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Palm Oil Fruit Bruise Detection and Classification with Texture and Shape Features Using Multi-Class Support Vector Machine

[1]Nur Syahirah Addenan, [1]Nurbaity Sabri, [2]Norizan Mat Diah, [2]Zaidah Ibrahim
[1]Faculty of Computer and Mathematical Sciences,
Universiti Teknologi MARA Cawangan Melaka Kampus Jasin,
77300 Merlimau, Melaka, Malaysia.
[2]Faculty of Computer and Mathematical Sciences,
Universiti Teknologi MARA, 40450 Shah Alam, Selangor, Malaysia.
nurbaity_sabri@uitm.edu.my, norizan289@uitm.edu.my, zaida782@uitm.edu.my

ABSTRACT

Palm oil is one of the largest and significant contributions to the Malaysian economy. As such, makes it important to improve the quality of this product since defects on palm oil fruit may affect the palm oil production. Bruise is one of the defects on palm oil as it is unavoidable during the field material activities. This can increase the number of Free Fatty Acid (FFA) and reduces the palm oil quality produced. The present study proposes an application to identify the bruises on palm oil fruit using image processing approach. This is performed by combining four texture features extracted from Grey Level Co-occurrence Matrix that are contrast, correlation, energy and homogeneity and six shape features which are area, perimeter, major axis length, minor axis length, eccentricity and equidiameter to identify four different bruise stages that are major, minor, moderate and no bruise. The bruise classification is conducted using Multi-Class Support Vector Machine (SVM). The present research manages to achieve 80.38% classification accuracy based on the dataset employed.

Key words: Palm oil fruit bruises, Grey Level Co-occurrence Matrix, shape features, Support Vector Machine.

1. INTRODUCTION

Oil palm is one of the contributors to Malaysian economy because it is one of the profitable agricultural products produced. As such, a lot of researches have been done to increase and maintain the quality of the palm oil [1]. This can be determined based on the surface color. Malaysia Palm Oil Board (MPOB) has listed three stages of palm oil as unripe, ripe and overripe. Each stage has their specific colors that differentiate between one another. However, these three categories could be easily damaged and bruised [2]. There are two types of oil produced by palm oil fruit, which are palm oil and palm oil kernel. The palm oil is obtained from mesocorp covered of the palm oil kernel while the palm oil kernel is produced by nut or seed of palm oil fruit [3]. The bruise usually happened on the mesocorp layer as this layer produces a Free Fatty Acid (FFA).

A correlation between FFA and bruises has been done where the FFA increases when there are major bruises on the oil fruit, and it will affect the quality of palm oil [2]. The FFA is derived from the hydrolytic rancidity of triglycerides chemical. It is an acid content of edible fats, in which it affects the palm oil quality. The higher the quantity of FFA in palm oil fruit, the lower the quality of palm oil produces by the palm oil fruit [4]. More so, it is very important to learn about bruises and the cause of bruises on FFB fruit to increase quality of palm oil [5].

Currently, bruise detection is performed manually by the experts. However, it is time consuming and less accurate [6]. The bruise damage seems to be almost unavoidable during harvesting and it eventually decreases the fruit quality. Thus, there is a need to improve the quality of agricultural products. To achieve this objective, various image analysis techniques are needed due to the demand of the growing population [7] and one of it is to automatically classify the bruises.

The present study is organized as follows; the first section introduces the problem of palm oil bruises and its effect to the quality of the production of palm oil. The next section discusses the related work on bruise detection followed by the explanation of the proposed method. Section 4 discusses the experimental results and the last section concludes the outcome of the present study.

2. LITERATURE REVIEW

Presently, there are many researches on fruit bruises detection using computer vision, such as apple [5][6][7], citrus [8], and pear [9]. Previous studies have proposed Near Infrared (NIR) imaging technique to detect bruises on pears [10]. The research uses hyper spectral imaging (waveband) and implements the F-value algorithm for classification. It manages to achieve 92% accuracy on bruise detection. However, there is need for a high specification device which is InGaAS Focal Plane Array (FPA) camera to capture the images of the fruits in the study.

Multispectral imaging technique is implemented using score and image space as feature extraction to identify the defect on the surface of an apple by machine vision. Past studies have used a clustering technique to cluster the defected area. However, due to glossy surface of apples, it incorrectly detects the bruises on the images. Also, another research on apple has been carried out using K-Means Clustering [11]. This technique manages to improve the precision of the segmentation of the defected apple and its computational time, but bruise classification was not conducted. Furthermore, the research also proposes a combination of texture features with other features to improve the accuracy of the defect segmentation. Disease detection on tomato using the same method that is K-Means Clustering algorithm has also been proposed which successfully achieve 90% accuracy [12]. Due to its good performance, K-Means Clustering will also be applied in this research.

Thus, the present research will investigate the implementation of bruise detection on palm oil using image processing technique which is the hybrid of texture and shape features using K-Means Clustering with Support Vector Machine (SVM) classifier to classify four different stages of palm oil bruises.

3. MATERIALS AND METHODS

Image processing has been used in many areas of research, such as in food industry, medical processing, textiles, engineering and many more. There were five components of an image processing system, which are image acquisition, capacity or storage, processing which can be implemented in software, communication and the visual representation of the output. These elements are necessary to achieve the goal which is to produce a desired result by following the steps of image processing technique [8]. Therefore, the same approach will be used to detect palm oil bruises. Four stages of bruises will be focused in the present research. These are; no bruise, minor bruises, moderate bruises and major bruises.

Figure 1 illustrates the overall process starting with pre-processing operation involving the image acquisition and segmentation of the region of interest (ROI). This is followed by the features extraction to extract important features from the segmented palm oil bruises. It also shows the classification process classifying the extracted features into one of the four stages of bruises, namely major, minor, and moderate or no bruises.

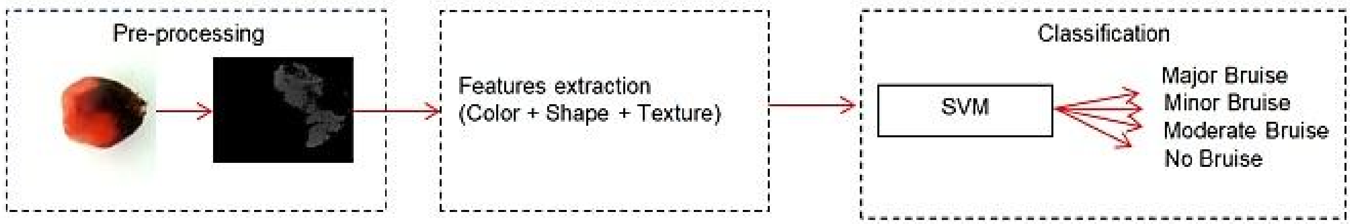

Figure 1: Flow of process for palm oil bruise detection and classification

3.1 Image acquisition

The present research uses 120 images of the four stages of palm oil bruises with 30 images from each stage, captured from various angles. Images used are collected from Sime Darby palm oil mills at Jasin, Melaka with the help of palm oil fruit expert using a mobile phone. For the system development, Matlab software was used due to its capability for image analysis and machine learning operation, such as SVM.

3.2 Image Segmentation

In this stage, different stages of palm oil surface are clustered according to their colors. To achieve this objective, K-means Clustering was implemented due to its fast and straightforward algorithm [5]. K-means technique is known as un-supervised clustering technique. It partitioned the data points into k clusters randomly. Generally, the goal is to assign a cluster to each data point. Afterwards, the center points of a cluster called as centroids were chosen. For each data point, the distance is calculated (using Euclidean distance measure) and assigned a data point to the closest cluster, where k is the number of cluster. For example if $i = 1, 2, 3 \ldots n$, then k is the mean point or centroid of all the points. The step of K-means clustering starts with the center of k cluster initialization. It works as initial centroids of clustering. Then, the data points are assigned according to the closest cluster. The new centroid is computed for each cluster. This process will continue until all the colors are clustered.

The bruise region was converted to gray scale image for further feature extraction process.

3.3. Features Extraction

Features are the representation of image and this characteristic will be used for further classification process. This research proposed two (2) features for features extraction. These are shape and texture.

A. Shape Features

The present research uses shape features to extract the boundary and region descriptor of the bruise region. Boundary used an external method to extract the boundary of palm oil bruise. While, region descriptor extracts the pixel of internal palm oil bruise region. [13] proposed six shape metrics, which are area, perimeter, major axis length, minor axis length, eccentricity and equidiameter to extract the features of date fruits. Therefore, the same approach is applied in the present research to focus on the segmented bruise region.

Area (A)

Area (A) calculates the area of segmented pixel of palm oil bruise. Equation (1) shows the sum of *b (i,j)* represented by pixel in i row and j column. The *M, N* represents the row and column of the image.

$$Area = \sum_{i,j=0}^{M,N} b(i,j) \tag{1}$$

Perimeter (P)

The pixel boundary of palm oil bruise is calculated by the accumulated distance between each adjoining pair of pixels. In equation (2), the *Ed (i,j)* is the boundary pixels of the region.

$$Perimeter = \sum_{i,j=0}^{M,N} E_d(i,j) \tag{2}$$

Major-axis Length

Major-axis length is the length of the major axis of the region of interest. It holds the maximum diameter of the palm oil bruise region. Equation (3) shows the max value of diameter where *Pi, Pj* represent the points on the boundary of D distance.

$$max = \max_{i,j}[D(p_i p_j)] \tag{3}$$

Minor-axis Length

Minor-axis length represents the length of the minor axis of the palm oil bruise region. It holds the minimum diameter value of the region as shown in (4).

$$min = \min_{i,j}[D(p_i p_j)] \tag{4}$$

Eccentricity (E)

Eccentricity (E) measures the aspect ratio of the distance between the lengths of major axis to the length of minor axis.

Equidiameter

Equidiameter represents the diameter of the region of interest. It is the numbers of the same circle diameter in the area region. Equation (5) shows the formula for equidiameter.

$$ED = \sqrt{(4 * A/\pi)}, \tag{5}$$

B. Texture Features

Gray-level co-occurrence matrix (GLCM) is proposed as the texture features for this research. It is important to describe the physical composition of the bruise surface. From the image provided, the image of palm oil with bruises has a fiber texture with a clean and shiny surface for non-bruised image. The segmented image of palm oil bruises is then converted to grayscale and GLCM is extracted. Then, four features which are contrast, correlation, energy and homogeneity are computed from the extracted GLCM [14]. The algorithm to compute the four features is explained next.

Contrast

It represents the intensity contrast between pixel and its neighbor of the segmented bruise. Equation (6) shows the value of contrast where *Pi,j* is the co-occurrence matrix and N is the size of the matrix.

$$Contrast = \sum_{i,j=0}^{N-1} P_{i,j}(i-j)^2 \tag{6}$$

Correlation

Correlation is the measurement of the correlated pixesl with the neighbor of the entire segmented image. The formula of the correlation can be computed as in equation (7).

$$Correlation = \sum_{i,j=0}^{N-1} P_{i,j}\left[\frac{(i-\mu_i)(j-\mu_j)}{\sqrt{(\sigma_i^2)(\sigma_j^2)}}\right] \tag{7}$$

Energy

Energy is the angular second moment method that measures the textural uniformity of the palm oil bruise. It works by extracting the highest value either constant or periodic form of gray-level distribution found in the bruise image. Equation (8) shows the equation to compute the energy.

$$Energy = \sum_{i,j=0}^{N-1} P_{i,j}^2 \tag{8}$$

Homogeneity

The number of features produced by homogeneity depends on the P matrix, where P matrix is the few dominant gray tone transitions as in (9).

$$Homogeneity = \sum_{i,j=0}^{N-1} \frac{P_{i,j}}{1+(i-j)^2} \tag{9}$$

Multi-Class SVM used in the present research to classify features extracted into four classes (minor, major, moderate and no-bruise). It works by differentiating the classes using hyperplane [15][16]. This hyperplane splits features into maximum distance. The kernel of the SVM will split this data into higher dimensional space.

4. RESULTS AND DISCUSSION

The result for palm oil bruise detection using image processing technique will be discussed as the accuracy for the developed system recorded. The features are collected from 120 images divided into testing and training data which are 80% and 20% respectively. Table 1 shows the labeling of the dataset for training and testing.

Table 1: Labeling of the dataset

Type of Bruise	Label
Major bruise	C1
Minor bruise	C2
Moderate bruise	C3
No bruise	C4

The present research used linear kernel due to its fast performance during training and classification of the dataset. Performance of linear kernel is excellent compared to other kernel functions such as polynomial and RBF where it is able to achieve 100% maximum of accuracy. Equation (10) shows the equation for linear kernel function [17].

$$K(i_N, j_M) = i_N . j_M \tag{10}$$

The performance of the system is evaluated using confusion matrix. A Confusion matrix consists of components which are true positive (TP), true negative (TN), false positive (FP) and false negative (FN). Table 2 shows the confusion matrix for 4-class scenario representing the four stages of palm oil bruise. The actual class is the labeled dataset as mentioned in the previous table while the predicted class represents the result predicted by the classifier.

As shown in the Table 2, C1C1 represents a result correctly predicted as major bruise. Meanwhile, C1C2, shows the major bruise wrongly predicted as minor bruise. This process continued for moderate and no bruise label dataset. From the result, the accuracy can be obtained using the formula as shown in equation (11) [16][18].

Table 2: Confusion Matrix for 4-Class major bruise, minor bruise, moderate bruise and no bruise.

		Predicted Class			
		C1	C2	C3	C4
Actual Class	C1	C1C1	C1C2	C1C3	C1C4
	C2	C2C1	C2C2	C2C3	C2C4
	C3	C3C1	C3C2	C3C3	C3C4
	C4	C4C1	C4C2	C4C3	C4C4

$$Accuracy = \frac{TP+TN}{TP+TN+FP+FN} \times 100 \tag{11}$$

The presented method was applied to the dataset with 120 images that consists of three stages of bruises which are major, minor, moderate and no bruises. The method was implemented in MATLAB software and shows that the developed system is able to detect and classify the different stages of bruises on palm oil fruit image. Figures 2 and 3 shows some sample interface as a result of the proposed method with major, minor, and moderate bruises, respectively. Results have shown that proposed method can successfully detect and classify the palm oil fruit bruises when the pre-processing operations, K-Means Clustering and multi-class SVM was applied to an input image.

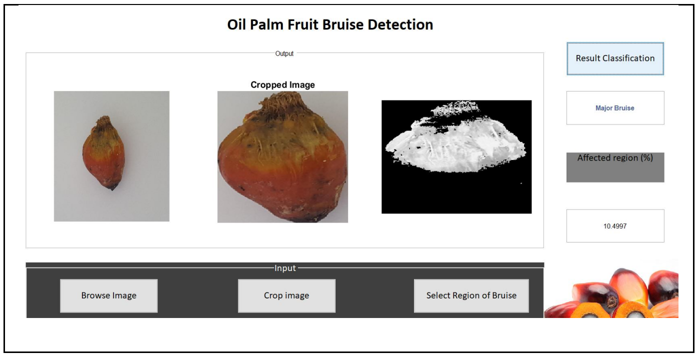

Figure 2: Sample interface of the system that shows the result for major bruises.

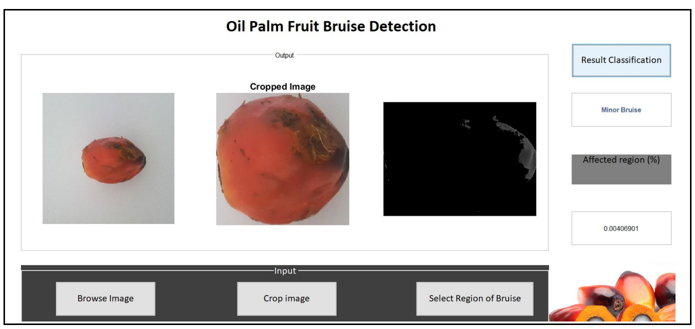

Figure 3: Sample interface of the system with a result for minor bruises.

4. CONCLUSION

The development of palm oil fruit bruise detection and classification executed in the present research and accuracy has been recorded accordingly. Four stages of palm oil bruise have been detected and classified with a satisfactorily result of an accuracy of 80.38%. The accuracy can be improved with a larger dataset. Additionally, the acquired image of palm oil fruit may contain noises from glossy and silhouette due to environment lighting during image acquisition which can also affect the accuracy. A combination of six shape features and four texture features with multi-Class SVM produce good result for bruise detection and classification. Therefore, these experimental results have shown that using an image processing technique, it was able to detect and classify palm oil bruise without using material or weight approach. More samples of palm oil fruit bruises are recommended for future study to improve the accuracy. Moreover, a mobile based application is suggested for future enhancement.

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