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Research on Strawberry Quality Inspection Based on Hyperspectral Imaging Technology

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ABSTRACT

This study integrates hyper-spectral imaging technology, data mining, and image processing to explore its application in non-destructive quality assessment of strawberries, including evaluations of appearance, maturity, and internal quality. It also investigates the impact of different feature selection algorithms on classification accuracy. The research contributes to the development of automated quality grading systems for off-season strawberries, reducing post-harvest losses and enhancing fruit quality. Key findings include: (1) Analysis of strawberry quality parameters and spectral characteristics changes (2) High-spectral imaging-based strawberry hardness detection method (3) Detection of Soluble Solid Content (SSC) in Strawberries Using Hyper-spectral Imaging

KEYWORDS

Hyper-spectral Technology; Cherry strawberry; Soluble Solid Content; Hardness Quality Detection.

1. INTRODUCTION

Strawberries belong to the Rosaceae family and rank first in the global production of small berries. Renowned for their soft, juicy texture and rich nutritional content, strawberries contain 50-100 milligrams of vitamin C per 100 grams—more than ten times the amount found in apples and grapes—earning them the reputation of the "Queen of Fruits". As the world's largest producer and consumer of strawberries, China accounts for over one-third of the global annual output.The external color and the content of soluble solids in strawberries are two crucial indicators for evaluating strawberry quality. Traditional physical and chemical methods involve measuring soluble solids with a handheld refractometer and determining acidity via titration. Although these conventional approaches yield relatively accurate results, they are time-consuming, labor-intensive, and destructive to the fruit. Thus, neither method is suitable for the rapid and non-destructive testing of strawberries [5-6]. With their thin skins and short shelf lives, strawberries are highly susceptible to damage. The drawbacks of traditional methods, such as destructiveness, cumbersome operations, and stringent experimental conditions, have severely hindered the development of the fruit industry.

In contrast to traditional quality testing methods, non-destructive testing (NDT) techniques offer advantages of speed, non-invasiveness, and high precision. They enable real-time analysis of internal quality while preserving the fruit's integrity, which is of great significance for the advancement of China's fruit industry [7].In recent years, non-destructive testing technologies such as hyperspectral imaging, computer vision, and information fusion have been widely applied and rapidly developed in fruit quality assessment [8-10]. The greatest merit of NDT techniques is that they do not require direct contact with the tested object, thereby avoiding secondary damage. By leveraging the response changes of the object’s internal chemical components and external characteristics to light, electricity, magnetism, and other stimuli, these techniques can detect both internal chemical compositions and

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external traits.Developing a rapid, accurate, and efficient method for strawberry quality testing is therefore imperative, as it plays a vital role in improving fruit quality and enhancing market competitiveness.

2. EXPERIMENTAL DATA AND ANALYSIS METHODS

Using strawberries as the experimental samples, hyperspectral image information and hardness data were collected within the wavelength range of 400nm to 1000nm. Preliminary experiments showed that strawberries stored at room temperature would show visible mold within 3 days, so this experiment only collected spectral data for strawberries over 3 days. The experimental samples were fresh strawberries from a certain strawberry farm, with a total of 200 strawberries harvested. They were sent to the laboratory within three hours after picking, and data collection experiments were conducted in the afternoon, with the same experiment repeated every 24 hours, completing three days of data collection. After removing moldy and damaged strawberries, spectral images and hardness data of 166 strawberries were finally retained.

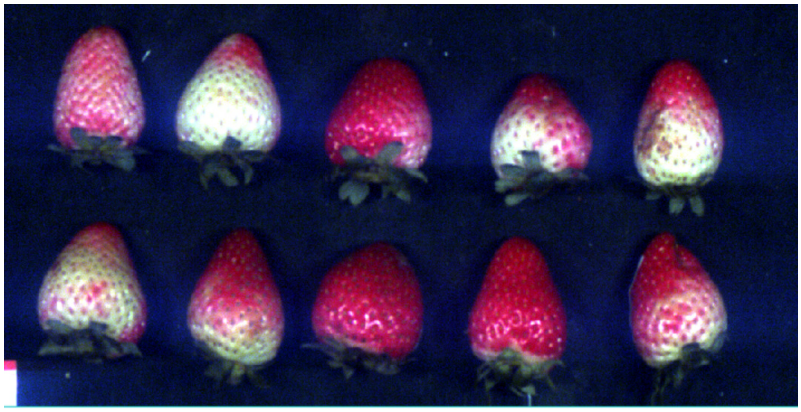


Figure 1. Strawberry sample image

2.1. Data acquisition

The hyper-spectral reflectance imaging system (hyperspectral imager) will be used to acquire hyperspectral images of all strawberry samples. The system has a spectral range of 400-1000 nm and a spectral resolution of 2.31 nm. The imaging system consists of a hyperspectral spectrometer, a CCD camera with a resolution of 696×696, two tungsten-halogen lamps with a wavelength range of 300–2500 nm, a moving platform, a dark box, and a computer equipped with hyperspectral image acquisition software Hyper-scanner [27,28], as shown in Figure 2.

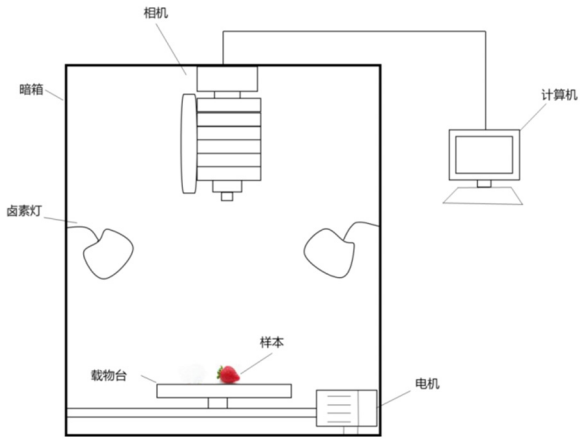


Figure 2. Visible-Near Infrared Hyper-spectral Imaging System

After the hyperspectral image acquisition is completed, the strawberry samples need to be immediately removed to minimize thermal damage from the tungsten halogen lamp. Due to interference from external factors such as uneven light distribution and camera dark current, the acquired hyperspectral images need to be corrected [19]. The correction formula is as follows:

$$R=\frac{R_{raw}-R_d}{R_w-R_d} \quad (1)$$

Here, R is the corrected hyperspectral image, Rraw is the original hyperspectral image, Rw is the white reference image obtained from a whiteboard with 99% reflectance, and Rd is the black reference image obtained by turning off the lights and covering the camera lens. The corrected hyperspectral image will be used for subsequent analysis.

After acquiring the hyperspectral image data, it is necessary to extract the spectral characteristics of the strawberries in the hyperspectral images. Since the hyperspectral images collected in the experiment contain backgrounds unrelated to the objects being detected, the strawberry regions in the images must first be selected. Removing these backgrounds and selecting the study area is also known as Region of Interest (ROI) extraction [16]. There are generally two methods for extracting an ROI: one is to extract the ROI through image segmentation techniques; the other is to use relevant specialized software, such as ENVI, to directly select the desired area and then treat that area as the ROI. This paper will use the second method to extract the ROI. After ROI extraction, the spectra of all pixels within this area can be extracted for subsequent analysis.

2.2. Analytical Method

Visible/near-infrared spectral analysis technology is a rapid, multifunctional, and non-destructive detection method that has been widely used in industrial production, food safety, and environmental protection. This study utilizes visible/near-infrared spectroscopy to analyze and detect the quality of strawberries. Specifically, visible light has a wavelength range of 380 to 780 nm, while near-infrared lies between visible and mid-infrared, ranging from 780 to 1100 nm. Almost all organic structures and functional groups can be identified using visible/near-infrared spectroscopy. When the light source illuminates the surface of a strawberry, phenomena such as reflection, absorption, transmission, and diffuse reflection occur. Due to changes in scattering and absorption processes, the spectral characteristics of the incident light change as it penetrates the strawberry. The light scattering properties of strawberries are closely related to their chemical composition and microstructure. There are various organic molecules in strawberries that can selectively absorb photons, triggering optical reactions and thereby altering the characteristics of visible/near-infrared light.

Convolutional Neural Networks (CNNs) are a type of deep feedforward neural network specifically designed to process grid-structured data and are one of the key algorithms in deep learning. Their core features include local connectivity and weight sharing, which enable outstanding performance in computer vision tasks, and they are widely used in image classification, object detection, and semantic segmentation. CNNs mainly consist of convolutional layers, activation functions, pooling layers, fully connected layers, and output layers, possessing strong representation learning capabilities, able to automatically extract features and efficiently represent complex patterns through a hierarchical structure.

2.3. Modeling Method

SVM models are commonly used to simplify complex learning processes by simulating nonlinear behaviors and obtaining necessary information to make appropriate decisions. In other words, in predictive problems involving uncertainties in various aspects, SVM models are a powerful approach. Their characteristics include control of the decision function's capacity, the use of kernel functions, and sparsity of the solution. SVM, based on the unique theory of the structural risk minimization

principle, estimates functions by minimizing the upper bound of the generalization error, therefore it is highly resistant to overfitting and ultimately achieves good generalization performance.

PLSR is a statistical algorithm that is somewhat related to principal component regression. It establishes a linear regression model by projecting both the dependent and independent variables into another common space. The PLSR model is also referred to as a bilinear factor model. More specifically, the PLSR method can analyze the information shared by the X and Y matrices, that is, it builds a latent variable model of the covariance structure in these two spaces [31].

3. RESULTS AND DISCUSSION

3.1. Strawberry Quality Parameters

The quality parameters of strawberries do not change independently; they are interconnected and influence each other. To reveal this internal relationship, a correlation analysis was conducted on three key quality indicators: hardness, SSC, and weight loss rate (Table 1).

Table 1. Correlation matrix of strawberry quality parameters (n=300)

Quality parameters	Hardness(N)	SSC	Weightlessness rate(%)
Hardness	1.00	0.58**	-0.82**
SSC	0.58**	1.00	-0.47**
Weightlessness rate	-0.82**	-0.47**	1.00

Note: **Indicates a significant correlation at the P<0.01 level

Key findings:

1. Hardness was significantly negatively correlated with weight loss rate (r=-0.82, P<0.01), indicating that water loss was one of the main reasons for strawberry softening. For every 1% increase in weight loss rate, the hardness decreases by about 0.28N.

2. Hardness was moderately positively correlated with SSC (r=0.58, P<0.01), indicating that the texture was usually maintained in the early stage of sugar accumulation, but the relationship between the two weakened after over-maturation.

3. SSC was negatively correlated with weight loss rate (r=-0.47, P<0.01), but the correlation was weak, indicating that SSC changes were not entirely caused by water evaporation, and material transformation also played an important role.

After systematically analyzing the changes of quality parameters and their relationship with hyperspectral characteristics during the storage period of 3-5 days, the main conclusions are as follows:

1. The weight loss rate increased linearly from 0% to 8.73%, and the average daily weight loss rate was about 1.75%, which was mainly controlled by water evaporation.

2. SSC showed a trend of first rising and then decreasing, peaking on day 2 (9.16°Brix) and decreasing due to respiratory expenditure in the later stage.

3. The hardness continued to decrease from 4.56N to 2.13N, a decrease of 53.3%, and the softening mainly occurred in the early stage of storage.

4. There was a significant correlation between various quality parameters, especially the hardness was highly negatively correlated with the weight loss rate (r=-0.82).

5. Visible light region (400-700 nm): The reflectivity of the 550 nm green peak increases, and the chlorophyll absorption valley becomes lighter at 670 nm, reflecting pigment degradation.

6. Red-edged area (700-750 nm): The red-edged area is blue-shifted, and the reflectivity decreases, which is a sensitive indicator of mature aging.

7. Near-infrared region (750-1000 nm): The decrease in reflectance at 850 nm reflects the disruption of cellular structure, and the shallow water absorption valley at 960 nm indicates water loss.

3.2. Strawberry Hardness Test

Through preliminary experiments, it was found that strawberries show visible mold after being stored at room temperature for 3 days. Therefore, this experiment only collected spectral data of strawberries for 3 days. After removing moldy and damaged strawberries, a total of 166 strawberries' spectral images and hardness data were retained.



Figure 3. Different components of strawberries

SVM and RF were used to establish a classification model for strawberry storage time, while PLSR, SVM, and RF were used to establish a predictive regression model for strawberry storage time. Among 200 strawberry samples, 120 samples were first selected and divided into two groups. According to the Kennard-Stone algorithm, 80 samples were chosen as the calibration set to build the model, and the remaining 40 samples served as the prediction set to evaluate the model's performance. The performance of the classification model was assessed using the calibration set accuracy (ACCC) and prediction set accuracy (ACCp). The performance of the regression model was evaluated using the coefficient of determination for the calibration set (Rc^2) and prediction set (Rp^2), as well as the root mean square error of the calibration set (RMSEC) and prediction set (RMSEP).

Here, the closer the correlation coefficient is to 1, the better the training and prediction performance. CCCS and CCPS < 0.3 indicate weak correlation, 0.3–0.5 indicates moderate correlation, and greater than 0.5 indicates strong correlation. The closer the root mean square error is to 0, the closer the model's predictions are to the true values. A larger RPD indicates better model prediction performance, with RPD > 2 representing excellent model performance. The calculation formulas for each indicator are as follows:

Correction set root mean square error:

$$RMSEC = \frac{\sqrt{\sum_{i=1}^{n}(h(x_i)-y_i)^2}}{n} \quad (2)$$

In the formula, $h(x_i)$ is the predicted value of the calibration set, y_i is the true value of the calibration set, and n is the number of samples in the calibration set.

Prediction set root mean square error:

$$RMSEP = \frac{\sqrt{\sum_{i=1}^{n}(h(x_i)-y_i)^2}}{n} \quad (3)$$

In the formula, $h(x_i)$ is the predicted value of the prediction set, y_i is the actual value of the prediction set, and n is the number of samples in the prediction set.

Adjusted correlation coefficient:

$$CCCS = \frac{\sum_{i=1}^{n}(x_i-\bar{x})(y_i-\bar{y})}{\sqrt{\sum_{i=1}^{n}(x_i-\bar{x})^2}-\sqrt{\sum_{i=1}^{n}(y_i-\bar{y})^2}} \quad (4)$$

In the formula, x_i is the predicted value of the calibration set, x is the mean predicted value of the calibration set, y_i is the actual value of the calibration set, y is the mean actual value of the calibration set, and n is the number of samples in the calibration set.

Prediction set correlation coefficient:

$$CCPS = \frac{\sum_{i=1}^{n}(x_i-\bar{x})(y_i-\bar{y})}{\sqrt{\sum_{i=1}^{n}(x_i-\bar{x})^2}-\sqrt{\sum_{i=1}^{n}(y_i-\bar{y})^2}} \quad (5)$$

In the formula, x_i is the predicted value of the prediction set, x is the mean of the predicted values of the prediction set, y_i is the actual value of the prediction set, y is the mean of the actual values of the prediction set, and n is the number of samples in the prediction set.

Correction set relative analysis error:

$$RPD = \frac{stdev}{rmse} \quad (6)$$

In the formula, stdev is the standard deviation of the calibration set samples, and rmse is the root mean square error of the calibration set samples.

The performance of partial least squares (PLS) models using different preprocessing methods is shown in Table 2.

Table 2. PLS Model Performance with Different Preprocessing

Preprocessing	Errata		Prediction set	
	R_C	RMSEC	R_P	RMSEP
Raw Spectrum	0.985	0.025	0.81	0.097
S-G	0.962	0.039	0.825	0.107
SVN	0.995	0.021	0.882	0.073
MSC	0.994	0.016	0.842	0.078

The results show that different preprocessing methods all have certain effects. Using spectra preprocessed by standard normal variate (SNV) transformation to establish a PLS prediction model, the correlation coefficients for the calibration set and validation set (RC and RP) were 0.989 and 0.882, respectively. The study results indicate that it is feasible to use hyperspectral imaging technology to predict the hardness of strawberries.

3.3. Detection of Soluble Solids in Strawberries

The reflectance spectra of strawberries extracted from hyperspectral images in the wavelength range of 400-1000 nm, where these bands reflect information about the physical parameters and biochemical characteristics of strawberries. In the visible light region, the absorption band near 680 nm may be related to chlorophyll [4], while the absorption band near 750 nm is attributed to the third

overtone of water [39]; in the near-infrared region, the absorption band near 960 nm is caused by the O-H of water [36]. The reflectance spectra of strawberries with different SSC and pH values show that in the 750-950 nm range, as SSC increases, the spectral reflectance also increases; in contrast, the spectral trend for pH is opposite, with spectral reflectance gradually decreasing as pH increases. In addition, for SSC and pH, the spectral changes in the 400-750 nm range are inconsistent with those in the 750-950 nm range, showing partial overlap in this region. In other words, the spectra of strawberries vary depending on their SSC and pH values. This phenomenon preliminarily demonstrates the feasibility of using HSI-extracted reflectance spectra to detect SSC and pH in strawberries.

4. SUMMARY

This study utilizes visible to near-infrared hyperspectral reflectance imaging technology (400-1000 nm) for detecting strawberry hardness, SSC, and pH. Hyperspectral imaging technology combines the advantages of spectroscopy and machine vision, allowing for both spectral features and image features such as color and texture to be extracted from hyperspectral images. Currently, there are very few studies using HSI for strawberry storage time or combining spectral and image features for SSC and pH detection. In this study, storage time is analyzed based on spectral features, while SSC and pH are analyzed using a combination of spectral, color, and texture features, and finally, the trends of SSC and pH changes over storage time are investigated. Compared with traditional conventional detection methods, the entire detection process is faster and more accurate, providing a novel method for non-destructive quality detection of strawberries and other fruits. This study not only offers a more efficient and convenient tool for practical strawberry quality detection but also provides a reference for future related research.

Overall, hyperspectral imaging technology shows great potential in the field of strawberry quality assessment, especially in detecting quality indicators such as SSC, acidity, hardness, and ripeness. This technology can effectively identify and classify the maturity levels of strawberries, predict their SSC, acidity, and hardness, providing a scientific basis for harvesting and grading. Although there are some technical and practical challenges, with the development of related technologies, hyperspectral imaging will gradually be more widely applied to the quality detection of strawberries and other agricultural products, offering solid technical support for agricultural production and food safety.

CONFLICTS OF INTEREST

The authors declare that they have no conflict of interest.

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