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# Color Based Classification for Berries of Japanese Blue Honeysuckle

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# Color Based Classification for Berries of Japanese Blue Honeysuckle

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## Abstract

Japanese blue honeysuckle (*Lonicera caerulea* L. var. *emphyllocalyx Nakai*) is a unique form of edible honeysuckle that has exceptionally tasty berries. Visual characteristics of the berry such as the color of the skin and the presence of defects are the most decisive factors in determining its quality. An image analysis based methodology for classifying the berries under uncontrolled outside lighting conditions was developed. A color sheet with hue value around 29° was determined as the background to support the berries whose hue values were found near 212°. With the thresholding level computed by Otsu's algorithm in the red channel, berries were segmented from the background successfully. Three parameters, average and standard deviation of hue component and average of saturation component, were chosen as the best descriptions for each berry according to the Fisher's least significant differences test. Three canonical functions and corresponding group centroids of each function obtained by discriminant analysis were able to classify the berries aimed for fresh market, processing, and waste at success rates of 95.1%, 85.1%, and 94.3%, respectively.


**KEYWORDS:** defect, discriminant analysis, Fisher's least significant difference, skin

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## 1. INTRODUCTION

Japanese blue honeysuckle (*Lonicera caerulea* L. var. *emphyllocalyx Nakai*) is a high quality berry bush native to Hokkaido Island in Japan, and virtually unknown outside this region (Thompson, 2006). It was used by the Ainu aboriginal people of Hokkaido, for its medicinal properties (Tanaka et al., 1994).
It appears to be the berry of the future due to its ease of cultivation, very early maturity, unique flavor, and high nutritional value. However, as little information about Japanese blue honeysuckle is available, especially in English publications, few people outside Hokkaido know about it. This plant is easy to grow in areas not traditionally suited for agriculture, and its flowers can withstand temperatures of −10 ˚C at full bloom (Thompson and Barney, 2007). It produces fruit that ripens ahead of other berry varieties, assuring a ready market for customers who want fresh fruit in the early spring, extending the working period and reducing the economic risk for farmers. It provides a tasty berry for jelly, jam, juice, and can be frozen for adding to ice cream or yogurt, or eaten fresh. And its berry is high in vitamin C and phenolic compounds that have antioxidant properties (Jin et al., 2006).

Its production in Hokkaido is traditional. The berries are handpicked and sorted manually before being sent to fresh market and processors. However, this method is labor intensive, tedious and highly repetitive, and must be accomplished within the shortest harvesting season. Therefore, a new harvesting method was developed by exploiting items that are common in farm sheds or easily found in the market, with considering small scale of orchard in Japan and induced limited budget which farmers would invest on it (Fu et al., 2011). The blade of a wood-cutting jigsaw was changed to a special metal hock which can vibrate branches to separate berries. A portable tarp catch was made for collecting separated berries, constructed with light pipes which are connected by fittings and covered by tarp. An electric fan was used to blow foreign materials. This harvesting system increased average per-worker production from 4.1 kg/h (conventional hand picking) to 19.7 kg/h, while without much added cost since jigsaw is not only a cheap device for Japanese farmers but also widely used for making farming device, and pipes and electric fan are easily obtained.

However, the new harvesting method remains unripe and damaged berries which are needed to be classified before qualified berries being sent out. Compare to traditional hand sorting, many applications have been developed using artificial vision as a technique for fruit classification: olives (Diaz et al., 2000, 2004; Riquelme et al., 2008), peaches (Lleo et al., 2009), mangoes (Savakar and Anami, 2009), citrus (Blasco et al., 2007; Kondo et al., 2000), cherries (Rosenberger et al., 2004) and especially apples (Kavdir and Guyer, 2004; Zou et al., 2007, 2010).

However, there is a lack of studies on machine vision based classification for the berries of Japanese blue honeysuckle.

Until now, most machine vision based fruit sorting system were under controlled lighting conditions. Riquelme et al. (2008) lit olives with fluorescent lights with high color rending index (model TL/95; Phillips, Royal Philips Electronics of the Netherlands). In Chong et al.'s (2008) eggplant fruit grading system, the illumination sources was 50W halogen bulbs (Philips, diamond coated, 3,200˚K color temperature, 38˚ radiation angle) powered by 12V DC. However, considering the limited budget on Japanese blue honeysuckle, the sorting system for its berries should also be low cost. Therefore, the cost for lighting was disregarded by utilizing natural lighting in this research. Developing an image processing based algorithm for classifying berries under uncontrolled lighting conditions is more challenging because the variability associated with outdoor lighting conditions (Tang et al., 2000). Daylight varies greatly in intensity as well as in color temperature (Wyszecki and Stiles, 1982; Henderson, 1977).

In small fruits such as olives and berries of Japanese blue honeysuckle, classification is based on visual characteristics like the color of the fruit skin and the presence of defects. Diaz et al. graded the olives into four quality categories depending on the defects of the fruits. And Riquelme et al. classified the olives into seven categories according to external damage by using image analysis. When regarding the cost, images of fruit should be collected by the cheapest common red, green, blue (RGB) color camera. However, the directly obtained red, green, and blue components are greatly varied by imaging conditions, especially the lighting conditions (Steward and Tian, 1999). Therefore, a relatively stable color model should be employed for utilizing color information to classify this berry.

The objective of this study was to investigate the optimal background color for the berries of Japanese blue honeysuckle, then develop an segmentation method to extract them from the background, and last tries to obtain classification functions to classify the berries into different groups according to their color features.

## 2. MATERIALS AND METHODS

### 2.1. Fruit

According to the end use, the harvested berries of Japanese blue honeysuckle can be divided into three groups: fresh market, processing, and waste. On the other hand, based on the external appearance of a berry's skin which is the most decisive factor in determining its quality, the berries can be classified into seven classes: 'nondefective', 'insect damaged', 'scarred', 'broken', 'shrunk', 'under ripe (red)', and 'unripe (green)'. Among them, only the 'nondefective' can be sent to the fresh market, the 'insect damaged', 'scarred', 'broken', and 'under ripe (red)' will be used for processing, while the 'unripe (green)' and 'shrunk' need to be discarded as waste. Inside the group for processing, 'under ripe (red)' are different from the left in color appearance, and that also happened between 'unripe (green)' and 'shrunk' within the group of waste. Therefore, the berries are re-classified into five categories: 'nondefective', 'damaged' (including the 'insect damaged', 'scarred', and 'broken'), 'under ripe (red)', 'unripe (green)', and 'shrunk'.

A representative sample of 143 berries was selected to define the mathematical model (Table 1). The set was divided for calibration and validation test. The calibration set was built with those samples which could be clearly classified ($N$ = 73 for the calibration), while the rest of berries were used for the validation set ($N$ = 70).

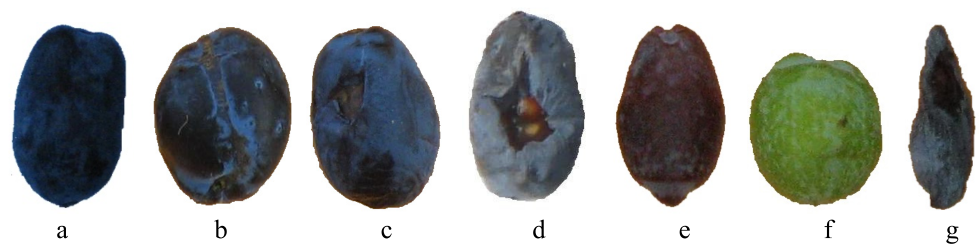



Fig. 1. Berries of Japanese blue honeysuckle are divided into seven groups based on the external appearance of fruit skin and the presence of defects: (a) 'nondefective', (b) 'insect damaged', (c) 'scarred', (d) 'broken', and (e) 'under ripe (red)', (f) 'unripe (green)', (g) 'shrunk'.

Table 1. Fruit number of each group in the calibration and validation sets

| Group | Calibration | Validation | Total |
|---|---|---|---|
| Nondefective | 31 | 30 | 61 |
| Insect damaged | 5 | 4 | 9 |
| Scarred | 5 | 5 | 10 |
| Broken | 4 | 4 | 8 |
| Under ripe (red) | 10 | 10 | 20 |
| Unripe (green) | 9 | 8 | 17 |
| Shrunk | 9 | 9 | 18 |
| Total | 73 | 70 | 143 |

## 2.2. Imaging system

Berry's images in RGB were acquired under static conditions with a single-sensor (one CCD: charge-coupled device) color camera (model Canon PowerShot A710, Canon Inc., Tokyo, Japan). In order to unify the lighting conditions for all images, they were taken at noon under shade lighting conditions. The distance between the object and the imaging system is 1 m.

### 2.3. Image processing

#### 2.3.1. Color model

As Gonzalez and Woods (1992) indicated, hue, saturation, and intensity (HSI) are general characteristics used to distinguish one color from another. The HSI color model decouples the intensity component from the color information, and the hue and saturation are related to the way in which human beings perceive color. Thus, the HSI model is an ideal tool for developing image processing algorithms based on some of the color sensing properties of the human visual system.

#### 2.3.2. Background color determination

The support for the fruit constituted the surrounding area of the fruit in the image, and obviously it should be of relatively high contrast to the fruit. The most often used dark background was unsuitable to the berries that are also dark. Moreover, this berry's red juice leaks out easily which excluded another often used bright background. Therefore, fourteen common color sheets that available in the market were bought to test as the backgrounds, as shown in Fig. 2.

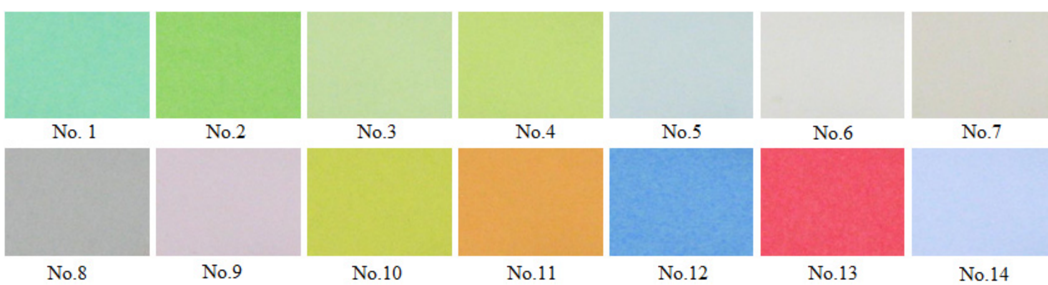



Fig. 2. The fourteen common color sheets that are available in the market

Table 2. The dates in which images were taken and the number of "nondefective' berries included

| Date of imaging | Number of berries |
|---|---|
| July 14, 2009 | 24 |
| July 17, 2009 | 28 |
| July 2, 2010 | 27 |
| July 16, 2010 | 32 |

For each background color sheet with the 'nondefective' berries on, a series of ten images were taken with different camera settings which changed in exposure compensation from -2 to +2 with the interval of 1 and with flash or without flash. Table 2 shows the dates on which images were taken and the number of berries included. The images were used to determine the color attributes of the berry and the fourteen background color sheets by analyzing pixels. The pixels were collected using an original sampling program, written in the programming language of C#, able to display RGB color images directly. After displaying each image, 1000 pixels of this berry were selected first by randomly clicking on the berry, followed by 1000 pixels of background. In order to avoid sampling the same pixel, a red mark appeared on the selected pixels which the color information was saved in a data file. Thus, definitions of the color of this berry and the fourteen color sheets could be obtained by analyzing distributions of the hue values that represents the dominant wavelength in a mixture of light waves. Based on the color wheel illustrating the relationships between hues, the background color could be selected.

### 2.3.3. Segmentation between berry and background

With the selected background color sheet, images of the 143 sampled berries were taken at the "AUTO" mode of the camera. To facilitate the following process, each image contained one berry.

The hue parameter is effective to segment the berry from the background, although, being a non-linear combination of the red, green, and blue values, it requires more computations. A RGB image contains all the information necessary to segment fruits from the background if the contrast is sufficient. Hence the contrast between berry and background was considered in red, green, and blue channels, respectively.

When the fruit is well contrasted against the background, fruit localization could be undertaken by classical supervised or unsupervised threshold techniques. The fruit area was separated from the background with the algorithm of Otsu (1979), which is a nonparametric and unsupervised method of automatic threshold selection for image segmentation, based on statistical and space information of histograms.

It was found that a simple thresholding was not enough, as the binary images showed one big elements (fruit area), and in some occasions, several little elements (due to shadows) in the background part of the images. Moreover, damages such as scarred and insect damaged parts would present holes in the fruit area. Thus, morphological operators were applied to eliminate noise and fill in the possible holes.

#### 2.3.4. Characterization of fruit images

After segmentation, the berries were characterized by different features taken from each fruit. The hue is a color attribute that describes a pure color, whereas the saturation gives a measure of the degree to which a pure color is diluted by white light. Both of them are considered to be very useful in image processing because their values are not affected by the difference in illumination while imaging. Therefore, the average and standard deviation of the hue and saturation components in the segmented fruit images contribute to the general description of the sampled berries, represented in *HueAvg*, *HueSdv*, *SatAvg*, and *SatSdv*, respectively. In addition, *Size* of each berry, which appeared in the pixels number on the fruit, was also included.

### 2.4. Statistical analysis for classification

Significant differences between groups of berries were determined using variance analysis (one-way ANOVA) which was performed by PASW Statistics 18 (SPSS Inc., an IBM Company, Chicago, Illinois, USA). Next, a Fisher's least significant differences (LSD) test was used to determine the significant differences between group means in an analysis of variance ($p \leq 0.05$). This test was applied to all parameters in order to reduce the amount of parameters analyzed.

Discriminant analysis technique was used in this work because it requires a low number of variables to create classification functions, a low computational power compared to other classifying techniques such as neural network, partial least squares and Mahalanobis distance, and it has yielded good results in previous studies (Valero et al., 2004; Hernandez-Sanchez et al., 2006). Therefore, the significant variables were introduced into a forward stepwise discriminant analysis to obtain the classification functions in successive steps. The priori probabilities to belong to each group were set as equal in all cases. The canonical function obtained is a linear combination of discriminating attributes, being the sum of raw canonical coefficients multiplied by the coefficients for each function. The validation of the model was performed with a sample of $N = 70$.

## 3. RESUTLS AND DISCUSSIONS

### 3.1. Background color determination

The hue values distribution of the 'nondefective' berries is as shown in Fig. 3, approaches to a normal distribution when disregard noise. The average hue value of all sampled berries image pixels is 212°. And the fourteen background color sheets' hue values, which are also distributed in normal distributions, are listed in table 3. According to the color wheel of hue, the background color sheets No. 7 (38°) and No. 11 (29°) were qualified since they are opposite to the hue value of fruit. Between them, No. 11 is closer to the color of berry's juice. Therefore, the color sheet No. 11 with hue value around 29° was determined as the background.

### 3.2. Segmentation between berry and background

The contrast between berry and background is more sufficient in the red channel than the blue and green channels, as shown in Fig. 4. With the thresholding level obtained by applying the Otsu's algorithm in the red channel, the fruit area was segmented from the background successfully. Next, a morphological opening operator with a disk-shaped structuring element considering a six-pixel radius was applied to remove noise from the image. Afterwards a morphological closing operator was used to fill in the possible holes presented in the segmented binary images. Therefore, the fruit area was completely separated.

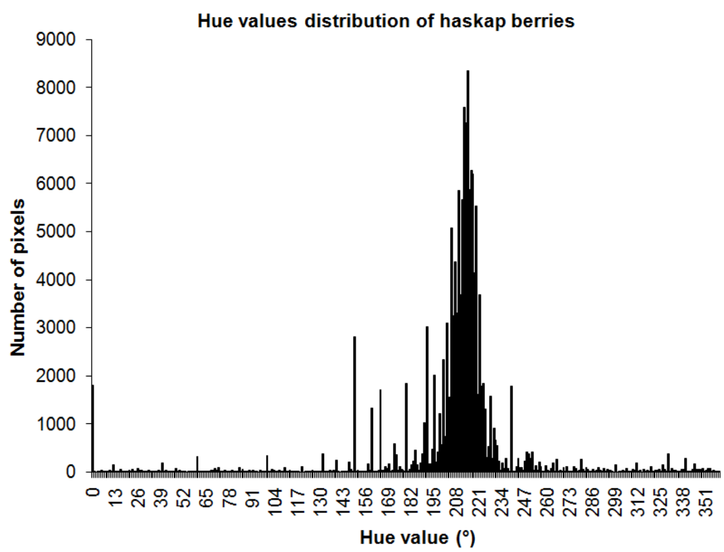
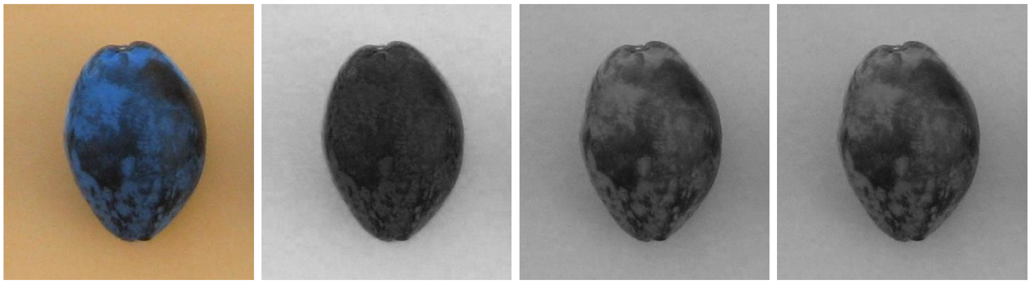



Fig. 3. Hue values distribution of sampled 'nondefective' berries pixels

Table 3. Hue values of the fourteen background color sheets

| Color sheet No. | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 10 | 11 | 12 | 13 | 14 |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Hue value (°) | 145 | 90 | 93 | 71 | 162 | 48 | 38 | 137 | 301 | 56 | 29 | 203 | 353 | 234 |



a b c d

Fig. 4. 'Nondefective' berry on the selected background sheet. (a) RGB color image, (b) red channel image, (c) green channel image, and (d) blue channel image.

### 3.3. Classification

Table 4 shows an ANOVA for the five parameters. Letters correspond to the LSD test. Data was arranged according to the average hue value of each sampled berry. Regarding color change with ripeness it was verified that: riper berries presenting higher hue values. A Fisher LSD test was used to determine the significant differences between group means in an analysis of variance, as shown in Table 4. The purpose of this test was to reduce the number of parameters analyzed, eliminating those variables which totally interrelated within homogeneous groups. Three parameters *HueAvg*, *HueSdv*, and *SatAvg* which scored the higher *F* of Fisher were chosen for the followed discriminant analysis.

Table 4. Results of ANOVA for berries classified into different groups studied

| Group | *N* | *HueAvg* | *HueSdv* | *SatAvg* | *SatSdv* | *Size* |
|---|---|---|---|---|---|---|
| Nondefective | 61 | 201 (4) $^{a}$ | 46 (7) $^{d}$ | 0.48 (0.05) $^{a}$ | 0.15 (0.01) $^{b}$ | 38814 (9313) $^{b}$ |
| Damaged | 27 | 190 (15) $^{a}$ | 71 (15) $^{c}$ | 0.33 (0.06) $^{b}$ | 0.15 (0.01) $^{bc}$ | 44026 (9896) $^{a}$ |
| Under ripe (red) | 20 | 121 (55) $^{b}$ | 133 (36) $^{a}$ | 0.36 (0.10) $^{b}$ | 0.16 (0.03) $^{b}$ | 26224 (4027) $^{cd}$ |
| Shrunk | 18 | 118 (34) $^{b}$ | 97 (27) $^{b}$ | 0.23 (0.06) $^{c}$ | 0.18 (0.03) $^{a}$ | 19695 (6063) $^{d}$ |
| Unripe (green) | 17 | 74 (12) $^{c}$ | 18 (8) $^{e}$ | 0.50 (0.08) $^{a}$ | 0.14 (0.02) $^{c}$ | 28998 (4612) $^{c}$ |
| *F* of Fisher | | 125 | 125 | 68 | 9 | 32 |

Mean (standard deviation)

*Note*. Different letters (*a*-*e*) determine the significant differences between group means; same letters in the same columns, there is no statistical significance between the groups ($p \leq 0.05$)

In the discriminant analysis, the calibration model was developed with 73 berries and three canonical functions were obtained to divide the berries into five groups, as shown in (1), (2), and (3). With the computed $f_1$, $f_2$, and $f_3$, berries were classified into different groups by comparing to the group centroids in each function, as shown in Table 5.

$$f_1 = 0.050 \times HueAvg - 0.050 \times HueSdv + 3.845 \times SatAvg - 6.290 \quad (1)$$

$$f_2 = 0.019 \times HueAvg + 0.015 \times HueSdv - 5.796 \times SatAvg - 1.690 \tag{2}$$

$$f_3 = 0.001 \times HueAvg - 0.041 \times HueSdv + 14.958 \times SatAvg - 8.908 \tag{3}$$

Table 5. Group Centroids of the five groups in each function

| Group | Function | | |
|---|---|---|---|
| | 1 | 2 | 3 |
| Nondefective | 3.161 | 0.011 | 0.388 |
| Damaged | 0.803 | 1.118 | -0.895 |
| Under ripe (red) | -5.378 | 0.607 | 1.730 |
| Shrunk | -4.533 | 0.647 | -1.443 |
| Unripe (green) | -1.631 | -3.096 | -0.422 |

The three canonical functions were analyzed by the chi-square test for determining which of them gives better discrimination, as shown in Table 6. The table contains the significant test for the three functions ($p$ < 0.01), being all significant. More parameters were also computed, as the eigenvalue (meaning the cumulative proportion of the variance explained by each function, a large eigenvalue is associated with a strong function), the canonical correlation (correlation between the discriminant scores and the levels of the dependent variable, a high correlation indicates a function that discriminates well), Wilks' lambda (contribution of each function to the overall performance, a small lambda indicates that group means appear to differ) and degree of freedom. In this case, all the three functions explain a high percentage of discrimination between groups.

Table 7 shows the classification result of calibration set and validation set. 'Unripe (green)' is perfectly segregated from the rest (100% calibration, 100% validation). For the 'nondefective', the only one would be sent to the fresh mark, are 96.8% in calibration and 93.3% in validation classified correctly, while the rest which account 4.9% in total are classified into the 'damaged'. The 'damaged' scores 85.7% in calibration and 76.9% in validation; the low score in validation may be due to red juice leaks out of some broken berries which are misclassified into 'under ripe (red)' (7.7%). Thus, 10.0% 'under ripe (red)' are grouped into 'damaged', while 80.0% in calibration and 90.0% in validation are successfully separated. Regarding the 'shrunk' group, 11.1% of both sets are wrong classified into 'under ripe (red)'. If re-classified all the sampled berries into three groups based on the end use, the success rates reach 95.1%, 85.1%, and 94.3% for berries aimed for fresh market, processing, and waste, respectively.

Nevertheless, there remains a problem that the percentage of the 'damaged' berries classified into the 'nondefective' group around 14.8% is still too high. It will affect Japanese consumer's acceptance even with little defects.

Therefore, it is necessary to develop another algorithm which can separate the 'damaged' from the 'nondefective' group in the future.

Table 6. The chi-square test with successive functions extracted for the discriminant analysis

| Function | Eigen-value | Canonical Correlation | Wilks' Lambda | Chi-square | Sig. |
|---|---|---|---|---|---|
| 1 | 12.014 | 0.961 | 0.015 | 286.572 | 0.000 |
| 2 | 1.636 | 0.788 | 0.192 | 112.082 | 0.000 |
| 3 | 0.973 | 0.702 | 0.507 | 46.180 | 0.000 |

Table 7. Berries were classified into different groups

| Dataset | Actual Group | Predicted Group Membership (%) | | | | |
|---|---|---|---|---|---|---|
| | | Nondefective | Damaged | Under ripe (red) | Shrunk | Unripe (green) |
| Calibration set | Nondefective | 96.8 | 3.2 | 0.0 | 0.0 | 0.0 |
| | Damaged | 14.3 | 85.7 | 0.0 | 0.0 | 0.0 |
| | Under ripe (red) | 0.0 | 10.0 | 80.0 | 10.0 | 0.0 |
| | Shrunk | 0.0 | 0.0 | 11.1 | 88.9 | 0.0 |
| | Unripe (green) | 0.0 | 0.0 | 0.0 | 0.0 | 100.0 |
| Validation set | Nondefective | 93.3 | 6.7 | 0.0 | 0.0 | 0.0 |
| | Damaged | 15.4 | 76.9 | 7.7 | 0.0 | 0.0 |
| | Under ripe (red) | 0.0 | 10.0 | 90.0 | 0.0 | 0.0 |
| | Shrunk | 0.0 | 0.0 | 11.1 | 88.9 | 0.0 |
| | Unripe (green) | 0.0 | 0.0 | 0.0 | 0.0 | 100.0 |

## 4. CONCLUSIONS

Developing an image analysis based algorithm for classifying the berries of Japanese blue honeysuckle under uncontrolled lighting conditions is the first step in developing an automatic sorting system. In this paper, the classification was based on the difference in the color features of the objects. The berries were divided into five groups: 'nondefective', 'damaged' ('scarred', 'insect damaged', and 'broken'), 'under ripe (red)', 'shrunk', and 'unripe (green)'.

By analyzing the hue values distribution which was obtained by sampling pixels from 'nondefective' berries, the color of this berry was found near 212°. The same method was used to investigate the optimal background color by testing the fourteen common color sheets that available in the market. One of them No.11 with the hue value around 29° was selected as the background to hold berries. With the thresholding level computed by Otsu's algorithm in the red channel, the berries were segmented successfully.

Three parameters, average and standard deviation of hue component, and average of saturation component, were chosen as the best descriptions for each berry. The three canonical functions and the corresponding group centroids of each function were able to classify 'nondefective', 'damaged', 'under ripe (red)',

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'shrunk', and 'unripe (green)' berries at success rates of 95.1%, 81.5%, 85.0%, 88.9%, and 100%, respectively.

This paper indicated that it is possible to classify the berries of Japanese blue honeysuckle under noon shade according to their color features by using imaging analysis with a RGB color camera. Using the methodology described, it was also probable to find the classification functions and group centroids. However, another algorithm which can separate the 'damaged' from the 'nondefective' group needs to be developed in the future.

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