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Starfruit Classification Based on Linear Hue Computation

M. M. Mokji* and **S. A. R. Abu Bakar**

Faculty of Electrical Engineering, Universiti Teknologi Malaysia, 81310 UTM Skudai, Johor, Malaysia.

*Corresponding author: musa@fke.utm.my (M. M. Mokji), Tel: 607-5535231, Fax: 607-5566272

Abstract: In this paper, a classification process to group starfruit into six maturity indices is proposed based on 1-dimensional color feature called hue, which is extracted from the starfruit image. As the original hue is quantified from the nonlinear transformation of the 3-dimensional Red, Green and Blue color, this paper proposes a linear hue transformation computation based on the 2 colors of Red and Green. The proposed hue computation leads to a reduced computational burden, less computational complexity and better class discriminant capability. The hue is then applied as the input for the maturity classification process. The classification process is based on the hypothesis that for each of the maturity index, certain area of the starfruit surface is supposed to have distinctive value of the hue. In this work, the said starfruit surface area is set as 70% of the total area and based on 600 samples, the proposed technique results in 93% classification accuracy.

Keywords: 2-D hue, Fisher's discriminant ratio, Maturity classification, Starfruit.

1. INTRODUCTION

Malaysia has been the largest exporter of starfruits in the world since 1989 [1]. The biggest starfruit farm has also been setup in Selangor in 2002 [2]. It becomes a serious production because the fruit is not only to be fond among Malaysian but also to the other communities over the world. Over the years, significant export growth has been recorded. Malaysia's export figures for 2000 and 2001 are 8,745 metric ton and 9,182 metric ton respectively. This is more than 60% increase from Malaysia's export in 1991, which was 2,723 metric ton [3].

Some of the major starfruit importers include the Netherlands, Germany, Singapore and Hong Kong. These four major importer countries contributed 82.28% to Malaysia's starfruit export in 2003 [3]. As an export commodity, the production of good quality starfruit is vital because most of the importer countries are a quality conscious customer. These countries are generally less price conscious and they are willing to pay more for good quality exotic tropical fruits such as the starfruit. Thus, an effort towards the best quality production of the starfruit should be discovered. Besides, it will complement Malaysia's ambition in expanding the agriculture products to support growth in the economy.

Quality of the starfruit is defined by its physical appearance and taste. Malaysia is acknowledged to have the best taste of starfruit amongst the importer country compared to other exporter countries [4]. However, good taste of the starfruit is only as important as attractive of its physical appearance. To ensure only good quality starfruit with good physical appearance go to the market, FAMA (Federal Agricultural Marketing Authority) created a quality label called Malaysia's Best. Under this label, every step from harvesting to packaging the fruit is described to ensure quality.

In this paper, attention is restricted to the process of grouping the starfruit into a predefined maturity levels according to the Malaysia's Best label will be discussed. Based on this label, starfruit is classified into six maturity indices [5]. The purpose of classifying the starfruit into its maturity index is to determine the market suitability. For export use, only Index 2, Index 3 and Index 4 are allowed. Exporting immature starfruit is to ensure it will only be mature at the time it arrive its destination. For domestic market, Index 5 and Index 6 are the most suitable indices as it can be eaten at the time the fruit is bought by the consumer. Until this proposal is written, the classification process of the starfruit is performed manually. Manual inspection will cause inconsistency in quality due to human subjective nature, slow processing and labor intensity. The classification also need experience worker to avoid misclassification. In the research reported in this paper, an automated starfruit classification process is proposed to improve the current manual system.

As the change of the starfruit maturity is perceived by human eyes based on the color change of the starfruit, color information will also be applied to this work. Thus, Section 2 of this paper will discuss the feature extraction process based on color information, where a method of selecting the best color feature is also described. A good feature is required because it usually gives good classification results. In Section 3, the classification process of the starfruit into the six maturity indices is described. The results of the starfruit classification will also be discussed in Section 3. Finally, the paper is concluded in Section 4.

2. FEATURE SELECTION

2.1 One-Dimensional Color Feature

High dimensionality of feature vector will always give high computational burden and complexity [6]. Therefore, if possible, lower dimensionality is preferable to avoid those problems. In starfruit classification for this work, color is used as the feature vector. However, the original color components or color vector captured from the camera is in three dimensions, which are red (R), green (G) and blue (B). To reduce the dimension of the color vector, a features (color) transformation is needed. There are a few typical and widely used color transformations from the RGB color such as HSV, HSI, CMYK, YIQ and YUV [7]. Each of these transformations has it specific purpose.

RGB color is generally used for monitor display [7] and color camera. Computer monitors generally use 24-bit RGB where each primary color has 8-bit data with 256 discrete values. RGB color is applied in monitors due to its simplicity in constructing color as it only involves additive color mixture. In contrast to additive mixture, CMYK color is constructed using subtractive mixture of RGB color [8]. It is generally designed for printing purposes. C refers to cyan, M to magenta and Y to yellow. Black (indicated by the letter K) is added as a fourth distinct color to enhance appearance, as the mixture of cyan, magenta, and yellow pigments does not normally generate pure black, but a dark murky color. Moreover, text is typically printed in black, and it is impractical to expect high speed and low cost printing of black color using cyan, magenta and yellow mixture.

Despite the fact that RGB color space is the most suitable for display, human observe color differently. HSL and HSV color are more appropriate for human sight [8]. Thus, these color space are suitable for computer vision and computer graphic application where human vision is interpreted by mathematical representation. HSL and HSV are non-linear deformations of the RGB color [8]. H stands for hue is referring to shade of color within the visible region of Electromagnetic Spectrum. Converting it from RGB color, hue is represents as angle value from 0^0 to 360^0. Each degree referring to a specific color. S as the second notation is called saturation, which is the intensity of the specific hue. Highly saturated hue has a vivid and intense color, while a less saturated hue appears more gray. Last alphabet in both color space differentiate between these two colors type. Both contained luminance information but in different way. Lightness (L) in HSL always spans the entire range from black through the chosen hue to white while Value (V) only goes half the way, from black to the chosen hue. Thus, graphically HSL is visualized as double cone and HSV is drawn as single cone.

The last two colors type, YIQ and YUV are designed for the purpose of color television broadcasting [7]. The YUV color space is used for the PAL broadcast television system used in Europe and the YIQ color space is used for the NTSC broadcast standard in North America. In both systems, Y is the luminance component while I and Q (or U and V) are the chromaticity components. YIQ and YUV color are designed in order to compressed the RGB color while at the same time conserving the color bandwidth that suit human visual system. Therefore, in general these color spaces are not suitable for digital image processing.

From the above discussion, for the purpose of the starfruit classification, HSV and HSL color are the most suitable. Although both color transformation into HSV and HSL also result three dimension feature vector, only certain feature is necessary. Thus, the feature dimensionality can be reduced. As mentioned in the previous topic, the starfruit classification is a process of grouping the starfruit according to its level of maturity. Naturally, the maturity change from immature to mature in starfruit can be observed as change in its color from green to orange. Feature that is most suitable to represents the color change is hue where it measure the shade of color. In later topic, a measure proving the hue as the best feature selection will be discussed. For now, the discussion will concentrate on the computation of the hue.

The transformation from RGB color to hue is a bit complicated where it is formulated as a nonlinear transformation as below [9]

$$H = \begin{cases} \dfrac{G-B}{\max-\min} \times 60 & if\ R\ is \max \\ \left(2+\dfrac{B-R}{\max-\min}\right) \times 60 & if\ G\ is \max \\ \left(4+\dfrac{R-G}{\max-\min}\right) \times 60 & if\ B\ is \max \end{cases} \tag{1}$$

Equation 1 consist three key operations, which involve a color difference (numerator), normalization and shifting. Color difference calculates the second dominance of color after the maximum color. As an example, if R has the maximum value and its color difference computation gives positive value, color produce from this combination is between red and green. How far the color located from red is depends on how big the difference value (domination level). Normalization in Equation 1 is referring to the fraction $\dfrac{1}{\max-\min} \times 60$. Its purpose is to fit the color difference value within a range of -60° and 60° since degree is used to indicate hue position. At 0°, the color difference value is equal to zero. Thus, each condition in the hue formulation will have range of 120°. As there are three color components, it complete the hue circle in 360°. Lastly, the shifting operation positioned each hue value properly to avoid cross-placement. When R is maximum, no shifting involved, means that hue starts with pure red at 0°. Then, when G is maximum, hue value is shifted by 120° and results pure green positioned at 120°. To complete the hue circle, pure blue is positioned at 240° by shifting its hue value by 240°.

In this work, a linear hue formulation is proposed in order to simplify the computation. Linear hue formulation is possible if one of the RGB color component is ignored. By normal human eyes observation, ignoring one of the RGB color component is acceptable because only red and green color are dominance in the starfruit while blue color is almost imperceptible. This circumstance is also proved by color density plot shown in Figure 1 where most of the blue color is concentrated at low pixel value. In this plot, the horizontal axis is representing the pixel value while the vertical axis represents color concentration.

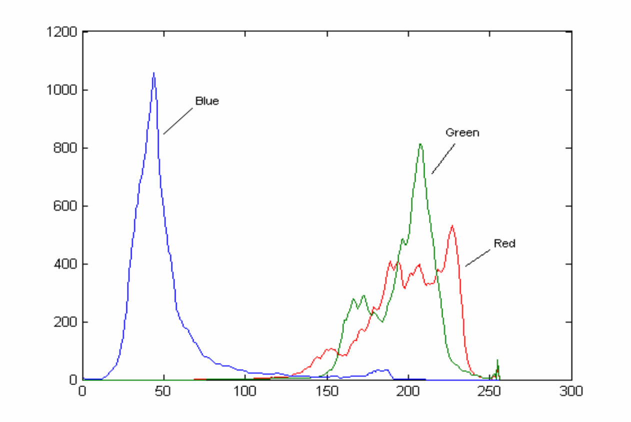


Figure 1. Starfruit color density plot

Eliminating blue component from the hue formulation is done by setting the blue value equals to zero. Thus, Equation 1 becomes

$$H = \begin{cases} \dfrac{G}{R} \times 60 & \text{if } R \text{ is max} \\ \left(2 - \dfrac{R}{G}\right) \times 60 & \text{if } G \text{ is max} \end{cases} \tag{2}$$

Now, the equation only has two constraints notation left. The third constraint is eliminated, as it is impossible that the blue component will have the maximum value compare to red and green because it was set to zero. The range of the hue is also different from the original hue where it is shorten to 120°. The new hue starts with pure red at 0° and ends with pure green at 120°. Thus, the entire original hue value that relates to blue component was eliminated. To complete the linearization of the hue formulation, Equation 2 is rearranged to eliminate the constraint notation, as both constraints are complement to each other. The linear version of the hue formulation is represented as Equation 3 below.

$$H1 = \left[(1-\alpha) - \frac{R(1-\alpha) - G(1+\alpha)}{G(1-\alpha) + R(1+\alpha)} \right] \times 60 \tag{3}$$

where

$$\alpha = \frac{R-G}{|R-G|}$$

Instead of the linearity of the new hue formulation, it also has the advantageous of reduced amount of data throughout the color transformation process where blue component is not considered in the formulation (Equation 3). Here the data is reduced by $\frac{1}{3}$ of the original data. Thus, it is showed that the linear version of RGB color transformation into hue is certainly reduced the computational burden and complexity.

2.2 Class Discriminant Measure

Having the advantage of less computationally burden and complexity is insignificant if the feature does not have a good discrimination capability. Poor discriminant capability will result poor classification. To quantify the discriminant capability, a class separable measure called Fisher's Discriminant Ratio (FDR) is applied [10]. Basically, FDR gives higher value when the distance of mean between two classes is far and the total variance of the two classes is small. This is shown by Equation 4 where μ_1 and σ_1^2 are the mean and variance of class 1 while μ_2 and σ_2^2 are the mean and variance for class 2.

$$FDR = \frac{(\mu_1 - \mu_2)^2}{\sigma_1^2 + \sigma_2^2} \tag{4}$$

For multi-class case, FDR is quantifying each possible class pairs and computes their average value as shown by Equation 5 where M is the total class [11].

$$FDR1 = \frac{1}{N} \sum_{i=1}^{M} \sum_{j=i+1}^{M} \frac{(\mu_i - \mu_j)^2}{\sigma_i^2 + \sigma_j^2} \tag{5}$$

where

$$N = \sum_{i}^{M-1} i$$

Separable measure based on the Equation 5 gives global information about the discriminant capability [11]. In some cases, where only a few class pairs results low FDR compared to the rest of the class pairs, unfortunately the global information will neglect the low FDR due to the averaging operation. In measuring the discriminant capability for multi-classes, in fact the low resulted FDR is more significant as it shows low discriminant capability while high discriminant capability measurement is less significant because good discriminant capability usually does not gives a difficulty for classification process. To formulate a low sensitivity of FDR value formulation, this paper proposed a computation as in Equation 6. This formulation is formulate specifically for the starfruit classification process and might not appropriate for other purposes.

$$FDR2 = \frac{1}{M-1} \sum_{i=1}^{M-1} \frac{(\mu_i - \mu_{i+1})^2}{\sigma_i^2 + \sigma_{i+1}^2} \tag{6}$$

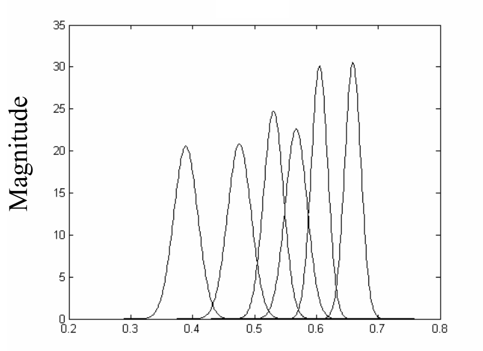
In Equation 6, FDR2 is computed between two adjacent class pair only. It is formulated such that because these are the class pair that will result lower FDR while the other class pair will most probably result higher FDR. As there are six maturity indices for the starfruit classification process, M is equals to 6. Thus, FDR2 will only compute the five most probably lower FDR. Table 1 shows the resulting FDR2 for hue (H1) as in the Equation 2 and also for a few other features as a comparison. Apart from the last row of Table 1, the rest of the features are in 1-dimensional. As can be seen in the table, the last feature is based on 3-dimensional color of RGB.

Table 1. Class separable measure for various type of color features

Feature	FDR1	FDR2
H1	33.2713	5.7289
H (original computation)	32.8763	5.3814
I (intensity)	3.5871	1.8638
S (saturation)	21.0347	4.0035
R (red)	18.8353	3.9818
G (green)	3.2836	1.5630
B (blue)	15.1069	2.6288
R, G, B	12.1100	3.0466

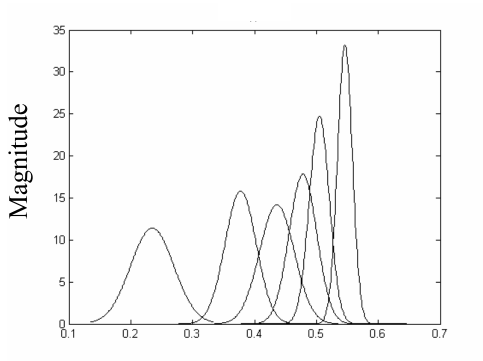
Table 1 also includes results for FDR1 (global value) where all of its results have higher value compare to FDR2. This proves that FDR2 computation is most likely picking up the five lowest FDR. Most of the FDR1 results are inaccurate because heuristically results above 20 will have a perfect class separation. However, as shown by Figure 2, the class separation is not perfect even for H1 that has the highest FDR1 value. Figure 2 is actually plots of normal distribution of the six maturity classes of the starfruit based on four selected color features (H1, R, G and S). All features have been normalized for better comparison. These features are selected to show various class separations for higher, middle and lower discriminant capability (FDR). As the whole four features show intersection between classes or imperfect class separation, it can be said that the class separable measure is more accurate based on FDR2 computation because it results values less than 20 for all features tested as in the Table 1.

Based on Table 1 and Figure 2, it can be concluded that HI, which has the highest value of FDR2 is the best feature for the classification process compared to the other features. Although using the 3-dimensional feature of RGB, the discriminant capability is still lower than the discriminant capability of H1. For H, which is the original computation of H1, the FDR value is slightly lower. This shows that discarding the blue component from the hue computation is worthy as it reduced the computational burden, less computational complexity and results slightly better class discriminant capability.



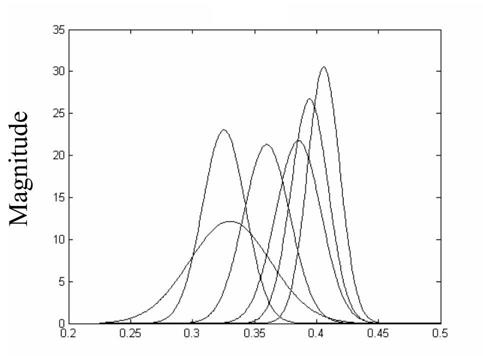
H1

(a)



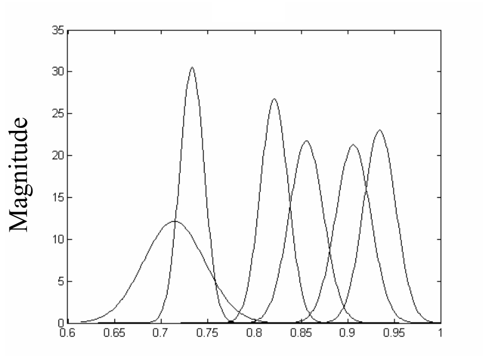
R

(b)



G

(c)



S

(d)

Figure 2. Normal distribution of the maturity classes. For each figure, class 1 to class 6 is referred as the most left plot to the most right plot accordingly. (a) H1, (b) R, (c) G, (d) S.

3. MATURITY INDEX CLASSIFICATION

From the previous section, H1 was chosen as the input feature for the starfruit classifier. Although H1 has been proven to be the best feature among the other features tested in this work, its class discriminant capability is still imperfect. Hence, the classification process will not be straightforward. To solve the problem, the classification process will be based on the hypothesis that for each maturity indices, certain area of the starfruit surface is supposed to have distinctive value of the hue (H1). Based on this hypothesis, it involves two parameters, which are the starfruit surface area (A) measures in area percentage (Equation 7) and hue (H1) as the thresholds that separate two maturity indices. Basically, as there are six maturity indices, thus each A and H1 will have five different values. The subsequent discussion will describe the search for the best values of A and H1. Then, a few rules are designed based on these values to classify the starfruit.

Searching for the A and H1 values are based on 600 pre-classified samples where there are 100 samples for each of the maturity indexes. Two steps are involves in the search of the A and H1 values, which are based on known H1 and known A. For the former technique, the five values of H1 or better noted as $H1_{(i,i+1)}$ are preselect to have similar distance between their adjacent values as shown in Figure 3.

The first value of $H1_{(i,i+1)}$ is selected equals to 40 while the end value is selected as 60 based on Figure 2(a) where most of the $H1_{(i,i+1)}$ values of the six maturity classes recline between this ranges. With the known $H1_{(i,i+1)}$ values, seven values of A are tested to quantify the class error between the classes. The class error is computed referring to Equation 7 where A_i and A_{i+1} are percentage of area of two starfruit samples with adjacent maturity index.

$$E = \sum P\{A_i \le A\} + \sum Q\{A_{i+1} > A\} \qquad (7)$$

In Equation 7, P{.} and Q{.} are equal to one if the arguments are true and set to zero if otherwise. Thus, E is actually the total number of misclassified samples of two adjacent maturity indices. A_i and A_{i+1} are represented by Equation 8 and 9 as below.

$$A_i = \frac{\text{total pixel of } C_i \le H1_{(i,i+1)}}{\text{total pixel of } C_i} \times 100 \qquad (8)$$

$$A_{i+1} = \frac{\text{total pixel of } C_{i+1} \le H1_{(i,i+1)}}{\text{total pixel of } C_{i+1}} \times 100 \qquad (9)$$

C_i and C_{i+1} are input samples of maturity index i and maturity index $i+1$ respectively where $1 \le i \le 5$. Results for the seven tested values of A are shown in Table 2. Logically, the best values of A at each of the $H1_{(i,i+1)}$ are the values with minimum E. However, to simplify the classification rules, which will be discussed later, a single value of A is picked for all value of $H1_{(i,i+1)}$. From Table 2, A equals to 60 is the best chosen value.

Table 2. Class error quantification for various values of A

A (%)	Class Error (E)				
	$H1_{(1,2)}$	$H1_{(2,3)}$	$H1_{(3,4)}$	$H1_{(4,5)}$	$H1_{(5,6)}$
100	50	50	50	50	50
90	10	24	44	30	29.5
80	3	16	32.5	23	9.5
70	**0**	7	22	14.5	**7**
60	1	**5**	**14**	**9**	16
50	1	7	19	30.5	28.5
30	7.5	11	32	49	48

Now, as value of A is known, the next step is to find the five best values of $H1_{(i,i+1)}$. This is done by scrolling each of the $H1_{(i,i+1)}$ values as shown in Figure 3 to higher and lower values. For each new value of the $H1_{(i,i+1)}$ and with A equals to 60, E is quantified. $H1_{(i,i+1)}$ with the lowest value of E will be chosen as the best value for the $H1_{(i,i+1)}$.Table 3 shows the results when $H1_{(i,i+1)}$ are change up to ±3 from the early-chosen value in Figure 3.

In the quantification, most of the $H1_{(i,i+1)}$ except for $H1_{(3,4)}$ and $H1_{(5,6)}$ results lowest E at zero change. $H1_{(3,4)}$ has the lowest E at value of 51 and $H1_{(5,6)}$ at 59. Hence, the chosen values for $H1_{(1,2)}$, $H1_{(2,3)}$, $H1_{(3,4)}$, $H1_{(4,5)}$ and $H1_{(5,6)}$ are 40, 45, 51, 55 and 59 accordingly.

Based on the chosen values of A and $H1_{(i,i+1)}$, the hypothesis of the starfruit maturity classification will be proved by creating rules. The rules are given in Figure 4. In this rules, A_i is computed based on Equation 8 and A = 60. Based on the 600 early-classified samples, which are also used in determining the values of A and $H1_{(i,i+1)}$, classification using rules given in Figure 4 results 93% of accuracy. Most of the misclassification is in Index 3 and Index 4 where 14 and 11 samples are misclassified accordingly.

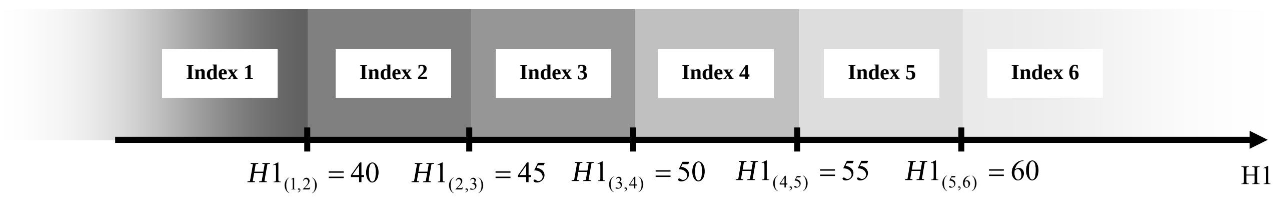


Figure 3. Predefined value of $H1_{(i,i+1)}$

Table 3. Class error quantification for various values of $H1_{(i,i+1)}$

$H1_{(i,i+1)}$ adjustment	Class Error (E)				
	$H1_{(1,2)}$	$H1_{(2,3)}$	$H1_{(3,4)}$	$H1_{(4,5)}$	$H1_{(5,6)}$
0	**1**	**5**	14	**9**	16
+1	5	7	**12.5**	25	22
-1	2.5	20	22	13.5	**7.5**
+2	12	8	21.5	34	30
-2	4	25	29	18	9
+3	25	16	34	48	37
-3	11.5	38	40	32	12

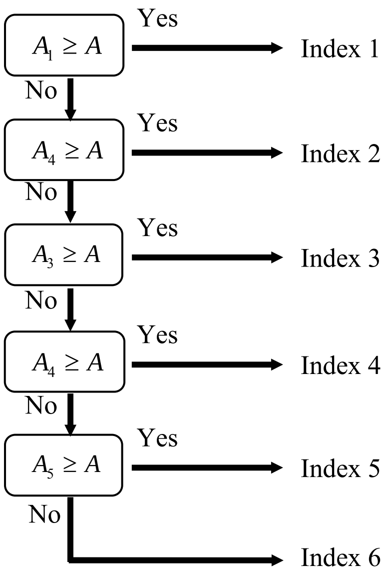


Figure 4. Maturity index classification rules

5 samples are misclassified for Index 2 and Index 5 while Index 1 and Index 6 samples are perfectly classified. Fortunately, the 600 samples, which have been classified earlier by the expert, are inaccurate. All the misclassified samples are then reclassified by the expert on the knowledge of the classification process perform in this work. Finally, the classification rules given in Figure 4 gives 100% of accuracy when the classification process is repeated. This shows that although the manual classification is performed by expert, confusion is unavoidable and machine vision approach can certainly avoid the confusion because it involves better precision of computation compared to human.

4. CONCLUSION

A linear one-dimensional color feature called hue (H1) has been introduced in this work to be used as input for starfruit maturity classifier. The purpose of using linear one-dimensional hue is to reduce the computational burden and computational complexity. The proposed hue (H1) has also proved to have the best class discriminant capability compared to the other color features discussed in this paper. Good class discriminant capability will ensure good classification accuracy. For the classification process, it is based on the hypothesis that for each maturity index, certain area of the starfruit surface is supposed to have distinctive value of the hue. Although a tedious process was performed searching for the best values of A and $H1_{(i,i+1)}$, the classification rules based on these values are fairly simple. The first classification process yielded 93% of accuracy. When the expert reclassifies the samples based on the second opinion from the first classification results, a perfect classification of 100% accuracy was obtained. The classification rules may also be designed using fuzzy logic approach where a simpler classifier design is expected.

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