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Surface color distribution analysis by computer vision compared to sensory testing: Vacuum fried fruits as a case study

Fitriyono Ayustaningwarno [a,b,c], Vincenzo Fogliano [a], Ruud Verkerk [a], Matthijs Dekker [a,*]

[a] Food Quality and Design, Wageningen University & Research, Bornse Weilanden 9, 6708 WG Wageningen, the Netherlands
[b] Department of Nutrition Science, Faculty of Medicine, Diponegoro University, Jalan Prof. Soedarto, SH Tembalang, Semarang, 1269 Jawa Tengah, Indonesia
[c] Center of Nutrition Research, Diponegoro University, Jalan Prof. Soedarto, SH Tembalang, Semarang, 1269 Jawa Tengah, Indonesia

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ABSTRACT

Color is a main factor in the perception of food product quality. Food surfaces are often not homogenous at micro-, meso-, and macroscopic scales. This matrix can include a variety of colors that are subject to changes during food processing. These different colors can be analyzed to provides more information than the average color. The objective of this study was to compare color analysis techniques on their ability to differentiate samples, quantify heterogeneity, and flexibility. The included techniques are sensory testing, Hunterlab colorimeter, a commercial CVS (IRIS-Alphasoft), and the custom made CVS (Canon-CVS) in analyzing nine different vacuum fried fruits. Sensory testing was a straightforward method and able to describe color heterogeneity. However, the subjectivity of the panelist is a limitation. Hunterlab was easy and accurate to measure homogeneous samples with high differentiation, without the color distribution information. IRIS-Alphasoft was quick and easy for color distribution analysis, however the closed system is the limit. The Canon-CVS protocol was able to assess the color heterogeneity, able to discriminate samples and flexible. As a take home massage, objective color distribution analysis has a potential to unlock the limitation of traditional color analysis by providing more detailed color distribution information which is important with respect to overall product quality.

1. Introduction

Food color and color distribution, in raw and processed products, are one of the key sensory quality characteristics for consumers and determine the acceptation of a food product. Therefore, color assessment is highly relevant in the total quality assessment of food products (Krokida, Oreopoulou, Maroulis, & Marinos-Kouris, 2001). Efforts to measure color of foods have been done using a variety of methods with the final aim of product quality analysis and standardization. Color analysis by sensory testing has been done for quality control of food production. Visual evaluation of color via sensorial experiments is valuable as it can be expanded to the consumer's demands and satisfaction. However, in general sensory testing has some limitations, including subjectivity, response variation and limitation in the number of samples (Borràs et al., 2015).

Instrumental quality control such as colorimetry is applied to overcome these limitations and provide better standardization. The tristimulus colorimeter became the most popular tool to analyze color thanks to the easiness of use and the wide application in color measurement. L*a*b* color space has been used widely by the food industry for measuring color; L* for the lightness (black to white), a* for green to red, and b* for blue to yellow (Wrolstad & Smith, 2010).

Conventional instrumental analysis uses a homogeneous or homogenized sample and it gives three coordinate of color in L*a*b* that represent one color as the average color of a product (Wexler, Perez, Cubero-Castillo, & Vaillant, 2016). However, in many cases the food matrix and surface are not homogenous but have different structures at micro-, meso-, and macroscopic scales (Capuano, Oliviero, & van Boekel, 2017). These structures could undergo changes during food processing and produce different local colors.

These different colors on the surface of a food can be analyzed by measuring the color distribution and this could provide more in-depth information than just the average color. Computer vision systems have become more popular as they enable to analyze the whole food product on a pixel-based level. Computer image analysis is very useful to compare samples; pictures are analyzed by various software tools (like imageJ and Adobe® Photoshop®) to get a value of color differences

* Corresponding author at: Food Quality and Design, Wageningen University & Research, Bornse Weilanden 9, 6708 WG Wageningen, the Netherlands.
E-mail addresses: ayustaningwarno@fk.undip.ac.id (F. Ayustaningwarno), vincenzo.fogliano@wur.nl (V. Fogliano), ruud.verkerk@wur.nl (R. Verkerk), matthijs.dekker@wur.nl (M. Dekker).

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Nomenclature

RGB2Lab R function to convert L*a*b*color into RGB color, input and output should be in matrix formula
$[R', G', B']$ data of RGB values (points with R, G and B values in 0–1)
$[R, G, B]$ data of RGB values in 24 bit (points with R, G and B values in 0–255)
$[R_6, G_6, B_6]$ data of RGB values in 6 bit (points with R, G and B values in 0–3)
$[R_{24}, G_{24}, B_{24}]_6$ data of RGB values in 24 bit (points with R, G and B values in 0, 85, 170, 255)
$[R_{12}, G_{12}, B_{12}]$ data of RGB values in 12 bit (points with R, G and B values in 0–15)
$[R_{24}, G_{24}, B_{24}]_{12}$ data of RGB values in 24 bit (points with R, G and B values in 0, 17, 34, …, 255)
$[R_{24}, G_{24}, B_{24}]$ data of RGB values in 24 bit (points with R, G and B values in 0–255)
Lab2RGB R function to convert RGB color into L*a*b* color, input and output should be in matrix formula
$[L, a, b]$ data of L*a*b* values (L should scale in 0–100, and (a,b) in $(-110) - 110$)
$[L, a, b]_a$ data of L*a*b* values without halo (L should scale in 0–100, and (a,b) in $(-110) - 110$)
$[L, a, b]_b$ data of L*a*b* values without background (L should scale in 0–100, and (a,b) in $(-110) - 110$)
$\approx$ rounding operator

between samples. This approach has been used for raw food products e.g. in plantain (Akinpelu et al., 2014), apple (Mariscal & Bouchon, 2008) and potato (Franco Pedreschi, León, Mery, & Moyano, 2006; Pedreschi, Mery, Bunger, & Yañez, 2011).

Instrumental color distribution analysis has been done for food for a variety of applications such as, sorting date maturity (Zhang, Lee, Tippetts, & Lillywhite, 2014), and melon maturity (Ahmad, 2017), or assessing quality of fresh-cut lettuce (Pace, Cefola, Da Pelo, Renna, & Attolico, 2014). Applications of color distribution analysis for more complex food products are microwaved pizza (Yam & Papadakis, 2004), and analysis of changes in surface color of chocolate (Briones & Aguilera, 2005). Goñi and Salvadori (2017) developed a computer vision system (CVS) and compared the color analysis with the conventional portable tristimulus colorimeter (Minolta CR-400) for 40 samples of raw and processed foods. Both systems provided equivalent results for most samples. Though, the color measured by the image analyses technique appeared to be more like the real ones.

A commercial computer vision system, named IRIS-Alphasoft, to perform color distribution analysis has recently been released and tested for different food applications; quality control of cooked ham (Barbieri et al., 2016), analysis of fish sauce (Nakano et al., 2018); origin identification of honey (Di Rosa, Leone, Scattareggia, & Chiofalo, 2018), to discriminate marine fish surimi (Zhang et al., 2017). This commercial photo box and software (IRIS-Alphasoft) can be operated with minimum knowledge and training, and appeared to be valuable in controlling the manufacturing processes and product quality of foods. Ayustaningwarno, Vitorino, et al. (2020) developed and applied a similar system to analyze the effect of ripening stages and frying temperature on the color of vacuum fried mango, and developed a kinetic model to describe the changes in color distribution (Ayustaningwarno, Verkerk, Fogliano, & Dekker, 2020).

Although many studies on color and color distribution analysis have been done, they were mostly done with a single-color analysis, without proper comparison between methods. Since the proper comparison between color analysis methods was not available, industries and interested parties require a specific color analysis method could have difficulties to choose a suitable color analysis method for them.

Based on those backgrounds the objective of this study was to compare various color analysis techniques on the ability to differentiate vacuum fried fruit samples, with emphasis on quantifying heterogeneity, and flexibility. The investigated techniques are sensory testing, the Hunterlab colorimeter, the CVS (IRIS-Alphasoft), and the self-developed CVS (Canon-CVS) in analyzing nine different types of vacuum fried fruits.

2. Materials and methods

2.1. Raw material

Vacuum fried apple, banana, jackfruit, pineapple, mango, salak, starfruit, and rambutan were purchased online from CV. Putri Alin Jaya, Batu, Indonesia (https://anekakeripikbatu.wordpress.com/) within their shelf life. These fruit chips were produced from fresh fruits and vacuum fried directly after order using coconut oil, and shipped within one week to Wageningen, The Netherlands to be analyzed. Vacuum fried durian within the shelf life was purchased online from CT Fruit Factory and Farm CO., LTD, Khao Saming, Thailand (https://www.orientalwebshop.nl/durio-durian-chips-sweet-75 g). It was vacuum fried with palm oil and sugar coated.

All vacuum fried fruits were packed in multilayer plastic and aluminum primer packaging with nitrogen filled to ensure stability during storage from moisture migration, microbial activity, and color changes. Furthermore, nitrogen filling also protects the product from physical damage during handling and storage. Once the packages were opened the fruit pictures were taken within two hours to minimize color changes.

2.2. Color analysis

As a novel approach, nine vacuum fried tropical fruits were used to compare four color analysis methods on the ability to differentiate vacuum fried fruit samples, with emphasis on quantifying heterogeneity, and flexibility.

2.2.1. Sensory testing

In total thirty seven panelists with an age of 21–54 year participated in the sensory testing based on their ability to rank the intensity of colors with the Farnsworth–Munsell 100 hue test (Everitt, 2018). Thirty panelists with an average score (16–100 errors) and 7 panelist with superior score (less than 16 errors) (Munsell Color, 2020) from 11 different nationalities, including Chinese, Dutch and Indonesian. Compensation in the form of a gift card of 15 euro is provided to each panelist after completion of the whole survey.

The tests were done by comparing the nine different vacuum fried fruit types with the Royal Horticultural Society (RHS) color chart containing 920 different colors (Sharma & Thakur, 2016). Each panelist had to judge ten randomized chips. In total twenty chips from each of the nine fruits was used in the tests. The tests were performed in duplicate. In total 180 chips were used, and 370 judgements were taken.

There were two types of color analysis performed by the panelist, namely overall color and color distribution (Supp. 1). To assess the individual ability to perceive overall color, the panelist should describe the color of the sample into a color from the RHS color chart. The obtained color information was converted into the L*a*b* color space (Gábor, 2016) and further converted into 12 bit color depth (eq. (1)–(4)) to produce pie charts. Frequency of a color was selected by the panelist used to produce the pie chart. A PCA chart was produced using L*a*b* values.

To assess the individual ability to perceive the color distribution within one sample, the panelist should pick three colors present on the surface and give the percentage of surface area for all three colors with the total composition of 100%. The obtained color information was converted into the L*a*b* color space (Gábor, 2016). In order to keep the color distribution information simple, the color depth was further converted into 6 bit (eq. (1), (2), (5), (6)). The average percentage of all colors observed per fruit was used to produce a pie chart. The percentage of each color of each fruit was used to produce PCA chart.

$$[R^{'}, G^{'}, B'] = Lab2RGB[L, a, b] \tag{1}$$

$$[R, G, B] = [R^{'}, G^{'}, B'] \times 255 \tag{2}$$

$$[R_{12}, G_{12}, B_{12}] \approx [R, G, B] \times \frac{15}{255} \tag{3}$$

$$[R_{24}, G_{24}, B_{24}]_{12} \approx [R_{12}, G_{12}, B_{12}] \times \frac{255}{15} \tag{4}$$

$$[R_6, G_6, B_6] \approx [R, G, B] \times \frac{3}{255} \tag{5}$$

$$[R_{24}, G_{24}, B_{24}]_6 \approx [R_6, G_6, B_6] \times \frac{255}{3} \tag{6}$$

2.2.2. Hunterlab

The Hunterlab Colorflex benchtop spectrophotometer was used to measure color of the vacuum fried fruits (Supp. 2A). Commonly homogenized samples are required (Iciek & Krysiak, 2009). Samples were milled using a small laboratory Waring blender, then further homogenized with the Fritsch vibratory ball mill (Ranasalva & Sudheer, 2018). The milled material can have a color different from the surface since also the inside of the material is exposed. Then the powdered sample was poured into the sample cuvette for 1 cm high and compacted using a tamper tool. After the machine was standardized with black and white tiles, the cuvette with sample inside was measured three time with turning the cuvette, with three replications and expressed in L*a*b* color space.

2.2.3. IRIS-Alphasoft

A visual analyzer (VA400IRIS, Alpha MOS, France) was used to take pictures of the fried fruit samples and analyze the data. The instrument is equipped with a CCD camera with resolution of 2592 × 1944 pixels and 24 bit (Barbieri et al., 2016). The camera was mounted in a light box equipped by top and bottom lightning (each position using 4x4 White LED) (Tretola et al., 2017) which was stabilized for 15 min before used; however since the sample was too thin, and become transparent, only top lightning was used (Di Rosa et al., 2018). The camera was equipped with a 25 mm f1:2.2 Basler lens by Fujion. The system was calibrated using Xrite Colour Checker Passport. The color sensor data were acquired with Alphasoft, version 16.0 and the background was removed using HSV color space (Hdioud, Mohammed, Rachid, & Faizi, 2018). The data were then analyzed with Principle Component Analysis (PCA) and creating histograms using R (Supp. 2B).

2.2.4. Custom made CVS

A novel visual analyzer was developed and described in detail. This visual analyzer was used to take pictures of the fried fruit samples and analyze the data. The system consists of two parts; the first part is the image acquisition system (Canon) and the second part is the software (CVS) (Fig. 1).

Images of vacuum fruit chips were taken using a color digital camera (Canon 1000D with Canon EFS 18-55 mm F3.5-5.6 IS lens, at 55 mm). This camera was mounted 25 cm from the product on Kaiser RT1 base with light sets inside a closed picture chamber (118 cm wide, 108 cm tall, 85 cm depth) made with thick card box laminated with white paper (Supp. 2). The light used was produced by 2 × 36 W 5400 k 40hz fluorescent light for each side mounted at 45° after 15 min of heating time, 45 cm from the sample. The fluorescent lights used have a color reproduction index (CRI) of 90–100 (Kaiser Fototechnik Gmbh & Co. Kg, 2021) which is able to reveal the colors of various objects faithfully in comparison with an ideal or natural light source.

Pictures were taken at f16 aperture with 1/15 s exposure time. The small aperture was needed to allow enough light to the camera since the exposure time was fixed. The slow exposure time was needed to eliminate the flicker produced by the fluorescent light, exposure time at 1/15 s able to receive about 2.67 light wave, so the wave signature produced by the fluorescent light flicker was eliminated. However, the exposure time cannot be slower since the aperture cannot be smaller. Pictures were taken remotely through the EOS Utility to avoid camera shaking.

Color calibration was done using Xrite Color Checker Passport and Adobe Lightroom to produce a calibrated tiff file. Then the image background was removed using quick selection tool and color decontamination tool from an image processing software (Adobe Photoshop

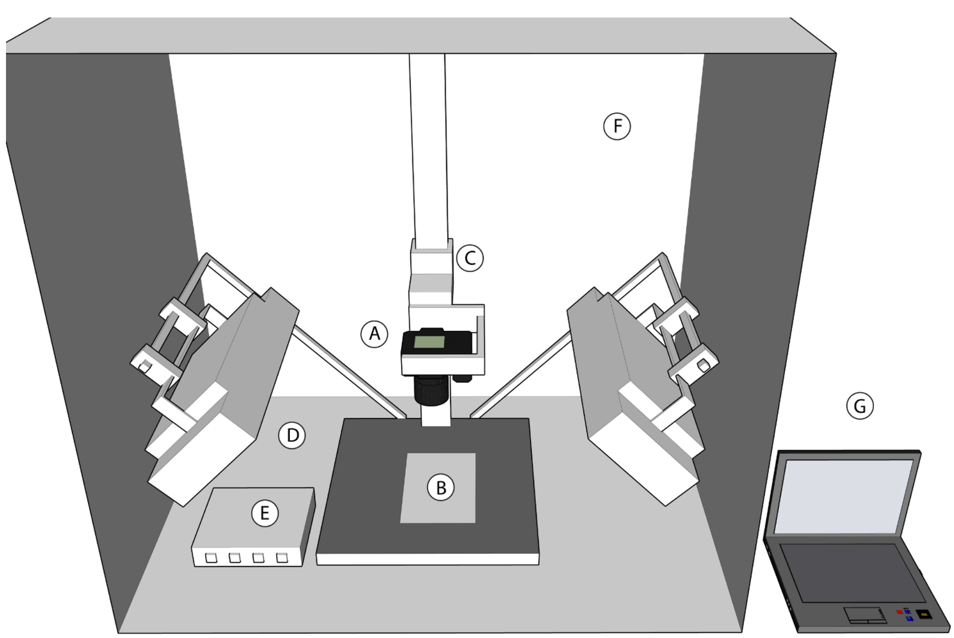

Fig. 1. Camera booth design. (a) Camera. (b) Sample. (c) Camera mount. (d) Light source. (e) Light controller. (f) Photo box. (g) Camera controller.

CC 2015) and the resulting image was saved into a tiff file. The tiff images were then analyzed using Wu (1992) color quantization method from Color Inspector 3D v 2.3 plugin (Barthel, 2006) within Fiji (Schindelin et al., 2012), an Image J 1.52 g repository (Rueden et al., 2017).

The obtained data from Color Inspector 3D was a look up table which contain information of 256 colors in a 24 bit RGB color space and how many pixels in the image are having that color within the sample (Fig. 1). Color Inspector 3D has been used in multiple fields such as in food chemistry to identify food dyes (Benkhelifa et al., 2019), also to quantify colors in dark field microscopy (Asiala, Marr, Gervinskas, Juodkazis, & Schultz, 2015). This RGB coordinate was 24 bit color depth which contains 16 million color combinations (Burger & Burge, 2016a). To make the color quantification more viable, a color conversion to a lower color depth was applied (Supp. 3). The 24 bit colors was reduced into 6 bit (eqs. (5) and (6)) and 12 bit (eqs. (3) and (4)) (Burger & Burge, 2016b). The obtained RGB color table was converted into *L* a* b** values using RGB2Lab function within the patchPlot package in R (Bruneau, 2013) (eqs. (7) and (8)). To eliminate halo (a white background artifact around the sample images), eq. (9) should be used, and to eliminate background, eq. (10) should be used.

$$[R^{'}, G^{'}, B'] = [R, G, B] \times \frac{1}{255} \tag{7}$$

$$[L, a, b] = RGB2Lab[R^{'}, G^{'}, B'] \tag{8}$$

$$[L, a, b]_a = [L, a, b] \quad with\ L^{''} < 99 \tag{9}$$

$$[L, a, b]_b = [L, a, b]_a \quad with\ L' > 0 \tag{10}$$

2.3. Data analysis

Data handling and data analysis was done using R. PCA analysis was used to identify each color analysis procedure discrimination performance and the percentage of variance in the sample explained by the color measurement (Westad, Hersleth, Lea, & Martens, 2003).

3. Results and discussion

The new and meaningful finding obtained during method comparison used to systematically compare the various color analysis methods and emphasize their pros and cons.

3.1. Sensory testing

Color analysis in the sensory testing by 37 panelists was done to describe overall color and color distribution of nine commercial vacuum fried fruits as shown in Fig. 2. Overall color analysis by sensory testing was done by selecting a color within the 920 colors of the RHS color chart which represents the overall color of the sample.

Despite the panelists were selected to have an appropriate color discrimination ability, when they analyzed the fruit, each panelist had a different perception of the color of the samples, which lead to a variety of colors perceived among the panelists (Fig. 3A). Furthermore, an actual color variation within the 20 samples per fruit will add to the variation in the observed colors. After a color conversion to 12 bit, we observed that a specific color was chosen by a majority of panelists for each fruit as shown in Fig. 3A. In Fig. 6B apple, banana, and durian were grouped together based on their light yellow; jackfruit, mango, pineapple, salak, and starfruit were grouped based on their orange color, and rambutan was separated because it has a dark brown color. However, the groups overlap considerable. From this result we learn that the overall color analysis by sensory testing can be done easily with help of a color chart, but it is not very discriminative (Fig. 3B).

During color distribution analysis by the sensory test, the panelists were able to perceive that the color of the sample was heterogenous, and they matched the different colors of the sample with the colors of the color chart. In the Fig. 4A, we can find that the major area of apple, banana and durian was light yellow (color 47); the major area of jackfruit, mango, pineapple, salak, and starfruit was orange (color 27); and the majority area of rambutan was dark brown color (color 22). This result showed that the color distribution analysis could give more information of the surface color of the fruit. The method showed that each fruit has a variety of colors. Apple does not only consist of light yellow (color 47), but also of darker yellow (color 43) which reflects the core of the apple. In banana, the method also could detect color variance coming from different colors of the core of banana being dark yellow (color 43) and black color (color 21). The method also could reveal the green color (color 10, and 26) which was the outer skin of the starfruit. This method enables quantification of the heterogeneity of vacuum fried fruit samples as shown in Fig. 4A.

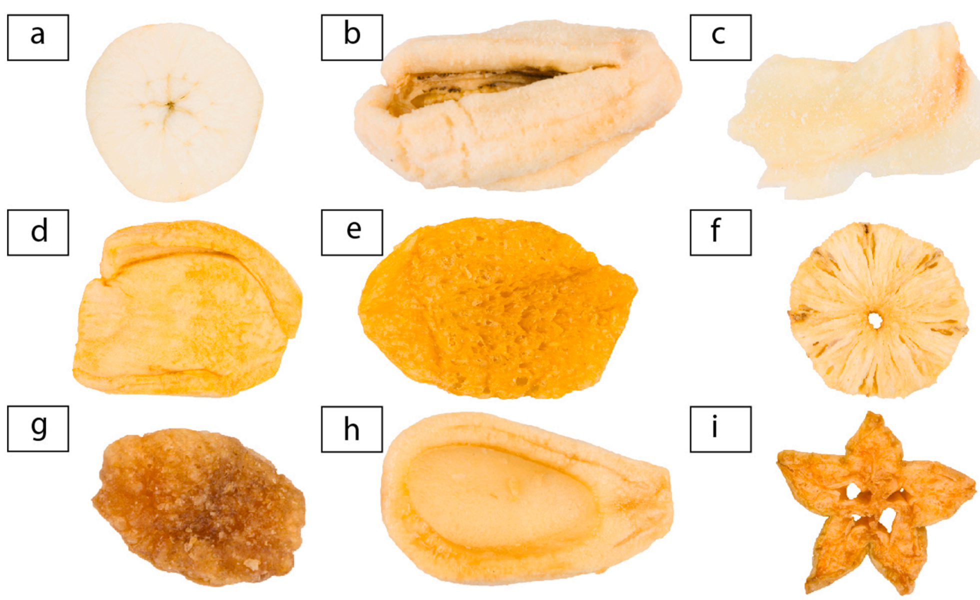

Fig. 2. Images of nine vacuum fried fruits: (a) Apple. (b) Banana. (c) Durian. (d) Jackfruit. € Mango. (f) Pineapple. (g) Rambutan. (h) Salak. (i) Starfruit. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

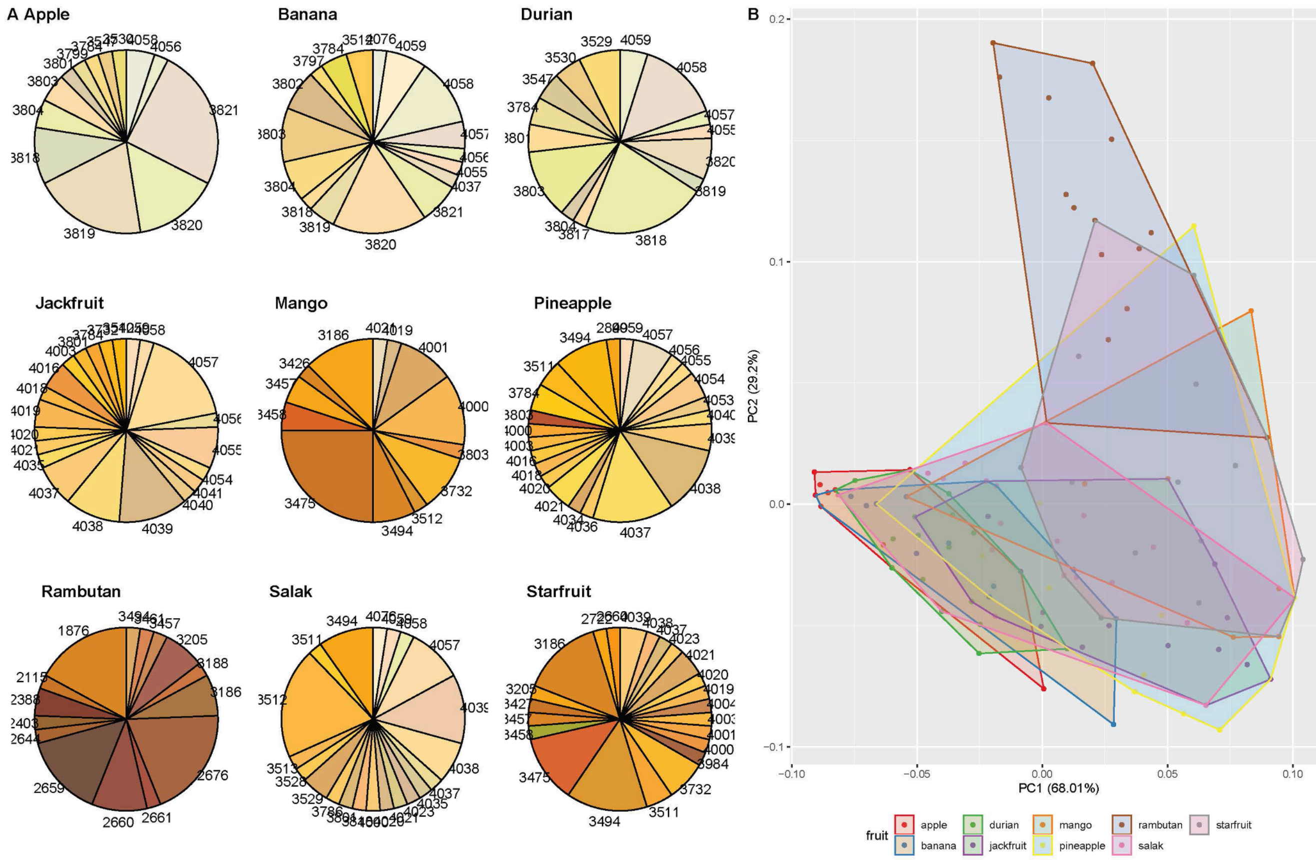

Fig. 3. Overall color by sensory test. (A) The frequency of a color chosen by panelists to describe overall color of fruit chip samples in 12 bit codes. (B) PCA plot of the L*a*b* value of fruits chips. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

The PCA analysis indicates that it is impossible to tell if one fruit is different from another by the sensory color distribution results (Fig. 4B). This result implies that color distribution analysis in a sensory testing is not suitable to use for a quality control procedure related to color inhomogeneity. However, since the method is fast and easy, this method is still widely used in small scale industry, e.g. to evaluate defects in cheese (Ojeda et al., 2015).

Sensory testing is a flexible method which can be customized depending on the product characteristics and the features which needs to be extracted from the sample. A wide range of color chart options are available to match the color range of the sample, such as the Pantone color chart (Arias-Carmona, Romero-Rodríguez, Muñoz-Ferreiro, & Vázquez-Odériz, 2012).

3.2. Hunterlab

A common instrumental method used to measure color is the colorimetric measurement using Hunterlab. Hunterlab readings were translated into 12 bit described in Supp 2 in order to visually show the color registered by the instrument. The result shows that the main color of apple, banana, durian, jackfruit and salak was brown, and the main color of mango, rambutan, and starfruit was dark brown (Fig. 5A). This color reading was darker compared with the overall sensory analysis result. The difference could be attributed to the homogenization process which mixes light and dark color areas and also mixes the surface material with internal tissue and oil which was not visible during the sensory observation (Arsoy, Ersoy, Evcin, & İçduygu, 2017). The L*a*b* values produced by the analysis was used directly to test the capability of Hunterlab to successfully differentiate fruit colors via the PCA test, having a very high variance contribution of the first two components (Fig. 5B). However, during the sample preparation, the sample was homogenized, so only one average color was obtained and it was not possible to describe the color distribution of the sample (Ranasalva & Sudheer, 2018). The Hunterlab can be an option to evaluate the overall color analysis in a simple way, however it cannot produce a color distribution analysis. Even though the system was able to differentiate samples very well as described in Fig. 5B.

3.3. IRIS-Alphasoft

The IRIS-Alphasoft is a computer vison analysis system in a controlled picture box, and measures the colors as a portion of the sample surface using the Alphasoft software. The color information was given in a number as a code for a specific RGB coordinates in 12 bit which can be displayed as a histogram with the color numbers on the X-axis and the percentage of color within the sample on the Y-axis Y, with a 2% threshold to reduce the complexity of the histogram (Barbieri et al., 2016).

The IRIS-Alphasoft analysis was able to describe the color distribution of vacuum fried fruit (Fig. 6A). Vacuum fried apple was described as having 30.4% of light pale yellow (color 4075) as the most abundant color which comes from the apple flesh. The system also measured a more dark color (color 4076) for 13.9% which represents the core of the apple. Vacuum fried pineapple was described as 13.1% of bright orange (color 3782) as the pineapple flesh. The system also measured 1.3% darker color (color 3216) as the eyes of the pineapple. Since the proportion of the eyes of the pineapple to the whole surface area is low, the color threshold should be decreased to 1% to make the color available in the graph.

The colors and the percentages were analyzed by PCA (Fig. 6B) to discriminate the samples. The system groups yellowish fruits, which consist of salak, pineapple and jackfruit (Fig. 6B). Furthermore, the

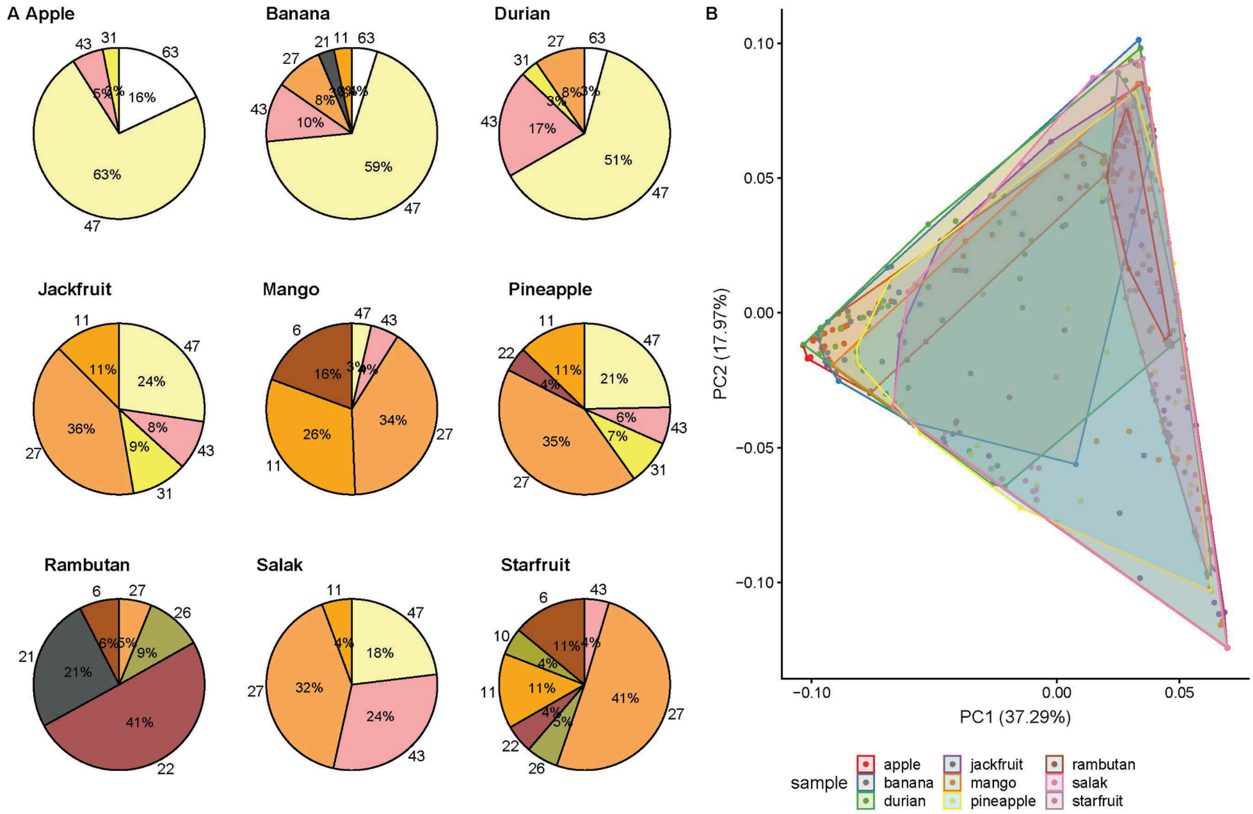

Fig. 4. Color distribution analysis by sensory testing for nine different fruit samples in 6 bit codes. (A) Perceived color and area perceived. (B) PCA analysis on perceived color and area. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

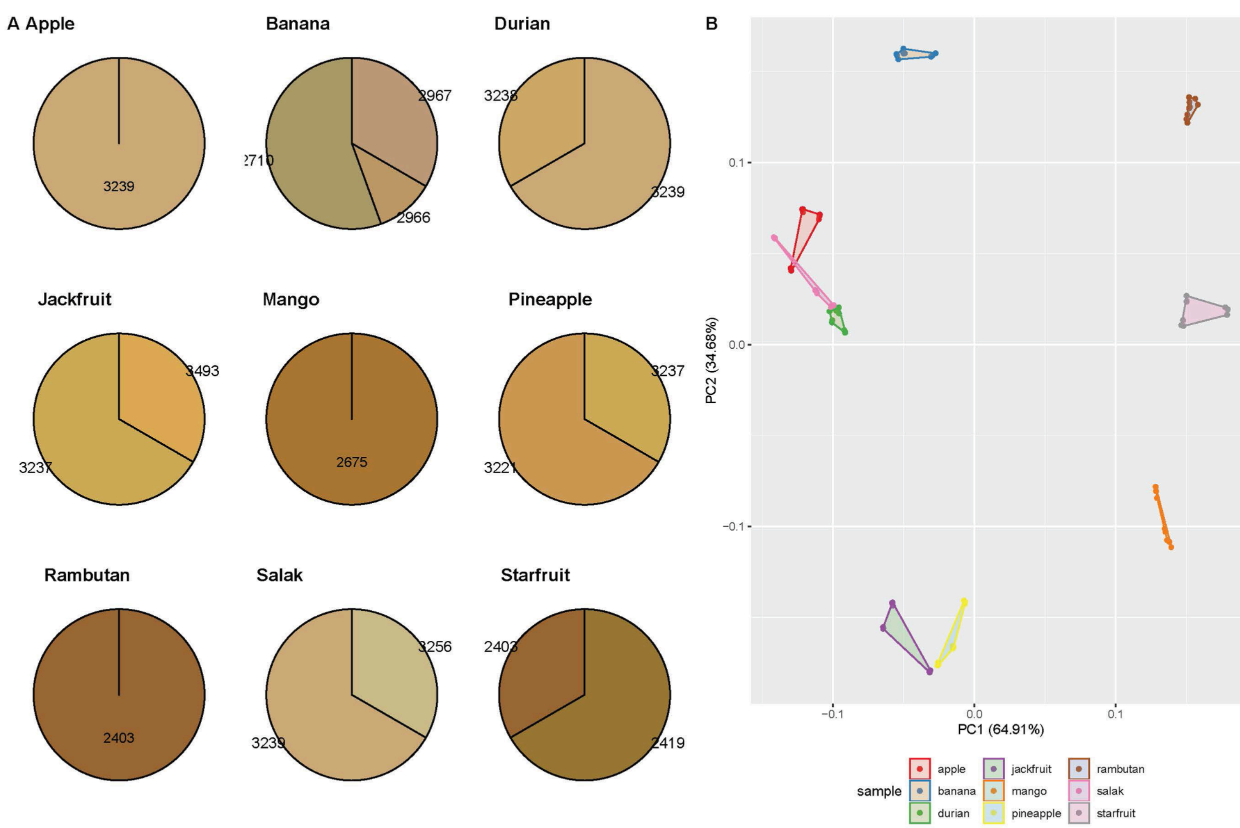

Fig. 5. (A) The frequency of a color measured by Hunterlab 6 bit for nine different fruit samples. (B) PCA plot of the L*a*b* value of fruits chips by Hunterlab. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

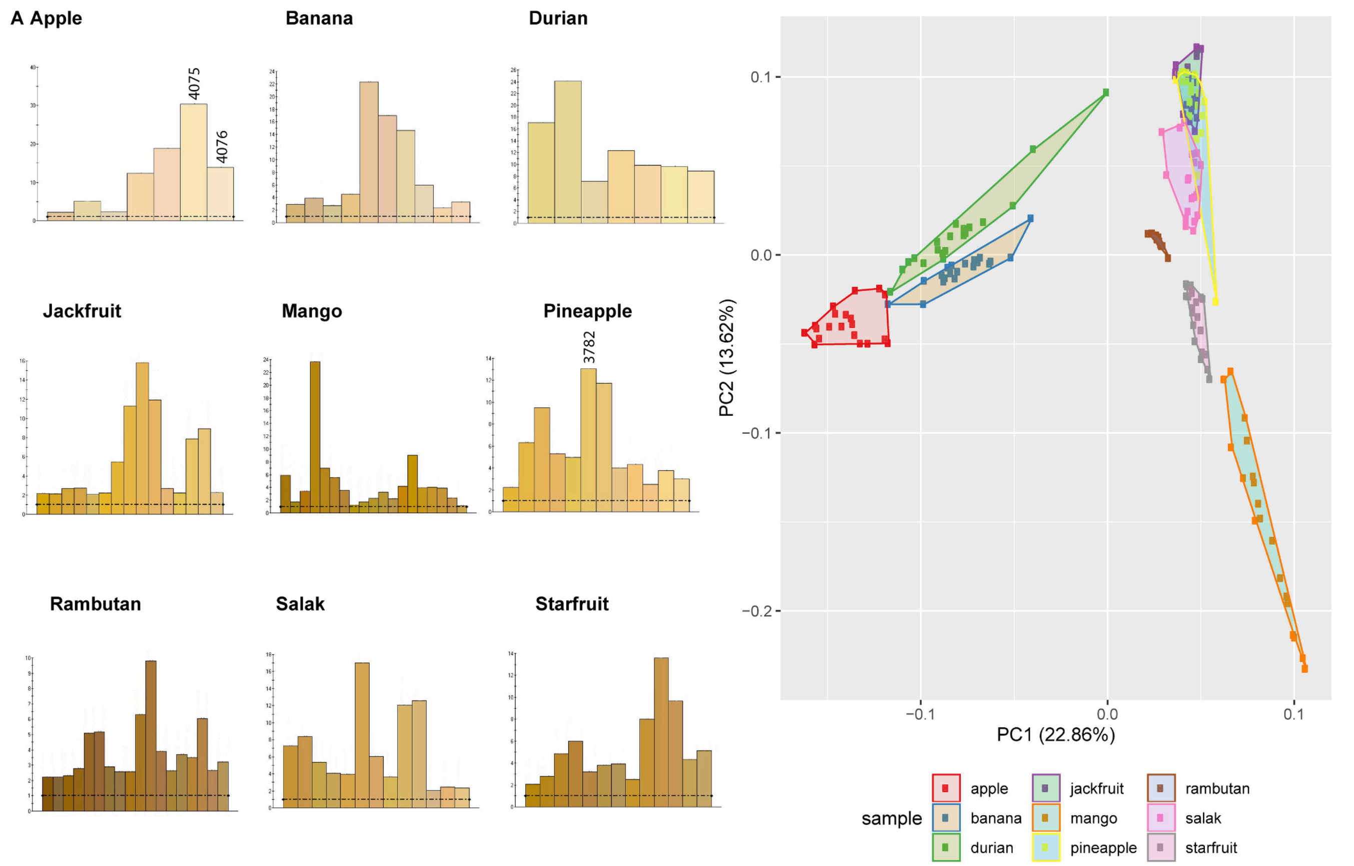

Fig. 6. (A) Color distribution result from vacuum fried fruit by IRIS-Alphasoft. (B) The PCA plot from nine different fruits. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

system describes a low percentage of variance of 36.48% (22.86% for PC1, and 13.62% for PC2), which may possibly produce a high error during interpretation of the data (Kánya, Forgács, Cserháti, & Illés, 2006).

This commercial photo box is a fast and easy protocol to perform color distribution analysis, and therefore suitable to analyze high number of samples and requires little training for the operator. However, since the data processing within the IRIS-Alphasoft is a closed system, the researcher is barely able to process the raw data into other forms, for example to decrease the color depth, from 12 bit into 6 bit in the heterogenous sample; or to use full color 24 bit colors, in highly homogenous sample.

3.4. Custom made CVS

The Canon-CVS was used to carry out color distribution analysis in a more flexible manner. The camera and lens used in the Canon-CVS can be substituted by any brand which can produce a raw file format and can be color calibrated by Xrite Color Checker Passport and Adobe Lightroom, while the IRIS-Alphasoft is only able to use a limited option of lenses. The lens focal length can be adjusted according the size of the sample. Initially, the Canon-CVS produce 24 bit and combined with resolution of 10.1 Mega pixel picture produced a highly detailed picture. Analyzing all of the 24 bit color will requires a high computing power. So, the color depth of the color analysis can be adjusted from 12 bit to the 6 bit colors depending on the color homogeneity. Highly inhomogeneous samples require low color depth. Meanwhile, low variety samples require a higher color depth. However, 64 color depth produced a less realistic color (Fig. 7) than 12 bit color (Fig. 8). Images with 12 bit color looks realistic, however a color reduction to 6 bit leads color which first appeared in 12 bit colors becoming merged into nearby color which fit in 64 color, which mean there was 4032 colors lost. The 64 colors produced sometimes was not the real color of the sample, but the color which lost in the conversion process and merged to the nearby color.

Specific attention should be given to the durian fruit chip sample which was sugar coated. In the sensory analysis, respondents reacted in various ways. In the overall color analysis, only a few panelists mentioned the bright color as the overall color, and the majority of the panelists mentioned the darker color of the chips. However, in the color distribution analysis, a 3% area was registered as very bright (color 63) which could come from the sugar-coating color. The Hunterlab could not retrieve this information. While the IRIS - Alphasoft seemed not to produce a color which matched with the color of the sugar, and the same result obtained with the Canon-CSV at 6 bit. But, at 12 bit, the whitish color was detected in a small portion. This comparison show the advantages of the color distribution analysis to describe specific features of a sample. Probably the IRIS – Alphasoft could not detect this color because of the low resolution of the camera, which was improved by the Canon-CVS. But only the Canon-CVS with a 12 bit process was able to detect this feature, and not with the 6 bit process. This result suggests that color depth plays an important role, 12 bit was the lowest color depth to capture this feature.

The system was able to describe the color distribution of vacuum fried fruits (Fig. 7A). Apple, banana, and durian have a big portion of light-yellow color (color 47), and a variety of portions of reddish color (color 43). Mango consists of two shades of orange color (color 11 and 27) which could result from the orange color of the mango and the shadow of the pores.

The combination of a low color number (6 bit color) and the accuracy of the measurement, assures the PCA test of Canon-CVS analysis to provide a good separation between fruits, and also a high total contribution of variance of 84% (PC1 = 74.29%, PC2 = 9.71%) (Fig. 7B).

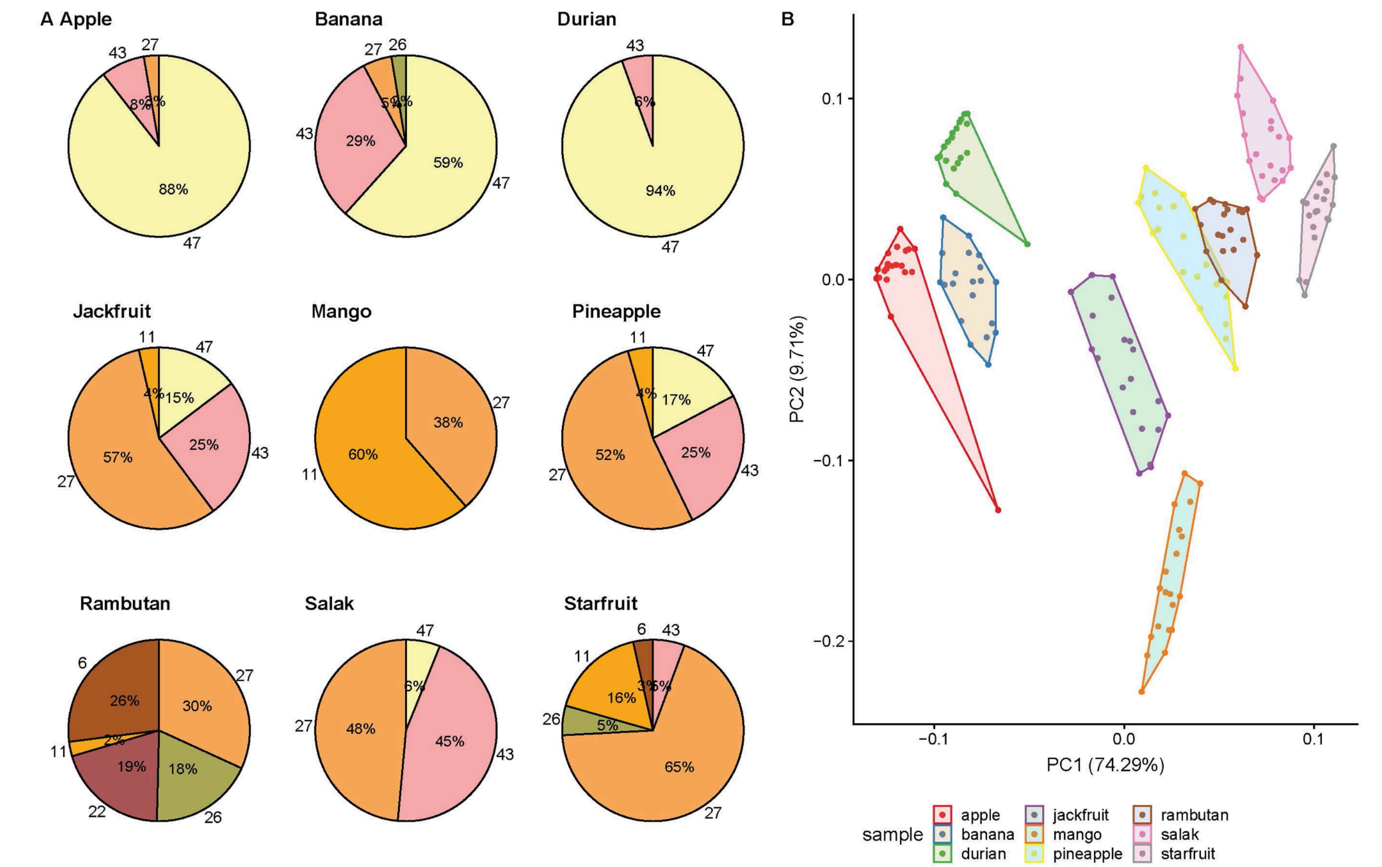

Fig. 7. Color distribution of nine different fruits by Canon-CVS in 6 bit. (A) The color distribution within the sample surface, with 2% threshold. (B) The PCA plot. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

The color distribution analysis usually requires a severe color reduction and image processing; e.g. (Pace et al., 2014) applied color reduction to only three colors, while (Briones & Aguilera, 2005) applied the Gaussian lowpass filter to smoothing the images. The Canon-CVS enables to shows the real color related to the sample with minimum modifications, or image processing which is possible by using a sufficiently high camera resolution and sensitivity to produce grain free images. This approach is necessary to accurately quantify the color distribution.

Canon-CVS was an economical choice for the color distribution analysis system, which additionally is a very flexible system compared to the commercial alternative. A wide price range of the camera body, lenses, camera mount, and lighting made the system affordable yet flexible to use in many cases from small lab to the industrial scale. Furthermore, the flexibility of the software, which described in a clear and precise way in the methodology, can be used and adapted or extended using an opensource program such as R (R Core Team, 2020).

The disadvantages of Canon-CVS are the requirements of having a skill sets including programing skills to write and adjust the program in R environment; an understanding on photography to select the best camera setting and lightning for a particular sample. Other limitations including the time needed to execute the whole protocol, particularly for the manual background removal. However, the possibility for flexible design and perhaps easier to custom built it in a process line an advantage compared to IRIS the Canon – CVS was appealing to use across the field.

4. Conclusions

The four-color analysis methods have their own advantages and disadvantages. Sensory testing with panelists is a relatively easy method which can be used if always the same product type is considered like it happens in many food factories. Although the sensory color distribution analysis is able to describe color heterogeneity, the subjectivity of the panelist limits the accuracy and the discrimination ability of the measurement. Hunterlab is found to be an easy, handy and accurate method to measure homogeneous samples; the analysis has a high differentiation ability, but the color distribution information was lost. IRIS-Alphasoft is a quick and easy method to perform a color distribution analysis, it is completely automatized and easy to use for untrained operators, however the closed system limits the analysis. The Canon-CVS system and protocol was able to assess sample color heterogeneity as well as to discriminate between the samples; furthermore the method was flexible and economical, which enables the user to customize the protocol based on the sample and the objective of the analysis but it requires trained operators especially for the data analysis. As a take home massage, color distribution analysis has a potential to unlock the limitation of traditional color analysis to give more color information of the sample which is important in product quality analysis.

CRediT authorship contribution statement

Fitriyono Ayustaningwarno: Conceptualization, Methodology, Software, Validation, Formal analysis, Investigation, Resources, Data curation, Writing - original draft, Writing - review & editing, Visualization, Supervision, Project administration, Funding acquisition. **Vincenzo Fogliano:** Conceptualization, Methodology, Writing - review & editing, Supervision. **Ruud Verkerk:** Conceptualization, Methodology, Writing - review & editing, Supervision. **Matthijs Dekker:** Conceptualization, Methodology, Writing - review & editing, Supervision.

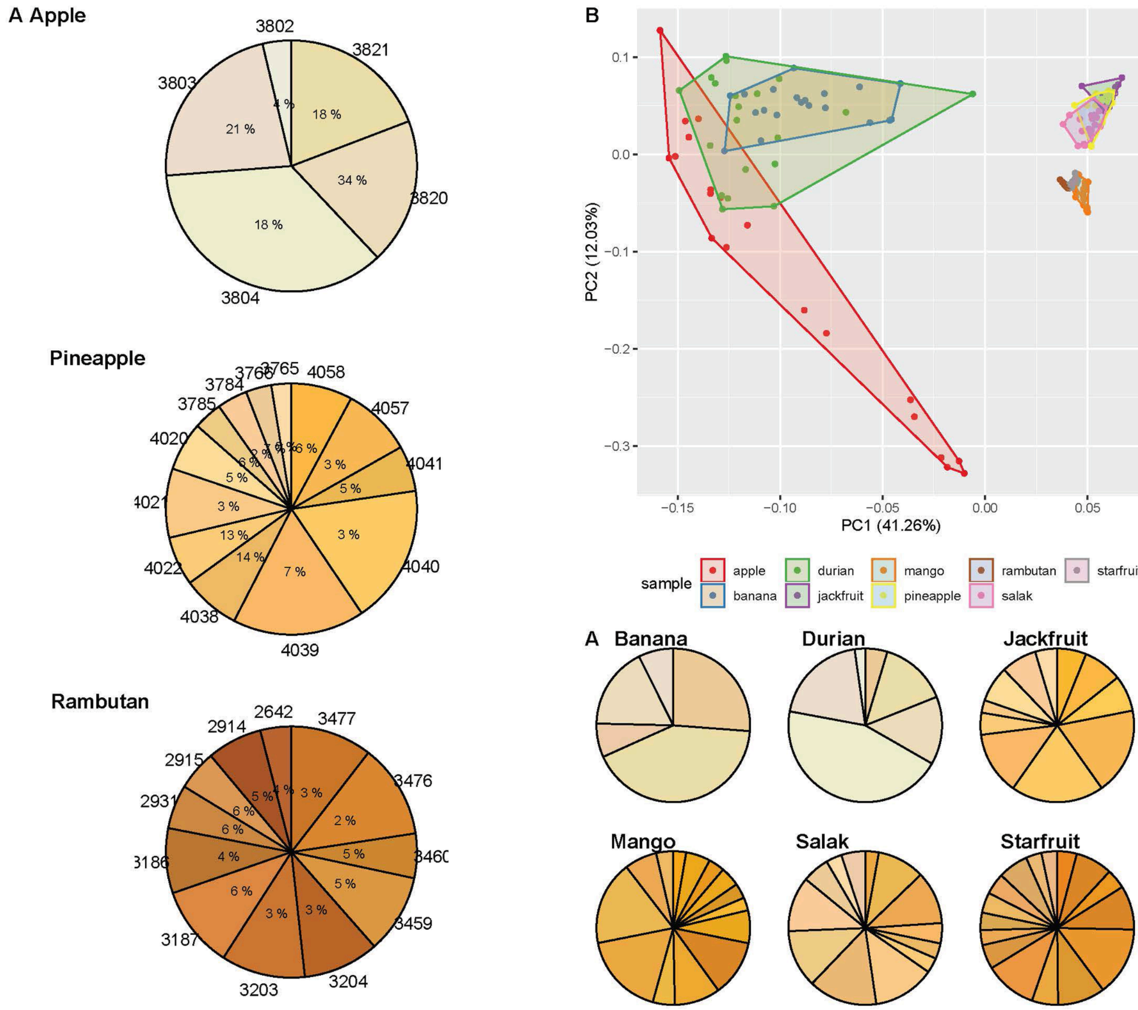

Fig. 8. Color distribution of nine different fruits by Canon-CVS in 12 bit. (A) The color distribution within the sample surface, with 2% threshold. (B) The PCA plot. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Appendix A. Supplementary material

Supplementary data to this article can be found online at https://doi.org/10.1016/j.foodres.2021.110230.

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