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# Surface Gloss Evaluation of Apples Based on Computer Vision and Support Vector Machine Method

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**Abstract** This paper investigates computer vision applications for surface gloss evaluation to determine a quick surface gloss evaluation method for apples. "Red Fuji" apples were wax-coated with different concentrations of shellac solutions to obtain the apple samples with different levels of surface gloss. The surface gloss values and the color scales of the apple samples were detected using a pinhole gloss meter and a color meter. The apple sample images were captured and processed, and the color parameters of the high light areas were extracted. Support vector machine (SVM) regression and classification models were built to predict the surface gloss values and the surface gloss levels of apples, respectively. The results showed that to predict the surface gloss of apple samples, the correlation coefficients of the SVM regression model were 0.94 and 0.90 for the training and the testing groups, respectively. The classification accuracy rates of the SVM classification model for the training and the testing groups were 100 and 96.7%, respectively. Finally, apple surface gloss level classification software was developed, which showed good operating results for both classification accuracy rates and calculation speed. This paper provided a new surface gloss evaluation method based on computer vision for apples.

**Keywords** Surface gloss · Computer vision technology · Apple · Evaluation · Support vector machine

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## Introduction

Apples are one of the most popular table fruits globally (Gao et al. 2016). The global production of apples is up to 80 billion tons in 2013 (Food and Agriculture Organization of the United Nations 2016). As life quality increases, sensory characteristics are becoming more important when people are evaluating fruit.

The surface gloss of an apple, which reflects freshness and its defects, is an important sensory characteristic. Fresh apples have a layer of wax on the surface. This wax is easily removed during storage, resulting in a decrease in surface gloss (Ward & Nussinovitch. 1996). The postharvest process of wax coating is usually performed to improve the apple surface gloss and reduce shrinkage and moisture damage of apples (Robert & Robert 1995). Although the surface gloss of apples can be increased using wax coating, it still decreases as the weight loss rate increases, or as disease occurs and develops. Therefore, surface gloss is an important sensory characteristic of apples that affects the purchasing tendency of consumers.

Because of the low objectivity and the high labor cost of artificial vision method, instrumental gloss detecting methods and standards has been studied (Mizrach et al. 2009). The gloss meter for gloss value detecting of flat surface has been successfully commercialized. However, it is not suitable for the materials with uneven and curved surface, such as the agriculture products (Hutchings 1994). To meet the need of surface gloss detection of agriculture products, Nussinovitch designed a gloss meter for agricultural products based on the laser diffuse reflection characteristic of the surface and detect the surface gloss of bananas, peppers, oranges, and tomatoes (Nussinovitch & Mey-Tal 1994; Nussinovitch et al. 1996a; Nussinovitch et al. 1996b). In order to evaluate the gloss of apples coated with different kinds of materials, Bai et al. (2003a, b) used a commercialized gloss meter (reflectance meter, micro-TRI-gloss, BYK Gardner, Inc., Silver Spring, MD) to measure the surface gloss of a coated apple and found that the surface gloss of "Gala" and "Delicious" apples coated with different coating formulations was between 2.3 GU and 11.3 GU, and the surface gloss of "Delicious," "Fuji," "Braeburn," and "Granny Smith" apples coated with different coating formulations was between 2.9 GU and 10.9 GU. Although the gloss meter used by Bai et al. for detecting the gloss of apples cannot be found, the similar type of gloss meter, Gloss Meter (micro-TRI-gloss 20/60/85 degree, BYK Gardner, Inc.), is still present in the market. This gloss meter detects the gloss value based on the laser diffuse reflection characteristic of the tested surface. The test hole is small, and in this scale, the curved surface can be similar to a flat surface. This kind of gloss meter is also called pinhole gloss meter for its small test hole and has been commercialized. However, due to the small detection area of pinhole gloss meters, tested materials with uneven surface need to be multiply tested using a pinhole gloss meter at different spots on the surface to gain a relatively high accuracy surface gloss observation. In order to develop a gloss detecting method with high accuracy and repeatability, Mizrach developed a spectrometer-based gloss measurement method for apples and other fresh products with the repeatability error of up to 16% for 90% of the measurements (Mizrach et al. 2009).

Computer vision technology (CVT) that simulates the human visual sense has been used for on-line quality detection and grading of food or agricultural products for many years (Ma et al. 2016; Hemad et al. 2015; Zhang et al. 2014). CVT may offer a better method for detection of the surface gloss of agricultural products because surface gloss is an intuitive parameter that is estimated visually by humans. However, there is little research on the development of CVT methods to evaluate the gloss of vegetables and fruits. Chong et al. (2008) developed a surface gloss measurement method for eggplants based on CVT and achieved accuracy rates up to 80%. However, CVT has been applied for quality grading and defects detection of apples (Ji & Wu 2000; Dubey & Jalal 2016; Zhang et al. 2015; Throop et al., 1991); the surface gloss evaluation of apples based on CVT was still not fully studied.

In this paper, apple samples were wax-coated with different concentrations of shellac solutions to obtain apple samples with different surface gloss levels. The surface gloss values and the color scales of the apple samples were detected using a pinhole gloss meter and a color meter, respectively. The apple sample images were then captured, and the color parameters of the high light areas of the apple images were extracted. Using the surface gloss values detected using a pinhole gloss meter, SVM regression and classification models were built to predict the surface gloss values and the surface gloss levels of the apples, respectively.

## Materials and Methods

### Sample Preparation

A total of 300 "Red Fuji" apples without obvious surface defect were purchased from Jianliang fruit store at Xiaowei Street, Nanjing, China. These apples were washed and wiped clean. A total of 100 of the apples were wax-coated with 12% shellac (Bocheng Chemical Limited Company, Dongguan, China), another 100 apples were wax-coated with 6% shellac, and the remaining 100 apples were not wax-coated. Before testing, the wax-coated apple samples were air-dried at room temperature (20 °C) for 2 h.

### Apple Image Capture

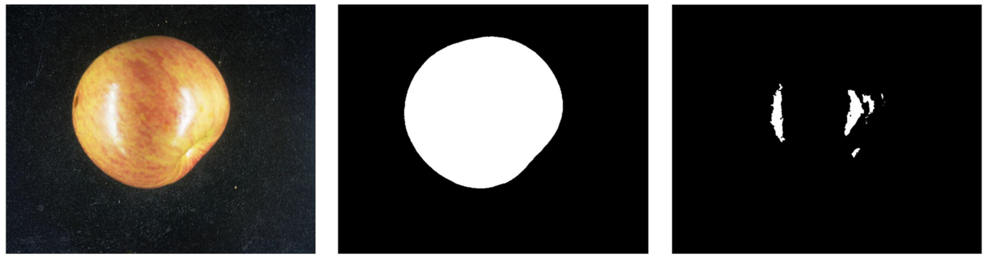
The 300 apple sample images were captured using a self-made computer vision system. The self-made computer vision system contained a digital camera, two strip light sources, a camera support, a black base, and a computer. Each strip light source had a length of 33 cm and contained 12 white LED tamps, with each tamp having 1 W power. The distance between the strip light source and the base and between the two strip light sources were 15 and 20 cm, respectively. The digital camera used was a Sony Nex-6 digital camera, and the lens was Sony SELP1650. The image sensor was Exmor APS HD CMOS, the Max Resolution was 4912 × 3264, the range of focal length was between 16 and 50 mm, and the range of aperture was from F36 to F5.6. The shooting parameters used were a focal length of 30 cm, an aperture of 4.5, and an exposure time of 1/15 s. The images were captured at 3287 × 3176 resolution and saved in .jpg format on the computer. For the apple image capture process, the strip light sources were firstly switched on and each apple was then placed on the base, directly facing the lens. Finally, the camera was triggered to capture the image. One of the captured apple images is shown in Fig. 1a.

### Surface Gloss Detection Using Pinhole Gloss Meter

The surface gloss of the 300 apple samples was detected using a WGG60-E4 pinhole gloss meter (Sannuo Instrument Limited Company, Shenzhen, China). The pinhole gloss meter determined the surface gloss based on the light diffuse reflection characteristic of tested materials. The test hole size was 1.5 × 3 mm, the color of the test light beam was white, and the incident angle of the test light beam was 60°.

Firstly, the pinhole gloss meter was calibrated using a standard white ceramic plate and a standard black glass plate. The pinhole of the pinhole gloss meter was then held to the surface of the apple. The gloss value was read directly from the display screen. Due to the nonuniformity of apple surfaces, 20 test points on the apple surface were randomly selected for

**Fig. 1** Image process procedure of apple samples. **a** Original image of apple sample. **b** Binary image of apple area. **c** Binary image of high light area of apple



(a) (b) (c)

(a) Original image of apple sample
(b) Binary image of apple area
(c) Binary image of high light area of apple

each apple. The surface gloss value of these 20 test points was detected, and the mean value was calculated as the surface gloss value of each tested apple.

### Color Scale Detection

The color scale of the 300 apple samples was detected using a CR-10 portable color meter (H. J. Unkel Limited Company, Shanghai, China). The color meter was firstly calibrated using a standard white ceramic plate. The apple was then held up to the measuring hole of the color meter. The color scale values of $L^*$, $a^*$, and $b^*$ can be read directly from the display screen, after pushing the "Test" button. Three test points of different areas of the apple surface were selected for each apple. The color values of these three test points were tested, and the mean values of $L^*$, $a^*$, and $b^*$ were calculated respectively to give the color values of the tested apple.

### Image Process and Characteristic Parameter Extraction

Matlab 2010b (Version 7.11, The Mathworks Inc., Natick, MA, USA, 2010) was used to process the apple images and extract the characteristic parameters. Under illumination by a suitable light source, one or two high light areas were formed in each image due to specular reflections on the apple surface. Apples with a higher surface gloss have more specular reflection, and the high light areas of the images are brighter and smoother. Therefore, the color parameters of the high light areas, including an average gray value *Ig*, an average *R* component value *Ir*, an average *G* component value *Ig*, an average *B* component value *Ib*, and the standard deviation of the gray value *Std* of the high light areas in image were selected as the characteristic parameters for the surface gloss value detection.

In order to segment the high light areas from the overall image, it was firstly necessary to segment the binary image of the apple area. The gray level histogram of the apple gray image is shown in Fig. 2. In the gray level histogram, there are two obvious peaks formed due to the black background and the apple area. Therefore, the automatic two-peak threshold segmenting method was used to find the most suitable segmentation threshold, and the binary image of the apple area was then segmented using this segmentation threshold. The binary image of the apple area is shown in Fig. 1b.

Secondly, it was necessary to segment the binary image of the high light areas. It was difficult to precisely segment the high light areas using a single threshold because each individual apple had different color and brightness levels. In this work, the high light areas were acquired by segmenting a certain number of pixels with higher gray values from the gray level image. The total number of white pixels $N$ in the binary image of the apple area was calculated, and $\frac{N}{20}$ was used for the number of segmented pixels. The gray level histogram of the gray apple image provided statistics on the number of different gray level pixels. The threshold for the $\frac{N}{20}$ pixels segmentation was obtained by accumulating the number of pixels from gray level 256 to gray level 1. When the accumulation result was just above the segmentation number of pixels, the accumulation process was stopped, and the current gray level was used as the segmentation threshold. The binary image of the high light area was then obtained by segmenting the gray level apple sample image using this calculated segmentation threshold. The binary images of the high light areas are shown in Fig. 1c.

The color parameters of the average gray value *Ig*, the average *R* component value *Ir*, the average *G* component value *Ig*, the average *B* component value *Ib*, and the standard

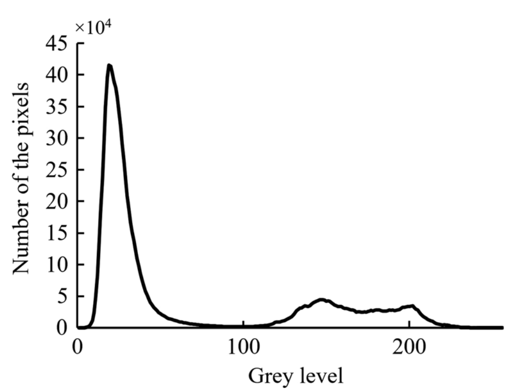



**Fig. 2** Gray level histogram of the gray image of apple sample

deviation of gray value *Std* were calculated using the *R*, *G*, and *B* components of the original image of the apple samples, using the binary image of the high light area as a template.

### SVM Model Development

Microsoft Excel 2016 (Microsoft corporation) was used to generate a random number between 0 and 1 for each apple sample (total 300 apple samples), and 70 apple samples with lower random number from each group of different wax-coating levels (total 210 apple samples) were used as the training group. The other 90 apples were used as the testing group. In order to build a gloss value prediction model, the color parameters of the high light areas extracted from the apple images in the training group were used as the input data, and the surface gloss values detected with the pinhole gloss meter were used as the output data. An SVM regression model was built using Matlab LibSVM toolbox 3.3.1 (Chang & Lin 2011) and tested using the apple data from the testing group. The correlation coefficients ($r$) and root mean square error (RMSE) were calculated using the formulas below for assessment of the model performance.

$$r = \frac{\sum_{i=1}^{N}\left(x_i - \overline{x}\right)\left(y_i - \overline{y}\right)}{\sqrt{\sum_{i=1}^{N}\left(x_i - \overline{x}\right)^2}\sqrt{\sum_{i=1}^{N}\left(y_i - \overline{y}\right)^2}} \quad (1)$$

$$\mathrm{RMSE} = \sqrt{\frac{\sum_{i=1}^{N}\left(x_i - y_i\right)^2}{N}} \quad (2)$$

$N$ is the number of samples, $x$ -is the predicted value of surface gloss, $\overline{x}$ is the average predicted value of surface gloss, $y$ is the training value of surface gloss, and $\overline{y}$ is the average predicted value of surface gloss. The correlation coefficient was used to reflect the degree of correlation between the predicted values and the actual values, and the root mean square error was used to reflect the error in the predicted value of each sample. A high correlation coefficient and a low root mean square error were required to develop a good prediction model.

In order to build a gloss level classification model, the color parameters of the high light areas extracted from the apple image in the training group were used as the input data, and the apple gloss groups (high gloss group, middle gloss group, and low gloss group) were used as the output data. The SVM classification model was built using Matlab LibSVM toolbox 3.3.1 (Chang & Lin 2011) and tested using the apple data of the testing group. Following this, an apple surface gloss evaluation application was developed in C++ code using Visual Studio 2013 (Microsoft Corporation, Redmond, WA, USA) and OpenCV 3.0 Libraries (Intel Corporation, Santa Clara, CA, USA) were used to implement the image process procedures. After that, the apple surface gloss evaluation application was tested to verify the effectiveness of the CVT method for evaluating the surface gloss of apples.

## Results

### Surface Gloss Value and Color Scale of Apple Samples

The surface gloss values detected with the pinhole gloss meter and the color scale values detected with the color meter are shown in Fig. 3. The surface gloss values of the apples coated with no shellac, 6% shellac, and 12% shellac were 6.8 ± 1.2, 11.1 ± 1.5, and 19.6 ± 2.5 Gu, respectively. The surface gloss values of apples significantly increased with higher levels of surface shellac coating ($P$ < 0.0001). However, there was no significant difference among the color scale values of the apples coated with different shellac levels (i.e., $P$ = 0.581 for $L^*$, $P$ = 0.707 for $a^*$, $P$ = 0.406 for $b^*$). This indicates that wax coating can significantly improve the surface gloss of apples but has no significant effect on their color.

### SVM Regression Model

The surface gloss of the apple samples coated with different concentrations of shellac in the training group were 6.9 ± 1.2, 11.3 ± 1.5, and 19.8 ± 2.4 Gu respectively, while that the surface gloss for the testing group were 6.5 ± 1.1, 11.0 ± 1.3, and 19.1 ± 2.5 Gu. There is no significant difference between the gloss values in the training and the testing group. A SVM regression model was built to detect the surface gloss of apples according to the color parameters extracted from the high light areas of the apple images. After the parameters were optimized to build the model, a radial basis function was used as the kernel function, and the gamma and the cost values were $5 \times 10^{-5}$ and 100, respectively. The SVM regression model was built with 112 support vectors. The number of support vectors was much lower than that of the samples in training group, which indicates that the model is not overfitting.

The predicted results of the SVM regression model are shown in Fig. 4. The correlation coefficients ($r$) of the predicted and the detected surface gloss values in the training group and the testing group were 0.94 and 0.90, respectively, and the RMSE were 1.86 and 2.21, respectively. However, although the correlation coefficients were above 0.9, the SVM regression model still cannot accurately predict the surface gloss detected with the pinhole gloss meter. Fifty percent of the predicted values had

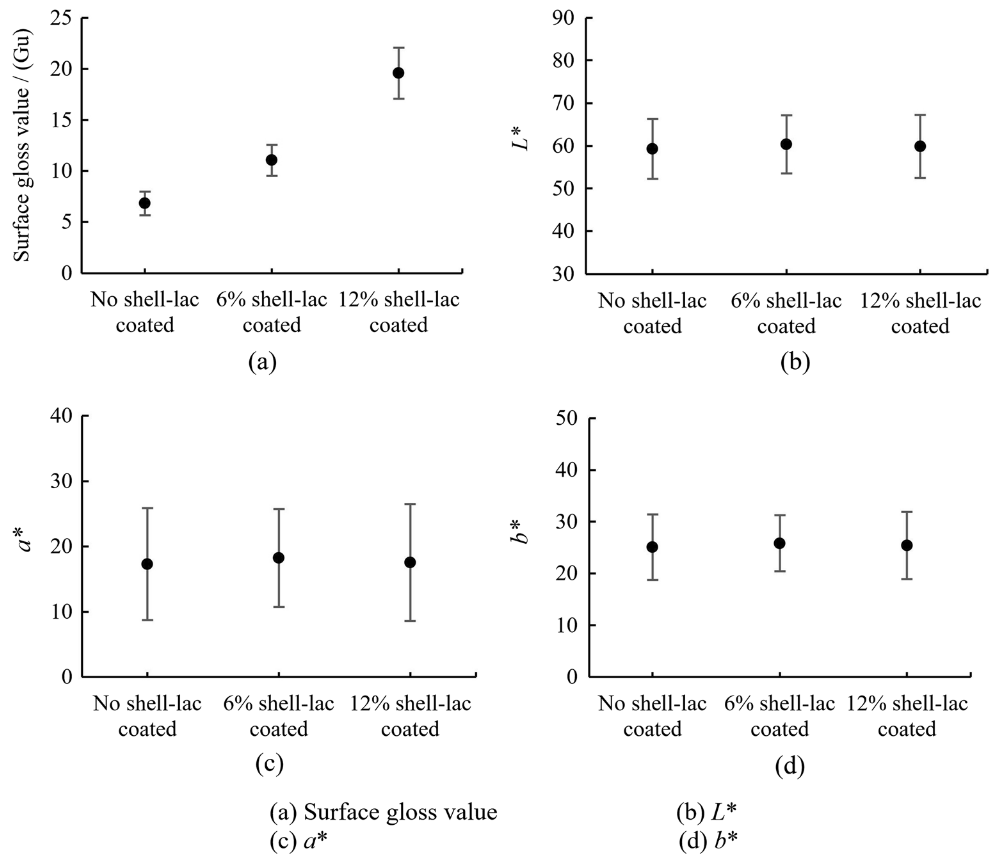



**Fig. 3** Surface gloss values and color scale values of apple samples

an error of more than 10% (data is not shown). This may be due to the accuracy limitation of the pinhole gloss meter and the different principles of measurement between CVT and the gloss meter.

## SVM Classification Model

A SVM classification model was built to classify the apple samples into the high gloss group, middle gloss group, or low gloss group. After the parameters were optimized to build the model, a radial basis function was used as the kernel function, and the gamma and the cost values were $5 \times 10^{-5}$ and 100, respectively. The SVM classification model was built with 24 support vectors. The number of support vectors was much lower than that of the samples in the training group, which indicates that the model is not overfitting. The classification accuracy rate of the SVM classification model is shown in Table 1. The SVM classification model had an accuracy rate of 100% for the training group classification and an accuracy rate of 96.7% for the testing group classification. The SVM classification had a high accuracy rate for classification of the different surface gloss levels of apples and could be applied to industrial gloss grades.

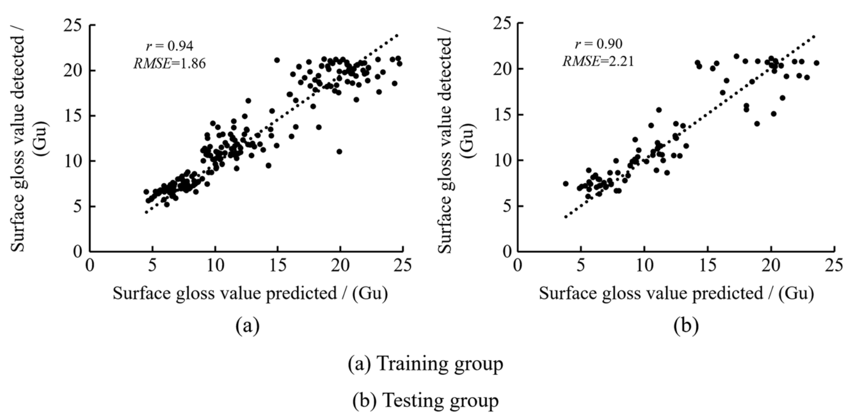



**Fig. 4** Effects of surface gloss prediction of SVM regression model for apple samples in the training and the testing groups. **a** Training group, **b** testing group

**Table 1** Accuracy of SVM classification model for gloss of apple samples

| Gloss level | Training group | Testing group |
|---|---|---|
| Low gloss | 100% (70/70) | 100% (30/30) |
| Middle gloss | 100% (70/70) | 100% (30/30) |
| High gloss | 100% (70/70) | 90% (27/30) |
| Total | 100% (210/210) | 96.7% (87/90) |

### Development of Surface Gloss Level Classification Software for Apples

Since the SVM regression model could not accurately predict the surface gloss value, which is not required for apple grading, the SVM classification model is more suitable for industrial grading of apples. Therefore, a surface gloss level classification software application for apples was developed. The calculation procedure of the software application is shown in Fig. 5. The image process and the characteristic parameter extraction procedures were the same as in "Image Process and Characteristic Parameter Extraction," and the classification model used to classify the deferent surface gloss level was the SVM classification model, which was built in "SVM Classification Model."

The apple surface gloss evaluation application was tested using all of the 300 apple samples. The testing environment used a Windows 7 operating system, Intel i7-4710 CPU, and 16 g RAM, and all other corollary equipment was the same as that in "Apple Image Capture." The operating results show that the software performed well. The accuracy of classification was 99%, and the average time to classify each apple was 553 ± 67 ms. The accuracy and the efficiency of this software meet the requirements of industrial automatic grading applications.

## Discussion

As an important sensory characteristic parameter of apples, surface gloss affects the purchasing intention of costumers. However, instrumental evaluation and detection methods for the surface gloss of apples have not previously been developed. This work presented a surface gloss evaluation method for apples based on CVT which can also be used as a reference for surface gloss method development for other fruits and vegetables.

Previously, researchers focused on developing gloss detecting method based on measurement of the relationship between the intensity of the specular reflection and diffuse reflection. This was similar to the principle of gloss meter and was used by Nussinovitch and Mizrach in gloss measurement research (Mizrach et al. 2009; Nussinovitch et al. 1996a; Nussinovitch et al. 1996b; Nussinovitch & Mey-Tal 1994). The principle of this method for detection of surface gloss evolved from the definition of gloss (Arney et al. 2006), so detection of surface gloss in this way can be used to obtain accurate values. However, it costs much time when detecting the surface gloss of agricultural products because the agricultural products have uneven surface and need multiple detection.

CVT was another method to evaluate the surface gloss of fruits. Chong et al. (2008) have previously used CVT to evaluate the gloss of eggplants based on the change in gray level of high light areas in the image (Chong et al. 2008), but this research was at an early stage of using CVT. In order to improve evaluation accuracy, our work has extracted multiple color parameters of high light areas and used an SVM model to obtain higher evaluation accuracy.

The output gloss values of the CVT method in our study cannot precisely predict the gloss values detected with a gloss meter. This may be due to a difference between the measurement principles of the gloss meter and the CVT method. The CVT method proposed was based on the brightness of the high light areas in the apple images (Chong et al. 2008), and these high light areas can be easily affected by the irregular shape of apple surfaces. Compared to the CVT method, the gloss meter has a higher focus on the details of the sampling points on the surface (Lindstrand 2005) and can thus obtain the gloss value by multi-point measurement. However, the principle of CVT methods is closer to humans for evaluating surface gloss. In our work, the effects of the apple surface

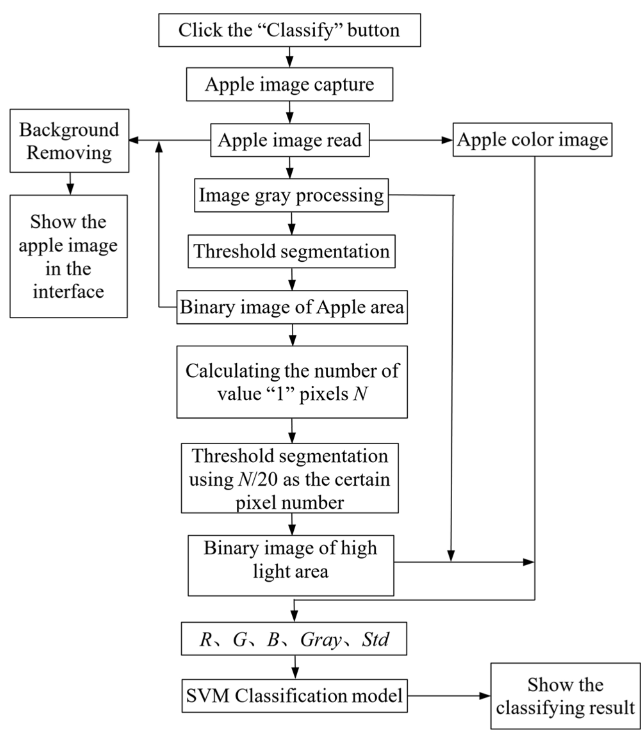



**Fig. 5** Calculation procedure of the self-compiled apple surface gloss evaluation application

gloss value detection and the apple surface gloss level evaluation using CVT were compared, and the latter was selected.

## Conclusions

This article has studied surface gloss evaluation of apples based on CVT. A gloss CVT evaluation method was proposed, consisting of image capture, extraction of color parameters of high light areas, and SVM model detection or classification. The correlation coefficients of the SVM regression model to predict the training and the testing groups were 0.94 and 0.90, and the mean square errors were 1.86 and 2.21, respectively. The classification accuracy rates of the SVM classification model for the training and the testing groups were 100 and 96.7%, respectively. Finally, an apple surface gloss level classification software application was developed using the SVM classification model and showed good operating results in terms of both classification accuracy rates and calculation speed.

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**Compliance with Ethical Standards**

**Conflict of Interest** Ke Sun declares that he has no conflict of interest. Ying Li declares that she has no conflict of interest. Jing Peng declares that she has no conflict of interest. Kang Tu declares that he has no conflict of interest. Leiqing Pan declares that he has no conflict of interest.

**Human and Animal Rights and Informed Consent** This article does not contain any studies with animals and human participants performed by any of the authors.

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