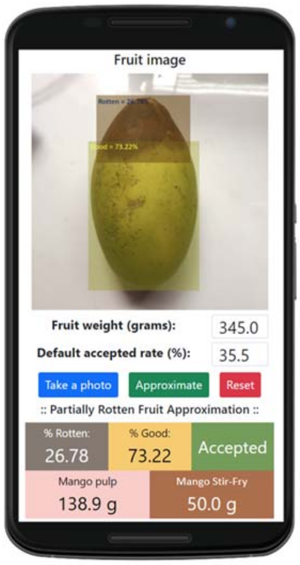

Figure 4. An example screen of the developed mobile application

Mangoes that have been assessed partially for rotten parts (if any) will be used to calculate the actual mango pulp content and the amount of yield obtained as Mango Stir-Fry, which is the final product. Mango fruit consists of the peel, pulp, and seed or kernel. Only the mango pulp contains between 50% and 60% of the mango weight, depending on mango varieties [4]. This work applied the average value of 55% of total mango weight (W_{total}) to calculate the remains of mango pulp weight (W_{pulp}). Thus, the mango pulp was estimated in equation (13).

$$W_{pulp} = 0.55W_{total} \tag{13}$$

Moreover, the mango pulp contains water between 75% and 85% [4]. Accordingly, 80% of the mango pulp is average water (w_{avg}) used to calculate the final product's weight. However, water content should be 5% of the total water content in the Mango Stir-Fry production process. This remaining water helps the product to be soft and easy to eat. Eventually, when processed, 95% of the water content of the mango pulp will be eliminated or removed (w_{rm}) Finally, the resulting weight of the Mango Stir-Fry (W_{final}) can be calculated in equation (14).

$$W_{final} = (1-(w_{avg} \times w_{rm}))W_{pulp} \tag{14}$$

3. Results

The Result of Effectiveness Evaluation

The proposed method of partially rotten fruit approximation was evaluated the effectiveness, including accuracy (Acc), precision (Prec), sensitivity (Sens), and F1 score. The result of effectiveness evaluation was showed in Table 2.

Table 2. The result of effectiveness evaluation of the partially rotten mango fruit approximation

Mango health	Acc (%)	Prec (%)	Sens (%)	F1 score
Yellow healthy	100.00	100.00	100.00	100.00
Yellow-Brown healthy	98.46	100.00	98.46	99.22
Brown healthy	99.09	99.09	100.00	99.54
Overall	99.06	99.69	99.37	99.53

According to Table 2., this research proposed that all yellow health mangoes can be correctly identified with all four efficiency values of 100.00%. However, while the yellow-brown health mangoes were identified as the rotten fruit with an accuracy of 98.46%, the precision was 100.00%, sensitivity was 98.46%, and the F1 score was 99.22%. For the rotten fruit, the brown health mangoes had an accuracy of 99.09% of classification, where precision was 99.09%, sensitivity was 100.00%, and F1 score was 99.54%. Overall, the partially rotten fruit approximation was able to classify ripe mangoes between good and bad fruit, which has rotten parts more than 35.5% (default accepted rate), with an accuracy of 99.06%, the precision of 99.69%, the sensitivity of 99.37%, and the F1 score of 99.53%. These evaluated effectiveness values can be compared as shown in Figure 5.

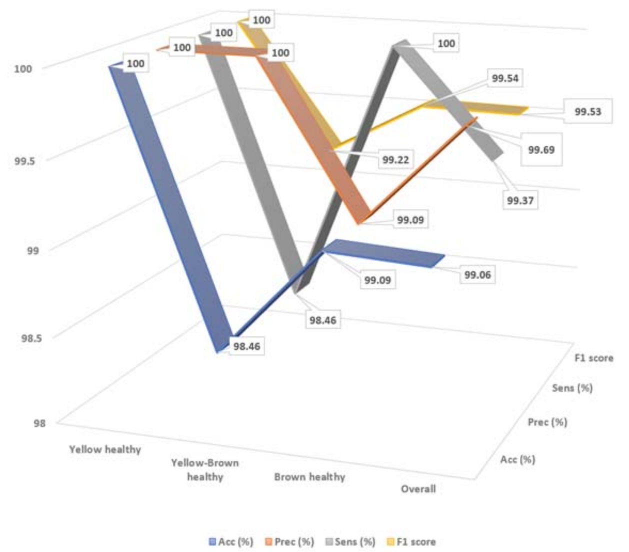

Figure 5. The result of effectiveness evaluation of the partially rotten mango fruit approximation

The Mango Stir-Fry approximation

According to Table 1., the 210 mangoes with a total weight of 88.059 kg are used to process the Mango Stir-Fry. After the peel, seeds, and rotten parts are removed, a good portion of mango pulp is left with a weight of 45.238 kg. Ultimately, when heated and dried or baked, it leaves a net weight of 10.993 kg, which is Mango Stir-Fry ready for eating or packing for further distribution. The partially rotten fruit approximation estimated the weight of mango pulp and the final product. The result will be as shown in Figure 6.

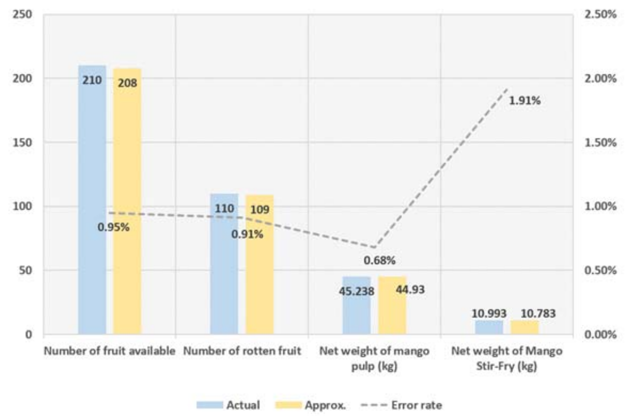

Figure 6. The result of the actual product compared with the approximation product

According to Figure 6., the actual number of fruit available for processing to Mango Stir-Fry is 210 fruits. However, in the partially rotten fruit approximation results, it was found that only 208 fruits were classified and could be processed. Therefore, the error was 0.95% for classifying the available mangoes. While the processing to classify rotten mangoes was not applicable, there was an error of one fruit equivalent to an error rate of 0.91%. Considering the approximated net weight of mango pulp, the error rate was 0.68%, while the error of the net weight of the Mango Stir-Fry was 1.91%.

When surveying the tolerances, it was found that mangoes with partial rotten, almost close to the accepted rate of 35.5%, were classified as unusable fruit. For this reason, when adding 30% of the number of pixels counted in the image color proportions step is calculated to estimate the rotten area closer to reality. Thus, the estimated percentage of the rotten area exceeds the accepted rate. In this case, the problem may be solved by adding a tool that can illuminate the surface under the mango peel, for example, using infrared light to assist in the photography to show the actual color of the mango pulp. A simple tool was used in this work, such as a smartphone that the cooks have and are already using. Unfortunately, the cameras in smartphones are few that can take pictures with infrared. However, in the case of large quantities of ripe mangoes, the cooks need a tool capable of conveyor belting continuous imaging of mangoes. Moreover, it can automatically sort out the rotten ones. This approach will increase the efficiency of the production process and provide better convenience for the cooks. Nevertheless, this requires investment in procuring tools with these capabilities as well.

4. Conclusion

Mangoes can be grown in many regions throughout Thailand and other Asian countries. Each mango tree can produce a large number of mangoes. However, ripe mangoes will not last long and hang on the tree. When it falls to the ground, it starts to spoil until it cannot be used or eaten in the end. Therefore, food preservation by making Mango Stir-Fry is a solution for elderly farmers, especially under the COVID-19 epidemic. Using smartphones to take pictures of mangoes to approximate partially rotten fruit could help improve the sorting process. The photographs of ripe mangoes were processed using techniques including Gaussian Mixture Model, HSV color model, dilation, erosion, Otsu's binarization thresholding, and image color proportions. These image processing techniques help separate each pixel of mango skin color between the rotten and the good parts of ripe mangoes. These techniques have been applied in conjunction with mobile applications for cooks and farmers. The developed mobile application can help classify ripe mangoes with a rotten ratio greater than 35.5% with an accuracy of 99.06%, a precision of 99.69%, a sensitivity of 99.37%, and an F1 score of 99.53%. In addition, the developed mobile application can approximate the amount of ripe mango pulp and Mango Stir-Fry from each fruit. In the approximation, there is a discrepancy of 1.91%. However, this feature allows the cooks to estimate the final product outcome, support the order quantity, or plan the next Mango Stir-Fry production.

The authors plan to develop an instrument or tool that supports much mango fruit for further work. This tool can combine with the internet of things, which is automatically processed to classify and sort out rotten fruit. Moreover, the author will develop the technique for photographing all around each fruit in a single shot and integrated with infrared. These may help identify the rotten area deep on fruit pulp to improve the percentage of partially rotten fruit approximation.

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