Towards Palm Bunch Ripeness Classification Using Colour and Canny Edge Detection

Ian K. T. Tan, Yue-Hng Lim, and Nyen-Ho Hon

Abstract The ripeness of the farm-able palm fruits is an important factor in the production of quality palm oil. The work presented is an image processing implementation in the palm oil industry to eliminate human errors in the judgment of the ripeness of palm fruit bunches as well as to introduce automation. Various techniques were employed to obtain data from the images provided for the data mining process. The features used are the colour of the palm fruit bunches and the amount of edges representing visible leaves in the palm fruit bunches, indicating empty sockets. The project is able to achieve an accuracy of up to 79.11%.

Keywords Ripeness · Palm kernel · Colour detection · Canny edge · Empty sockets

1 Introduction

The determining factor of palm oil production starts with the classification of the palm fruit bunch ripeness. This classification process is typically done manually and is prone to human errors, availability of human experts, and inconsistencies in the classification process due to various environmental aspects such as lighting. This manual process depends on visual cues; such as colour, texture, and the shape of the oil palm fruit bunch. Furthermore, the speed of this classification is an important factor for consideration. The palm fruit bunches are delivered in batches (truckloads) which arrives at irregular intervals. The pressure to classify them quickly increases

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the amount of human errors. Hence the use of technology is needed to address these drawbacks.

Technology that assist in moving towards automation of this classification process is an important area as the yield and quality of the palm oil production is highly dependent on the ripeness of the palm fruit bunches.

2 Literature Review

Image processing for farming had been researched and implemented for actual use to increase yield as well as to introduce automation for error reduction. One of the earlier published work in this area was by Meyer et al. [1] in 1998. Their work was to automatically differentiate weeds from corn crops in order to implement an anti-weed strategy using computer vision and statistical analysis. Features such as texture and excess of the plant's green colour were used in their work.

In recent years, image processing to determine ripeness has also been attempted. Abbaszadeh et al. [2] used image processing on the rind texture of watermelons to determine their ripeness. The pattern on the rind is processed to determine the stretch of the wavy patterns which in turn provides the cue on the ripeness of the watermelon. In their work, they also used colour analysis to grade the ripeness appropriately.

In the specific area of palm fruit ripeness, Choong et al. [3] published that the oil content of palm fruits is highly correlated to the redness of the palm oil fruits. They used a controlled environment where the height of the camera to the fruit is always at the same exact height (which means that the camera has to move to compensate for the fruit size) and lighting is illuminated from all angles in order to capture the images. The images were then individually manually edited for consistency using image processing application.

Ghazali et al. [4] used the RGB (Red, Green and Blue) colour components as the features for their work. In their work, they processed the images captured by eliminating the non-red colours and used the resulting images to classify them into three categories; ripe, under-ripe and unripe. Their work was limited by the carefully curated 30 sample images for each of the classification categories. Their work claimed to have an accuracy of 100% of the ripe category, and between 80-85% for the under-ripe and unripe categories.

A more recent work by Shabdin et al. [5], conducted a similar research to use the colour components to determine the ripeness of the palm fruit bunches but they included the use of the hue saturation and the colour intensity as the main feature. For their analysis, they used Artificial Neural Networks (ANN) and they reported an overall accuracy of 70%.

Using similar techniques as Shabdin et al. [5], Saaed et al. [6] also conducted their classification using ANN but with specialized hyperspectral active sensor system. The equipment used has 824 spectral bands which covers the colour frequency range of 400 to 1000 nm. This range of orange and red are in the region of 590–625 and

625–740 nm respectively and hence the sensor they used is of a very high accuracy and can be configured to capture the colour ranges accurately.

Although Ghazali et al. [4] claimed an accuracy of 100% for ripe palm fruit bunches and a very good 80-85% accuracy for the other two categories, the images were carefully curated and does not represent the actual plantation environment. Even with additional features included by Shabdin et al. [5], the overall accuracy is about 70%.

3 Data

The image collection by past researchers tend to veer towards the highest quality images possible with minimal noise. Sophisticated capturing devices, such as Hyperspectral Sensor [6], Microsoft Lifecam NX-600 [7] and Vivotek IP8332 Network Bullet Cameras [8] were used in a highly controlled lighting environment in order to minimize noise, lighting differences and varying backgrounds. Past work with high accuracy rates were likely to have used images captured in a highly controlled environment to ensure high accuracy of classification.

In the work presented in this manuscript, the images used were captured by a camera phone at an actual palm fruit bunch sorting area and not in a laboratory. The use of a camera phone is to simulate the use of low-cost camera modules that is planned for the overall automation system.

This work also attempts to simulate image captured on a purpose-built sorting conveyor belt, where the moving belt is white in colour to assist in the contrast needed for the image capturing. Hence the images captured for this project have a white (but generally dirty or slightly off white) background.

3.1 Dataset

There were initially more than 900 images in JPEG format provided by Melangking Oil Palm Plantation. Since the images were captured by the worker who manually classified the palm fruit bunches, many of the images were discarded due to the images being unusable. The images were discarded due to various reasons such as partial fruit bunch captured or the background was too noisy (littered with loose fruits or leaves). In the planned automated system, the fruit bunches will be on the conveyor belt and there will not have partial image capture as the camera will capture the whole conveyor belt area and there will be minimal loose fruits (fruitlets) as it is planned that the conveyor belt will have a mechanism to flush out the fruitlets. The final dataset[1] used consists of 514 images classified into 6 classes:

[1]Dataset is available at https://www.teradatauniversitynetwork.com/Library/Items/Datasets-from-Melangking-Palm-Oil-Corporation.

- Empty Bunches (57 images)
- Ripe Bunches (190 images)
- Dirty Ripe Bunches (80 images)
- Rotten Bunches (62 images)
- Under Ripe Bunches (53 images)
- Unripe Bunches (72 images).

Although the images were classified by experienced sorting workers, some human errors were expected. The classifications were then validated by the palm fruit bunch sorting supervisor to ensure correctness. Since the image capturing was not controlled, preliminary processing will be required as the background would be dirty and there will be lighting differences due the fact that the images were captured at varying times of the day.

4 Methodology

The project employs the following process (Fig. 1).

1. Data pre-processing
2. Feature extraction
3. Modeling.

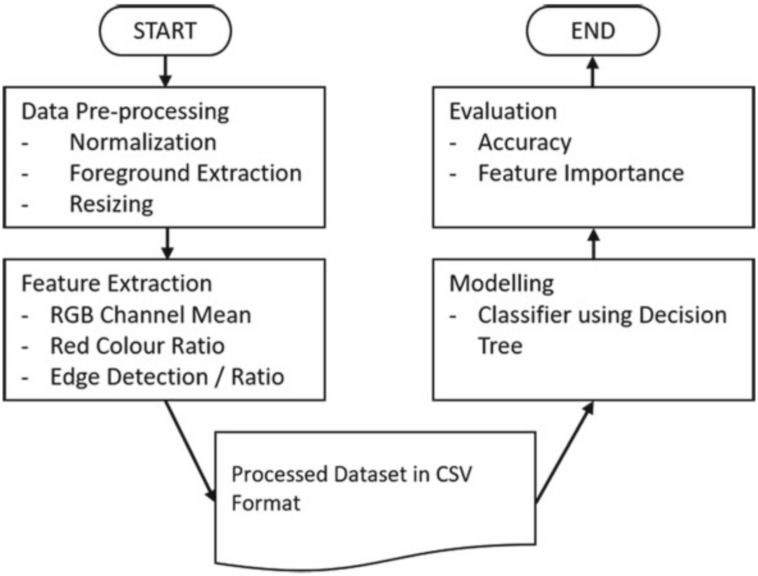

Fig. 1 Methodology

4.1 Data Pre-processing

The data pre-processing consists of normalization and foreground extraction.

Normalization. Due to the varying lighting conditions for each of the images captured, a normalization process is required. The uncontrolled environment caused varying saturation of the images. The Hue Saturation Intensity (HSI) values of the images were used for the normalization. This is based on the centre pixel intensity values and the resulting image will have reduced glare to enable a fairer comparison of the images.

Foreground Extraction. The next process is to remove the background of the images. The backgrounds of the images are not useful in determining the classification process. The images were captured in an actual production environment and hence the white background used is smeared with dirt and some may even have loose fruits.

The technique used to remove the background is the GrabCut foreground extraction method developed by Rother, Kolmogorov, and Blake [9]. GrabCut, available in the OpenCV library (https://opencv.org/), is a segmentation algorithm that utilizes edges and region detection in order to extract the foreground wanted. GrabCut also uses a system where a user may mark a certain region as foreground or background. This can be done using by either manually marking the image using a mask, or setting a rectangle in order to capture the foreground region. The latter was chosen as the method was more dynamic and suitable for the large number of images needed to be processed.

Figure 2 shows the result of the palm fruit bunch extracted from the background. The unsupervised GrabCut method is able to pre-process about 90% of the images

Fig. 2 Example image with background removed

successfully. For the images that were not processed correctly, some pre-processing to define the rectangle for the GrabCut process were done. The images were then resized automatically to 900 pixels wide. This is in order for the modeling to execute within a reasonable time frame.

4.2 Feature Extraction

There are five features that are used, namely the mean of each of the Red, Green and Blue colour channels, the ratio of the red colour in the image and the amount of edges detected.

The images were initially converted to HSV (Hue, Saturation, Value). This is to simplify the manipulation and to enable the usage of a mask. A mask is then created for each image to utilize a threshold to remove pixels. The threshold ranges of Hue values used for the colour of red is 0-10 for the lower range and is set to 180 for the upper range.

RGB Colour Mean. The most reliable feature indicating the ripeness of a palm fruit bunch is the amount of the colour "light red". The other colours would be influential in determining the other classifications (other than ripe) and hence the work processed the means of each of the colour channels. A mask was applied to the image to ensure that the result of the mean function would be an accurate average of each colour channel while excluding the black pixels (the mask) of the background.

Red Colour Ratio. In order to determine the ripeness, the ratio of the amount of red in the image was determined. The approach used here is to find the ratio of the red pixels in the image and divide it with the total number of pixels of fruit bunch (the foreground that was extracted). This ratio will then be used as a feature for the classification model.

Figure 3 depicts the normalized image where the red pixels are to be extracted from, whilst Fig. 4 depicts the image after applying the threshold values to extract the red pixels. From visual checks, the process was able to successfully extract the palm fruit kernels. Figure 4 is illustrated to also show that even for un-ripe palm fruit bunches that consists of dark kernels, the thresholds applied was sufficient to differentiate the un-ripe fruit kernels. The thresholds are not only for the colour red but also for the cut-off value for the lower end intensity.

Edges (Spikiness). The spikiness feature that is being considered in this work is defined as the magnitude of the edges belonging to the palm fruit bunches. This feature was considered due to there being a visually observable difference in roughness of the silhouette of an empty jagged palm fruit bunch and a ripe palm fruit bunch. Thus, canny edge [10] detection algorithm in the OpenCV library [11] was applied to the images (Fig. 5).

To determine the spikiness, the work counted the number of pixels that are considered as edges. The rationale is that the longer the length of the spikes, there will be

Fig. 3 Normalized image prior to extracting red pixels

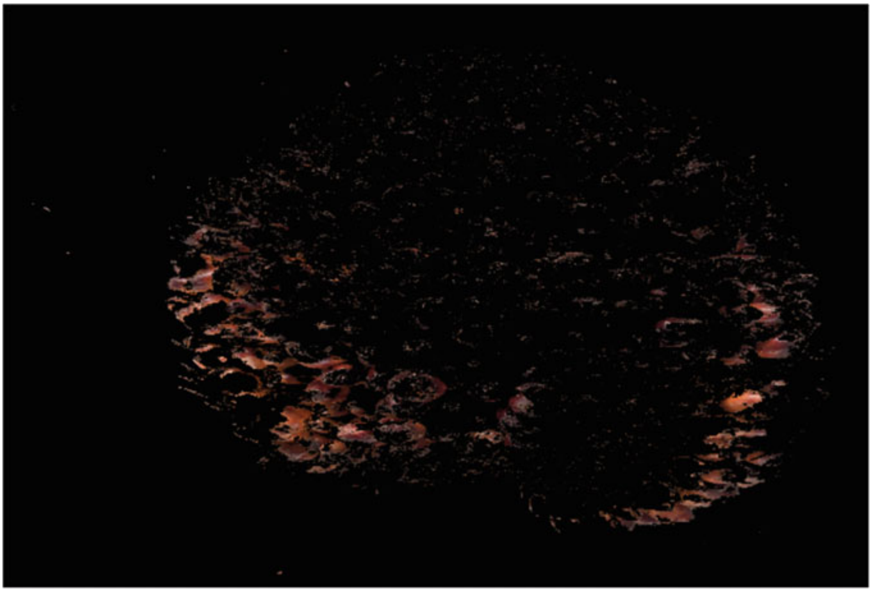

Fig. 4 Extracted red pixels from normalized image

Fig. 5 Edge detection of a palm fruit bunch

more pixels used to denote the edges. The number of pixels counted is divided by the total number of pixels in the fruit to obtain the ratio.

4.3 Modeling

After refining the data acquisition methods, the acquired data was stored in a comma-separated values (CSV) file. The data in the CSV files were then normalized to be in the range of 0-1 based on the minimum and maximum value of each attribute (Min-Max Normalization). Instead of using 6 different classes, the images were evaluated based on ripe and unripe as well as ripe, under-ripe and unripe.

For this work, we decided on the Decision Tree (DT) method as the processed dataset is not large and the DT method reflects how a manual plantation worker decision is made, that is from the colour visualized and the spikiness of the palm fruit bunch.

The data was then split into training and test sets where 70% of the data is allocated for the training set and 30% of the data for the test set.

5 Evaluation: Results and Discussion

The experiment was conducted 15 times without the setting of the random seed. Results produced by the data modeling of the processed CSV file gave an average accuracy score of 71.11% (Table 1). The accuracy score was computed from the sum of the correctly classified samples over the total sample population.

A noteworthy observation is that the classifications of ripe, under-ripe, and unripe resulted in a lower average accuracy score compared to the performance of binary classification of ripe and unripe. It stands to reason that it would be lower, as it gets more demanding on the decision tree algorithm with the addition of another class.

Observing the confusion matrix (Fig. 6) indicated that ripe fruits have the best performance with about 87% accuracy rating (62 of the 81 samples classified correctly). However, the unripe and under-ripe do not perform as well, with about 50% of the test images were confused to be under the ripe category (13 divide by 28 samples classified correctly). This could be caused by insufficient features for the algorithm to correctly split the set. Moreover, there are quite a few images that are questionable as to whether the images were incorrectly labeled, in other words data noise caused by human error.

The low accuracy in classifying ripe/unripe and ripe/under-ripe could be caused partially by the number of features being insufficient data for the model to correctly classify between under-ripe and unripe. Moreover, after some observation, it was observed that the colour scheme is somewhat similar when comparing under-ripe fruits and unripe fruits.

Our current method of determining spikiness using edge detection has a moderately significant influence as empty and rotten fruit bunches tended to be spikier. However, our current definition of spikiness can be further improved.

Table 1 Classification accuracy

	Maximum (%)	Average (%)
ripe/unripe	79.16	71.11
ripe/under-ripe/unripe	68.75	64.67

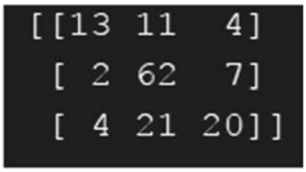

Fig. 6 Confusion matrix for classifier

6 Conclusion

The work presented here provides two main contributions. Firstly, the images can be obtained without specialized cameras or in a controlled environment. The use of colours have been well documented and the work here, used the means of the RGB channels independently and the ratio of the red colour itself. Secondly, although the spikiness could do with a better method, using the Canny Edge detection algorithm and conducting the feature engineering of the spikiness factor using the edge to image ratio has shown a significant contribution to the classifier. With a binary classifier, the work presented here is able to achieve up to 79.16% accuracy and with a tri-class classifier, it was able to achieve up to 68.75% accuracy.

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