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Oil Palm Fruit Ripeness Detection Kit for Harvesting Decision

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Abstract—Ripeness classification of oil palm fresh fruit bunches (FFB) during harvesting is essential to ensure that they are harvested at optimum maturity stage for maximum palm oil production. This paper presents an oil palm fruit ripeness detection kit that detects the fruit ripeness prior harvesting and provides a reliable harvesting decision. This embedded kit utilizes the National Instruments sbRIO-9632XT controller board, an internet protocol camera, and a LCD touch panel display model. The system works in the following way: (1) acquire oil palm FFB image; (2) perform fruit image segmentation; (3) extract hue values from processed image; (4) classify the fruit ripeness using multilayer perceptron (MLP) neural network; and (5) display the fruit ripeness and harvesting decision on the LCD panel. Investigation on the best feature extraction method and MLP neural network model were carried out. The ripeness classification accuracy achieved for the final design is 80.88% and its harvesting decision accuracy is 86.76%.

Keywords: oil palm fresh fruit bunches, National Instruments sbRIO-9632XT, image segmentation, multilayer perceptron (MLP) neural network

1. INTRODUCTION

Malaysia produced 18.79 million tons of crude palm oil on 5 million hectares of land in 2012 and this constitutes to the world's second largest producer of palm oil [1]. Oil palm FFB ripeness can be classified into four stages, which are unripe, underripe, ripe and overripe. Malaysia Palm Oil Board (MPOB) identified purplish black fruits as unripe, reddish black as underripe, red as ripe, and reddish orange as overripe [2]. The change in the skin colour of FFB is due to the accumulation of the carotene pigments, which also corresponds to the oil content inside the fruit when analyzed [3]. The oil content increases when the fruit progresses from unripe to overripe but the oil quality starts to deteriorate when the fruit is overripe. Hence, oil palm fruit has the optimum oil content with highest quality when it is in ripe stage.

Since oil palm FFB are located high up in tree, it is difficult to judge its colour using naked eyes from the ground. Therefore, it is common for harvester to look for loose fruits on the ground in the vicinity of the targeted palm tree to determine if the FFB on the tree is ripe. A number of five loose fruits indicate that the tree has at least one ripe FFB. However, this technique is not reliable and is merely a rough indicator of fruit ripeness. This is due to variations in tree phenology and characteristics; loose fruit might fall under different tree and can be stuck within the fronds. There is also a possibility that the loose fruits are being washed away by heavy rain or taken by animals in the estate. Hence, unripe and underripe FFB are frequently harvested in many estates in Malaysia. This reduces the oil extraction rate (OER) in palm oil industry and increases the production cost.

Due to the positive correlation between the colour of oil palm FFB and their oil contents [4, 5], optical properties of FFB can be used to identify its ripeness categories. The red, green and blue (RGB) colour model of oil palm FFB images were used commonly in oil palm FFB ripeness classification [6-8]. However, a study on the relationship between FFB colour, light intensity, and oil content for different ripeness stages by Hudzari et al. [9] revealed that RGB pixel values increase with the light intensity. Hence, the RGB colour model is not suitable for analyzing images that were captured in field under natural light environment. Thus, Ismail et al. [3] used hue, saturation and intensity (HSI) colour model in their study and found out that hue value is the best colour component to differentiate the ripeness categories under natural light condition. It has been proven that the variances of lighting intensity do not affect the hue value of the target colour because HSI colour model separates the colour information of an image from its intensity information [10]. Therefore, hue value is an important attribute for analyzing FFB colour in natural light environment.

For automated oil palm FFB ripeness classifier, there were studies on the application of artificial intelligent. Jamil et al. [11] used neuro-fuzzy approach to do the colour classification of oil palm FFB and achieved ripeness classification of 73.3%. May and Amaran [12] developed a model of automated grading for oil palm fruit using RGB colour model and artificial fuzzy logic. Their system reported a ripeness classification accuracy of 86.67% but the system could only classify individual fruit in controlled lighting environment. In a recent study by Fadilah et al. [13], they developed an intelligent ripeness classification system using artificial neural network (ANN). In their work, multilayer perceptron (MLP) neural network, a commonly used ANN architecture is employed as the ripeness classifier. Their research returned 93.33% correct ripeness classification but it is limited to cut-off FFB, not prior harvesting.

Generally a successfully trained MLP neural network is capable to model the function that relates the input variables to the output variables and is also able to give a reasonable output or answers with any inputs provided to the network. This is also proven for ripeness classifier by Fadilah et al.[13] with accuracy of 93.33%. However the realization of the MLP neural network as an electronic embedded system is very difficult, considering the nonlinear computation of the activation function, the number of data bits that are necessary to obtain high precision and the limitation of resources to implement a true parallel computation and processing of the neural network. Most of the previous studies require complicated setup and can only be carried out under controlled environment. To make it portable and applicable for real oil palm estate, National Instruments (NI) single-board Reconfigurable Input/Output (sbRIO) controller platform is used in this study.

This controller board is interfaced using LabVIEW software, which is a graphical development environment whereby program or system can be developed in a visual way by connecting blocks of virtual instrument (VI). The sbRIO-9632XT model features a 400 MHz real-time processor for deterministic real-time application and a Xilinx Spartan-3 FPGA for time-critical and parallel processing application. Teng et al. [14] used this board for image processing to locate any electronic component using 2-D location pointing system on a device under test. Lau et al. [15] implemented modified Gaussian filter and fast Fourier transform for automated personal identification based on finger vein. Hence, the sbRIO board is suitable for on-board image processing application.

The objective of this work is to develop an embedded device that carries out oil palm fruit ripeness detection in-situ prior harvesting and deliver a reliable harvesting decision using NI sbRIO-9632XT controller platform. This project proposes the use of image processing technique and artificial neural network for fruit ripeness classification. Feature extraction method and ANN ripeness classifier were investigated to obtain the most optimum combination that gives the highest ripeness classification accuracy of oil palm FFB.

2. METHODOLOGY

This project is progressed in five stages, which cover the software development and hardware implementation. Matlab software is used for the software development while LabVIEW software is used during the hardware implementation. Each of the stages is discussed in the following subsection.

2.1. Acquisition of Oil Palm FFB Sample Images

For sample preparation, oil palm FFB of type DxP Tenara were sourced from Felda Agricultural Services Sdn. Bhd. (FASSB). A total of 451 oil palm FFB sample images from four ripeness classes (unripe, underripe, ripe and overripe) are obtained from the same plantation, where one image is taken for each FFB. The FFB images are taken in their original condition, without cutting them off from the tree. Four sample images from different ripeness classes are shown in Figure 1.

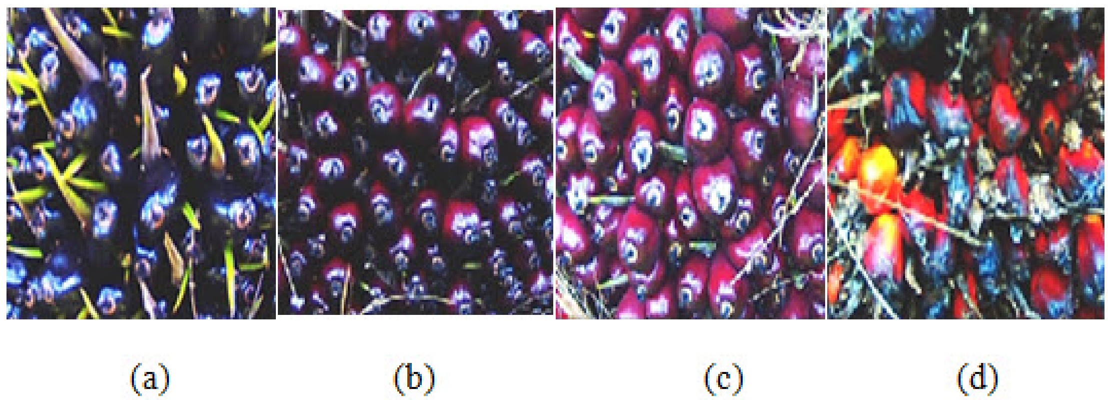

Figure 1: Oil palm FFB images for four ripeness classes: (a) Unripe; (b) Underripe; (c) Ripe; (d) Overripe

An IP camera that is fixed on a pole is used to acquire the FFB image. The size of each image is 640×480 pixels in 24-bit RGB format. The acquisition of FFB images is accompanied by a FASSB's trained grade inspector in order to identify the ripeness class of the oil palm FFB. The sample images are divided into training set and independent test set. 15% of the images from each ripeness class are randomly selected and grouped as the independent test set, while the rest of the images are grouped as the training set.

2.2. Image Processing

Oil palm fruit colour in the captured FFB image is important for ripeness classification. However, the captured FFB image contains unwanted non-fruit components such as spikes, braches or dirt which will affect classification process later on. To eliminate those unwanted components from the image, image segmentation technique proposed by Fadilah et al. [13] is used for this project.

The RGB image is first converted into L*a*b* colour space. Only a* and b* components are used for processing as they define the colour information of the image. Then, K-means clustering algorithm is applied to the a*-b* plot. This is aimed to group the pixels into several different clusters which represent different range of colours in the image. In this study, six clusters are used for the image segmentation, three clusters are combined to form the segmented fruit image while the other three clusters are combined to form the non-fruit image. Figure 2 shows the resulting clusters where different colour represents different cluster in the plot.

For hardware implementation purpose later on, the centroid point of each cluster is fixed by averaging the centroid points obtained from the K-means clustering algorithm that applied on randomly selected five images from each ripeness class. These fixed centroid points are known as color markers and they are used to cluster every pixel in an image by calculating the Euclidean distance between each pixel and each color markers. The pixel with the smallest distance to a particular color marker will be clustered under that color marker. There are six color markers that are used in this project. They are named as green, brown, grey, dark red, red and purple. They

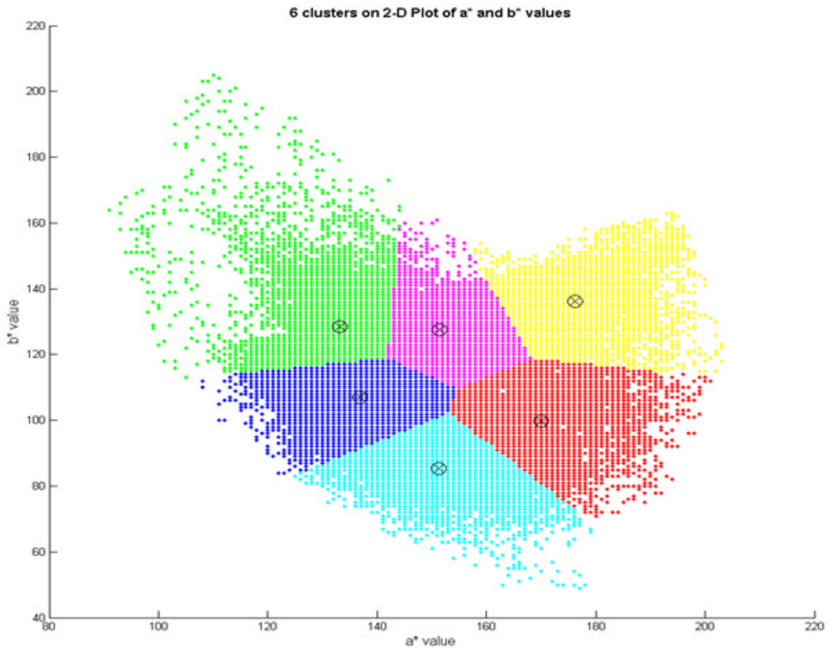

Figure 2: 6 clusters of points on 2-D plot of a* and b* values

carry the label from 1 to 6 respectively. Table 1 shows a summary of the colour markers with their coordinates on the a*b*plot.

Table 1: Summary of the colour markers

Colour Marker	Label	Coordinates in a*b* plot
Green	1	(118.72, 159.11)
Brown	2	(138.10, 138.16)
Grey	3	(133.21, 127.99)
Dark red	4	(154.26, 129.45)
Red	5	(184.80, 149.65)
Purple	6	(144.61, 104.02)

After all the pixels in the image have been labeled, a new image is created for each label. For each image, the pixels with the corresponding label will be remained and the pixels with different label are masked into black colour (R=0, G=0, B=0). The final step of the image processing method is to combine the segmented images that make up the oil palm fruit. Segmented images with colour markers of dark red, red and purple are added together to form the fruit image while the unwanted components are made up of the segmented images with color markers of green, brown and grey.

Only the segmented fruit image will be saved for feature extraction while the other one will be discarded. Figure 3a shows the original FFB image, Figure 3b shows the segmented images of oil palm FFB and Figure 3c shows the unwanted components of oil palm FFB. Only the segmented image will be saved for feature extraction while the unwanted image will be discarded.

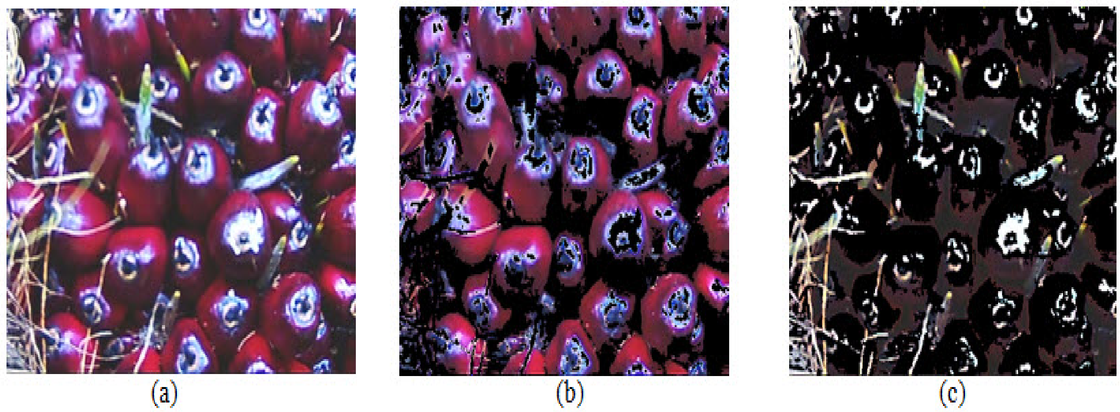

Figure 3: (a) Original FFB image; (b) Segmented images of oil palm FFB; (c) Segmented image of unwanted components

After acquiring the oil palm FFB image, the 320×240 pixels image is used in image processing. Image segmentation is performed in image processing and its flow is shown in Figure 4.

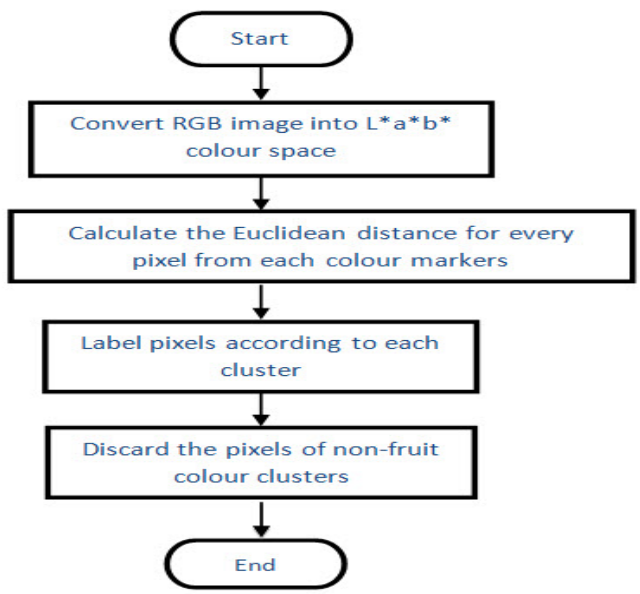

Figure 4: Flowchart of image segmentation

2.3. Image Feature Extraction Method

Color of the oil palm fruits is an important feature to determine its ripeness class. It is known that colour component extraction using HIS colour model is found out to be better than RGB color model for image that are captured under natural sunlight. On the other hand, feature reduction using PCA also has been proven to improve the ANN learning as it removes the correlated component within the extracted feature. Therefore, the image extraction method used for this project covers the application of HIS color model and PCA. A flowchart of image feature extraction step is shown in Figure 5.

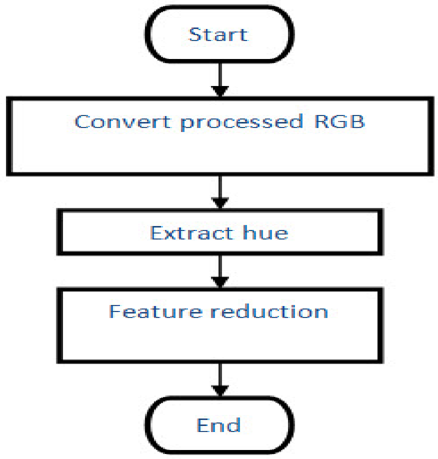

Figure 5: Image feature extraction flow chart

The first step of the image feature extraction process is to convert the processed image into HIS color model. The RGB to HIS conversion formula is as below:

$$
\begin{aligned}
H &= \begin{cases} cos^{-1}\frac{\frac{1}{2}[(R-G)+(R-B)]}{\left[(R-G)^2+(R-B)(G-B)\right]^{\frac{1}{2}}} & if B \leq G \\ 360 - cos^{-1}\frac{\frac{1}{2}[(R-G)+(R-B)]}{\left[(R-G)^2+(R-B)(G-B)\right]^{\frac{1}{2}}} & if B > G \end{cases} \\
S &= 1 - \frac{3}{(R+G+B)}\left[min\left(R,G,B\right)\right] \\
I &= \frac{1}{3}\left(R+G+B\right)
\end{aligned}
\tag{1}
$$

The hue component is the only required component since hue represents the true color of the image. The hue values of the image are extracted in the form of a histogram and the histogram patterns are different for all four ripeness classes. The histogram is generated in 100 bins, 50 bins and 20 bins to be experimented on which number of bins will produce the best result for this application. The number of extracted bins for each type of histogram is shown in Table 2.

Next, principle component analysis (PCA) is applied to the extracted data to reduce the extracted features by removing the correlated components while keeping as much variation in the original data as possible. The number of principle component is selected in such way that the reduced features retain at least 95% variance. The reduced features will be used as inputs for the ANN learning. The whole PCA algorithm will not be implemented in the hardware as it requires heavy computation and takes long time to process. Only the eigenvector matrix will be used to multiply with the feature vector to reduce the extracted features during hardware implementation. Combination of the number of extracted bins and principle components are shown in Table 3.

Table 2: Number of extracted bins for each type of histogram

Total number of histogram bins	Number of extracted bins
100	55(1-9th bins and 55-100th bins)
50	28 (1-5th bins and 28-50th bins)
20	12(1-2nd bins and 11-20th bins)

Table 3: Combination of the number of extracted bins and principle components

Method	Number of extracted bins	Number of principle components	Variance retained
A1	55	8	95.41%
A2		12	98.13%
A3		16	99.06%
B1	28	7	95.12%
B2		10	98.11%
B3		13	99.16%
C1	12	6	95.13%
C2		8	98.45%

2.4. Development of ANN Ripeness Classifier

In this project, an artificial neural network (ANN) with multilayer perceptron (MLP) model is developed to do the classification of oil palm FFB ripeness based on the extracted features. The usage of ANN ripeness classifier and the implementation of ANN using MLP network model are shown in Figure 6 and Figure 7 respectively. To determine the most optimum MLP model, various combination of activation functions for hidden and output layers as listed in Table 4 are being investigated.

In this project, for input preprocessing, data is being normalized to minimum and maximum value of -1 and 1. On the other hand, the post processing function is the reverse of the pre-processing function except the maximum and minimum values are 1 and 0. The total sample images are limited to 451 images, majority of the sample (85%) are used as training set in order to obtain a good neural network classifier, while only 15% of sample images are used as test set to verify the performance of the system. In a training process, MLP network will update the trained-weights in the input and hidden layers after every training cycle to improve its performance. The best-performed MLP model is chosen based on the highest classification accuracy when tested using the test set. For the best performed MLP network, the weight values and bias values of all the neurons will be saved for the hardware implementation of the MLP network model.

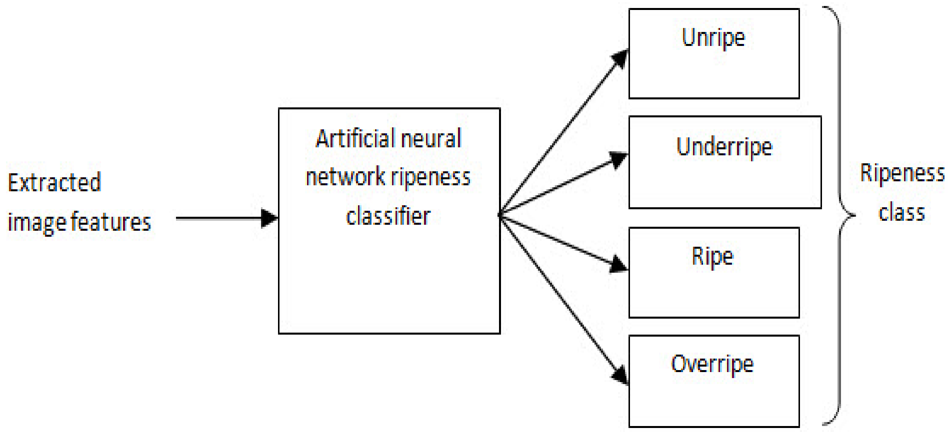

Figure 6: Usage of ANN ripeness classifier

Table 4: Combination of activation functions for MLP neural network training

Combination label	Activation Function for Hidden Layer	Activation Function for Output layer
LT	logsig	tansig
TT	tansig	tansig
LP	logsig	purelin
TP	tansig	purelin

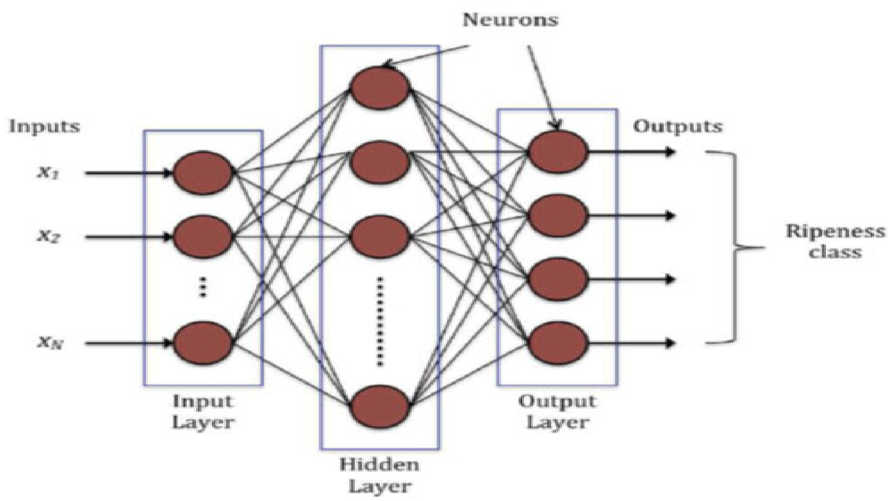

Figure 7: Implementation using MLP network model

2.5. Hardware Implementation

The algorithm and parameters obtained have to be plotted to the hardware to make the system works. The controller platform used in this project is the NI sbRIO-9632XT board. The 400MHz real-time processor is suitable for image processing and feature extraction application for this project. Meanwhile the on-board 2M gates Xilinx Spartan-3 FPGA is used for ANN implementation to take advantage of the parallelism. This board also features an Ethernet port which is used to communicate with computer and internet protocol (IP) camera in this project. Besides that, a serial port also exists on the board where a serial LCD display module can be interfaced to it.

Axis M1031-W IP camera is used to capture the image of oil palm FFB. The camera supports video streaming in Motion JPEG video format with 30 fps of frame rate. The display module from Reach Technology is used to display the captured oil palm FFB image and the classification result through a graphical user interface (GUI). It is supported by LabVIEW driver and can communicate with the sbRIO-9632XT via serial communication. An example of the GUI for this system is shown in Figure 8.

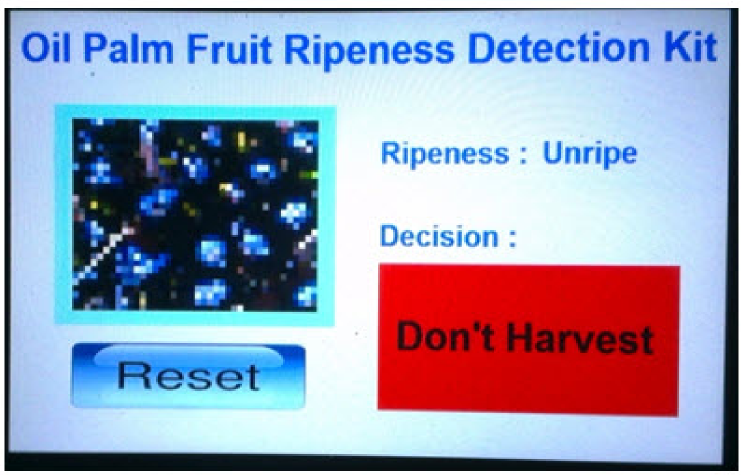

Figure 8: An example of GUI of the system

2.6. System Operation of Oil Palm Fruit Ripeness Detection Kit

The algorithm that was developed is plotted into the sbRIO-9632XT controller after the best feature extraction method and MLP network model has been determined. The system is built in the sbRIO controller by using the fixed parameters that were generated from the software development. Figure 9 shows the system organization in the controller board.

From Figure 9, the system of the oil palm fruit ripeness detection kit operates by utilizing both real-time processor and FPGA. All of the processes including image acquisition, image processing, and features extraction are running using the real-time processor except the MLP neural network which is implemented in FPGA.

The embedded kit system starts by detecting the LCD display module and IP camera. Once they have been detected, it will display the front panel GUI on the LCD display module. There is a capture image button in the GUI, which will trigger the camera to capture image when it is pressed. After the image acquisition, the system proceeds with image processing and feature extraction on the captured image. The extracted data will be passed as inputs to the MLP neural network ripeness classifier. The output from the ripeness classifier will be interpreted and the ripeness result and harvesting decision will be displayed back on the LCD screen. The result page GUI has a reset

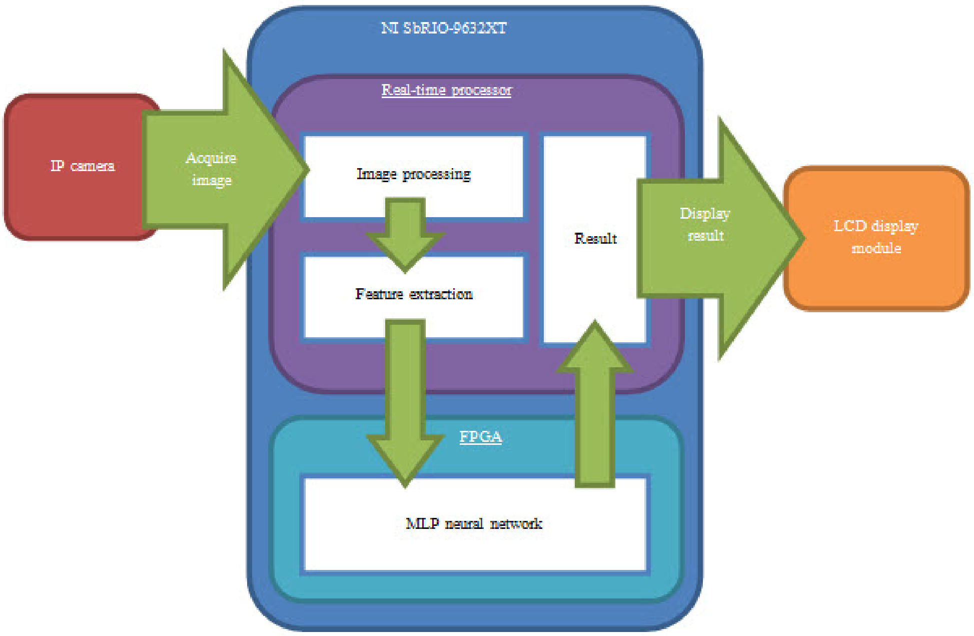

Figure 9: System Organization in the sbRIO-9632XT controller

button on it. If it is not pressed, the LCD screen will remain at the result page, else the system will repeat the process again by displaying the front panel GUI on LCD screen.

The MLP network model obtained from the software development is constructed in the FPGA of the controller board. The programming of FPGA is done in LabVIEW software. Figure 10 shows an example of a logsig activation function constructed in FPGA using LabVIEW software. Since floating point is not supported in FPGA, fixed point representation is used in the FPGA programming. The input word length and integer word length used for the MLP network are 32 bits and 16 bits respectively, then the LabVIEW software automatically adapts to that representation for the rest of the network.

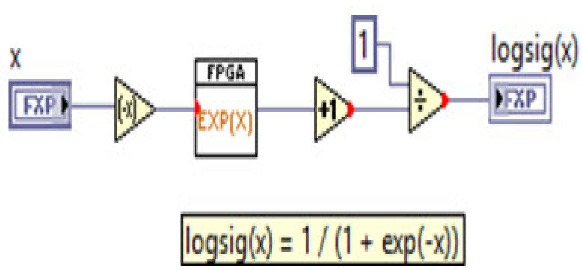

Figure 10: Logsig activation function constructed in FPGA

The reduced extracted data from the feature extraction stage is used as the input to the MLP neural network. The MLP neural network processes the inputs and produces four analog outputs as there are four output nodes. These outputs value will be converted to 1 and 0 in such way that the maximum output value is set to 1 and the rest are set to 0. Then, the outputs are decoded into the ripeness class according to Table 5. After the classification result is obtained from the MLP neural network, the system will display the ripeness class and harvesting decision on the LCD screen. If the ripeness class are unripe and underripe, the decision is do not harvest whereas if the ripeness class are ripe and overripe, the decision is harvest.

Table 5: Output coding representation

Ripeness Class	**MLP Output**			
	1	**2**	**3**	**4**
Unripe	1	0	0	0
Underripe	0	1	0	0
Ripe	0	0	1	0
Overripe	0	0	0	1

3. RESULT AND DISCUSSION

Each feature extraction method as shown in Table 3 was tested with each activation function combination against one hidden neuron to 15 hidden neurons. The combination of feature extraction method and MLP network model that gives the highest classification accuracy will be implemented in the system. Table 6 shows the combination of feature extraction method, the activation function with number of hidden neurons for the best accuracy.

Table 6: Combination of feature extraction method with activation function and number of neurons for the best accuracy

Feature Extraction Method	**Activation Function**	**Number of Neuron**	**Accuracy (%)**
A1	TT	3	79.41
	LP	4	
	TP	3	
A2	LT	6	76.47
	TT	2	
	LP	3	
A3	LT	7	77.94
	LP	3	
	TP	3	
B1	LT	3	80.88
B2	TT	4	77.94
	TP	3	
B3	TT	2	77.94
C1	TT	3	79.41
	LP	3	
	TP	3	
C2	LT	2	79.41
	TT	2	

Hence, the best feature extraction method chosen is the method B1, where 28 bins (1-5th bins and 28-50th bins) are extracted from the 50-bin histogram and 7 principal components are used for the PCA transformation. One possible reason for this feature extraction method turned out to be the best is that 50-bin histogram gives a more distinct hue pattern compared to 100-bin histogram and 20-bin histogram. It is believed that the 100-bin histogram is too sensitive to the hue variation in the image compared to the 50-bin histogram and it produces hue patterns that are not so consistent for each of the ripeness class. This complicates the learning process of the neural network and reduces the classification accuracy. For 20-bin histogram, this histogram type is not that sensitive to the hue variation compared to 50-bin histogram and it produces hue patterns that are not significantly different from each of the ripeness class. Thus, it results in lower classification accuracy. PCA using 7 principal components give the highest performance as it eliminates most of the correlation in the data, whose existence may confuse the neural network learning process.

The best MLP network model chosen is of three hidden neurons with logsig function as the hidden layer activation function and tansig function as the output layer activation function. Figure 11 shows the training confusion matrix for the best-performing MLP network model. The target class represents the training set images, where 1, 2, 3, and 4 represent unripe, underripe, ripe, and overripe class respectively. The output class represents the ripeness classification result by the MLP neural network on the training set images. The green box indicates the number of images which are classified correctly. For example, in the first column, out of the 92 unripe images from the training set, 90 of them were classified correctly while two of them were classified as underripe. The overall classification accuracy for the training set is shown in the right-bottom corner box, which is 90.9%.

Figure 11: Training confusion matrix for the best-performing MLP network model

When the MLP neural network was tested with the test set images, the expected performance had been obtained. Figure 12 shows the test confusion matrix for the best-performing MLP network. From the matrix, the MLP network also exhibits higher confusion for underripe and ripe classes compared to the other classes. The MLP network tends to misclassify underripe with ripe class and ripe with underripe class.

Hence, in Table 8, the classification accuracy is lower for underripe and ripe classes but underripe class had the lowest classification accuracy. Four out of total 17 underripe test images were classified as ripe by the MLP network. The possible reason is that the training data for underripe class has extracted hue pattern that are similar to the ripe class, therefore, the MLP network could not differentiate the underripe class accurately when it is tested with new, unseen image.

Although the methodology for the software development is similar to those in Fadilah et al. study [13], the highest ripeness classification accuracy achieved in this project (80.88%) is lower

Table 7: Classification accuracy for training set images

Ripeness Class	Classification Accuracy (%)
Unripe	97.83
Underripe	85.85
Ripe	89.13
Overripe	91.40
Overall	90.86

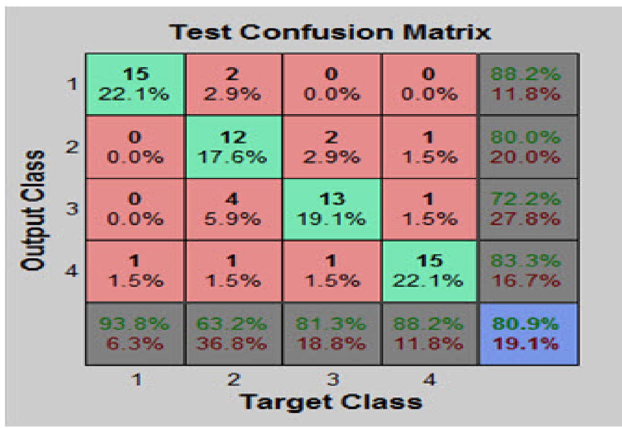

Figure 12: Test confusion matrix for the best-performing MLP network model

Table 8: Classification accuracy for test set images

Ripeness Class	Classification Accuracy (%)
Unripe	93.75
Underripe	63.16
Ripe	81.25
Overripe	88.24
Overall	80.88

than that in their study (93.33%). This is due to different image data set is used in this project. In their study, the sample images of FFB were obtained after cutting off from the oil palm trees as mentioned by Fadilah et al. [13], while in this project, the sample images of FFB were obtained without cutting off from the trees. Despite the images were captured from the top of the tree, the lighting condition for the captured images is different for this project and their study. On top of the tree, the fruits are partially hidden by the fronds and are in deep shade. However, for the cutting off fruit, the whole bunch is exposed to the same lighting condition. The problems of hidden by the fronds and deep shade are not arise. The number of hue that is using in this project is also different, where the number of hue that is using in this project is only 28. Hence, the performance is expected to be different for both studies.

The best-performing MLP neural network was implemented in FPGA of the controller board. From the FPGA design compilation report, the three-layer MLP neural network utilizes 57.3% of the slice registers, 96.6% of the slice look up tables (LUTs), and all of the 18×18 multiplier blocks. Since fixed point representation was used in FPGA computation, an accuracy test was conducted to compare the output values from MLP network in FPGA and the output values from MLP network in computer (Matlab). The equation used to compute the average accuracy of the FPGA-based MLP network is shown in Equation (2).

$$\text{average accuracy} = \frac{\sum_{i=0}^{n} (1 - |y_i - x_i|)}{n} \times 100\% \tag{2}$$

Where y_i is the output value from FPGA-based MLP network, x_i is the output value from computer-based MLP network, and n is the total number of outputs. All the test set images had been used for this accuracy test and the average accuracy of the FPGA-based MLP network was found out to be 99.9971%. Hence, for this project, the FPGA-based MLP network is almost the same as the computer-based MLP network.

To verify that the FPGA-based MLP network will produce the same ripeness classification accuracy on the embedded kit, the same test set images were used to test the classification accuracy on the embedded kit. Table 9 shows the classification result matrix. From the matrix in Table 9, the results obtained are exactly the same as the test confusion matrix (Figure 12) generated in computer. Hence, the classification accuracy of the embedded kit for each ripeness class is the same as that in Table 8 with an overall accuracy of 80.88%. This validates that the hardware implemented system has the same performance as the software developed system.

Table 9: Classification result matrix for the embedded kit

Target Class / Output Class	Unripe	Underripe	Ripe	Overripe
Unripe	15	2	0	0
Underripe	0	12	2	1
Ripe	0	4	13	1
Overripe	1	1	1	15

The harvesting decision is an important factor to consider when it comes to real application, the harvester should harvest the oil palm FFB only when they are ripe or overripe. Even though there are some misclassifications in ripeness, if the final harvesting decision is correct, it will still solve the current low oil extraction rate problem. An analysis on the harvesting decision accuracy of the embedded kit was carried out. The equation used to calculate the harvesting decision accuracy is shown in Equation (3).

$$\text{Harvesting decision accuracy} = \frac{n}{N_{test}} \times 100\% \tag{3}$$

Where n is the image with correct harvesting decision and N_{test} is the total test images. High harvesting decision accuracy signifies that more ripe or overripe FFB can be harvested and the chance to harvest unripe or underripe FFB will be lower. Higher harvesting decision accuracy will result in higher oil palm OER. From the classification result matrix, the harvesting decision accuracy of the system is found out to be 86.76% where 9 out of 68 total test images were classified into wrong harvesting decision.

4. CONCLUSION

In conclusion, the oil palm fruit ripeness detection kit has been developed to detect the fruit ripeness prior harvesting and deliver a reliable harvesting decision. The detection kit is embedded using the sbRIO-9632XT controller board with Xilinx Spartan-3 FPGA for time-critical and parallel processing application. The resources that have been utilized in this application are 57.3% of the slice registers, 96.6% of the slice look up tables (LUTs), and all of the 18×18 multiplier blocks. The ripeness classification accuracy of the detection kit is 80.88% and its harvesting decision accuracy is 86.76%. The accuracy might be improved by increasing the number of hue as the input features in this application. However a bigger capacity of FPGA device is recommended for the improvement.

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