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Review

Research Progress on Non-Destructive Detection of Internal Quality of Fruits with Large Size and Thick Peel: A Review

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Abstract: Postharvest quality detection and grading are important factors to improve the commercial value of fruit. The natural biological characteristics bring challenges to the rapid and non-destructive evaluation of the internal quality of fruits with large size and thick peel. A lot of studies have tried to establish a feasible technique to achieve rapid, non-destructive, and accurate detection for this kind of fruit in commercial real-time grading. This article focuses on large-sized and thick-skinned fruits and comprehensively reviews the latest technical progress in the non-destructive detection of internal quality. It can provide a valuable reference for the development of postharvest processing technology for this kind of fruit.

Keywords: fruit; large size and thick peel; internal quality; non-destructive detection technique; application

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1. Introduction

In China, the fruit industry has become the third largest agricultural planting industry after grains and vegetables, with orchard and fruit production ranking first globally and occupying an important position in the national economy. According to the data from the National Bureau of Statistics, in 2021, China's annual fruit output reached 299 million tons. In order to improve the commercial value and competitiveness of fruit in the markets, postharvest commercial grading is very important [1]. At present, the detection technology and equipment for the quality of apples [2,3], pears [4], oranges [5], and other fruits have developed fast and gradually face commercial application. However, for large-size and thick-skinned fruits (such as watermelon), the non-destructive detection and classification of the internal quality still have great challenges [6]. In addition, the decision for subsequent purchases of fruits is dependent upon consumer satisfaction based on flavor and internal quality, and low-quality products reduce the purchase intention [7]. Different from the previous reviews [8–11], this paper encompasses a diverse array of commonly encountered large-sized, thick-skinned fruits, with a central emphasis on non-destructive testing of their internal quality. The comprehensive review systematically reviews the latest progress of non-destructive techniques and studies the internal quality of fruits with large size and thick skin over the past ten years, which can provide a valuable reference for scientific research, new technology development, and industry application.

2. Internal Quality of Fruits with Large Size and Thick Skin

Typical large-size and thick-skinned fruits include melon, watermelon, pineapple, pomelo, durian, etc. In the evaluation of internal quality, the most commonly measured quality attributes are soluble solid content (SSC), titratable acidity (TA), hardness, moisture, and maturity [8,10]. For specific fruits, there are also some unique quality indicators. For example, dry matter (DM) serves as an indicator for assessing the quality of durian, pineapple, and pomelo; β-carotene is an indicator for watermelon and pomelo, while lycopene is an indicator for watermelon. Figure 1 shows the five types of typical large-size and thick-skinned fruits and the related internal quality indicators. This article focuses on these five types of fruits and reviews the research progress on the non-destructive detection of these common internal qualities.

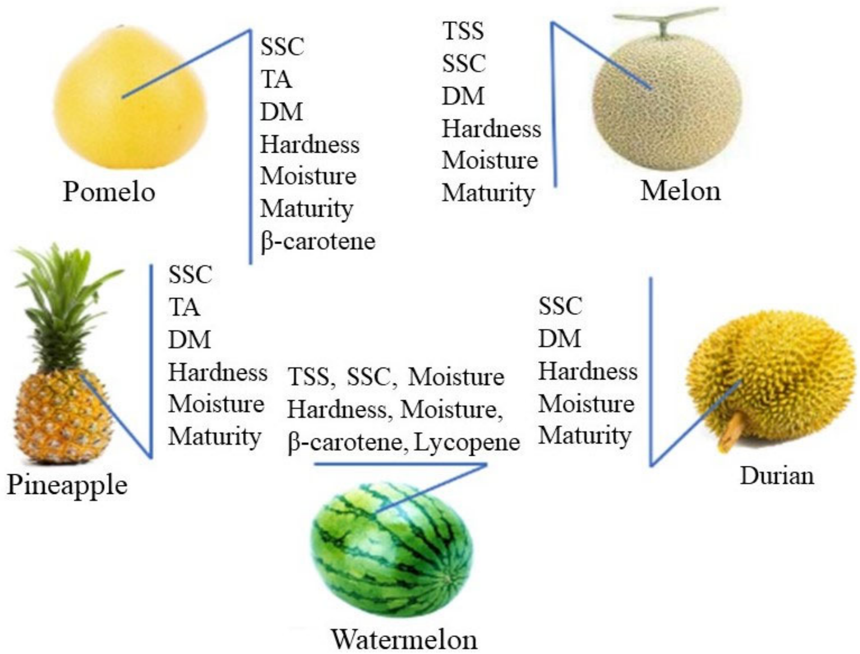

Figure 1. Typical fruit with large size and thick peel and the corresponding main internal quality attributes (SSC, soluble solid content; TA, titratable acidity; DM, dry matter; TSS, total soluble solids).

3. Non-Destructive Detection Techniques and Applications

3.1. Visible and Near-Infrared Spectroscopy

With the development of computer and data processing, visible and near-infrared (Vis-NIR) spectroscopy combined with chemometrics has become the most widely used technology in the field of the non-destructive detection of fruit quality. The wavelength range of visible light is 380–780 nm, which is sensitive to the change in fruit peel color. The American Society for Testing and Materials (ASTM) defines the electromagnetic wave with a wavelength range of 780–2526 nm as NIR light, which is usually divided into short-wave near-infrared and long-wave near-infrared. NIR light can record the frequency doubling and frequency combination absorption information of chemical bond vibrations, such as C-H, O-H, and N-H, and can obtain the physical and chemical properties of fruits [12,13].

Chia et al. [14] used Vis-NIR light to detect the SSC content of pineapple. The results showed that the models constructed using short-wave Vis-NIR (662–1005 nm) and short-wave NIR (700–1005 nm) could effectively predict the SSC of pineapple. The root mean square errors of cross-validation (RMSECVs) of the two models were 0.91° Brix and 0.88° Brix, respectively. Ibrahim et al. [15] predicted the internal quality of watermelon, including flesh color, sugar content, lycopene, total carotenoids, and vitamin C, based on Vis-NIR spectral data of 475–1075 nm and NIR spectral data of 950–1650 nm. The experimental results showed that the wavelength range of the NIR spectrum was more reliable in evaluating the physical and chemical properties of watermelon and more suitable for evaluating its maturity. There are three typical modes of diffuse reflection, diffuse transmission, and full transmission in the detection of the internal quality of fruit using Vis-NIR spectroscopy, as shown in Figure 2.

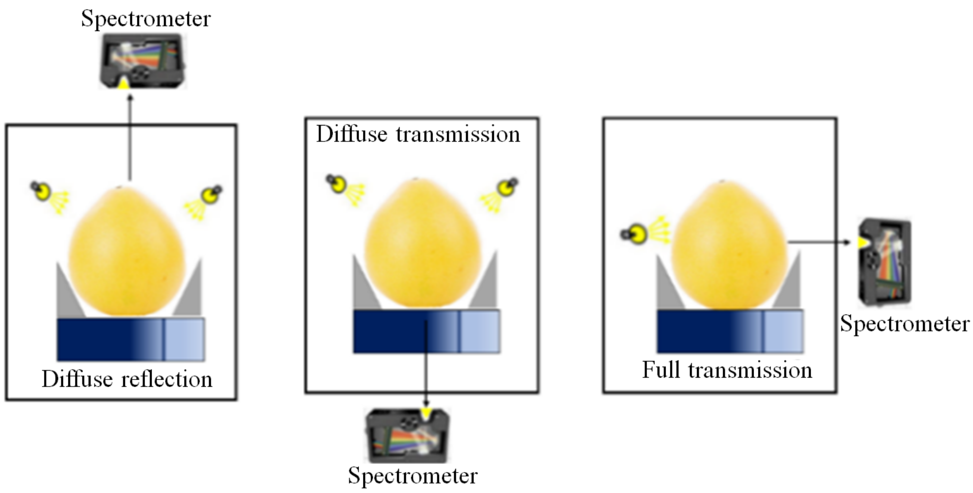

Figure 2. Schematic diagram of three spectral modes.

Considering the limited penetration depth of Vis-NIR, the diffuse reflectance is the most commonly used detection mode for large-size and thick-skinned fruits. Olarewaju et al. [16] constructed a partial least squares model (PLS) model to predict the contents of sucrose, total carotenoids, and vitamin B in pomelo and achieved results that the determination coefficient R^2 of the three quality attributes was 0.97–0.99. Vega-Castellote et al. [17] constructed a PLS model to detect SSC content in watermelon, with a standard error of prediction (SECV) value of 1.02%. Also, the partial least squares discriminant analysis (PLS-DA) was used to develop a model for the maturity classification of fruits. It was found that the watermelon peel had an effect on the maturity classification results. The experimental results showed that the accuracy of maturity classification of light-green striped watermelon was only 66.4%, while that of deep-green striped watermelon was 82.8%. In subsequent studies, Vega-Castellote et al. [18] employed an interactive NIR system to assess the depth of NIR light penetration through both intact watermelon and the red flesh of the cut fruit. Their investigation revealed that optimal outcomes for determining SSC were achieved with an illumination area interval of 28 mm, resulting in R^2 = 0.73 and RMSECV = 0.39%. Additionally, the detection position of fruit has a great influence on the detection results. Li et al. [19] compared the performance of the PLS model based on the spectral information of the navel and equatorial positions of three types of melons in the detection of SSC content and found that the navel position model had the best predictive accuracy. For the three types of melons, the range of prediction root mean square error (RMSEP) of the models was 0.67–0.78° Brix. In order to accurately detect the sugar content of Hami melon, Zhang et al. [20] compared the three parts (i.e., muskmelon calyx, equator, and pedicel) and developed PLS and least squares–support vector machine (LS-SVM) models. The results showed that the model based on the equator had the best performance, and the RMSEP values of PLS and LS-SVM models were 0.8359° Brix and 0.8958° Brix, respectively. On this basis, Hu et al. [21] also developed a multiple linear regression (MLR) model to analyze the effects of different positions, including calyx, equator, and pedicel, on the detection of SSC in Hami melon. The results showed that the calyx position was more accurate for PLS, LS-SVM, and MLR models, and the RMSEP value range was 0.95–0.99° Brix. Onsawai et al. [22] selected the biggest locule and the stylar end of durian pulp to construct a PLS model to detect SSC and DM content. The results showed that the model of the biggest locule of intact durian fruit had the best detection performance, and the RMSEP values of SSC and DM prediction models were 1.92° Brix and 5.23%, respectively. In the study of the maturity of durian, Timkhum [23] and Somton [24] built models based on this spine and the combination of both rind and stem, and the classification accuracies were 94.7% and 94.4%, respectively. Ditcharoen et al. [25] used the LDA model developed by the combination of rind and stem spectra to classify the maturity of durian fruit and achieved 97.28% and 100% accuracy in the LWNIR and SWNIR spectral ranges, respectively.

Cheepsomsong et al. [26] introduced a multi-parameter maturity index (MI) for assessing the maturity of durian. This index incorporates factors such as days after anthesis (DAA), total soluble solids (TSS) of the pulp, and the pulp dry matter content (DMC). Their research revealed that in comparison to the DMC prediction model, the MI prediction model based on near-infrared spectra from stems, rind, and pulp exhibited a stronger correlation with the near-infrared spectra.

Diffuse transmission is also a commonly used detection mode for the internal quality assessment of large-size and thick-skinned fruits. Han et al. [27] used diffuse transmission mode to detect the SSC content of small watermelons, measured the navel and equatorial parts, and constructed PLS models. The RMSEP values of the models were 0.666° Brix and 0.732° Brix, respectively. Zeb et al. [28] used diffuse transmission mode to detect the internal quality of watermelon and compared the effects of MLR, SVM, and artificial neural network (ANN) models on detecting SSC content in watermelon. The results showed that the MLR model was the best, and its RMSEP was 1.63° Brix. In addition, Jie et al. [29] also attempted to use diffuse transmission mode to detect SSC content in watermelon and compared the performance of PLS models constructed using full spectrum (680–950 nm) and characteristic wavelengths. The experimental results showed that the Monte-Carlo uninformative variable elimination based on the genetic algorithm and PLS (MC-UVE-GA-PLS) combined with the variable selection method could optimize the model. The model finally selected 14 variables, which greatly simplified the model structure and improved the efficiency of modeling. Jie et al. [30] carried out a study on the ratio of two peaks (RPP) and differential peak intensity (NDIP) based on the diffuse transmission mode to determine the maturity of watermelon. The study indicated that the accuracy of maturity classification based on RPP is 88.1%, which was higher than that of the LS-SVM model (only 76.7%) to evaluate watermelon maturity. This method could avoid complex model calculation and was conducive to the implementation of online detection tasks. Table 1 summarizes the typical studies on the applications of Vis-NIR spectroscopy to detect the internal quality of large-size and thick-skinned fruits.

Table 1. Applications of visible and near-infrared spectroscopy in the internal quality detection of fruits with large size and thick peel.

Fruits	Detection Properties	Equipment	Data Acquisition Modes	Spectral Range	Models	Results	References
Durian	DM Maturity	USB2000; Ocean Optics, Dunedin, FL, USA	Diffuse reflection	110–2500 nm	PLSR	RMSEP = 1.61–2.22% CCR = 94.4%	[24]
Durian	DM SSC	MPA, Bruker Optik GmbH, Ettlingen, Germany	Diffuse reflection	800–2500 nm	PLS	RMSEP = 3.60% RMSEP = 1.63° Brix	[22]
Durian	Maturity	USB2000 Ocean Optics, Dunedin, FL, USA	Diffuse reflection	350–750 nm	PLS-DA	CCR = 94.7%	[23]
Melon	SSC	K-BA100R, Kubota Co., Osaka, Japan	Diffuse reflection	550–950 nm	MC-UVE-SPA-MLR	RMSEP = 0.95° Brix	[21]
Melon	SSC	MMS-1, Felix Instruments, Camas, WA, USA	Diffuse transmission	310–1100 nm	PCA-MLR	RMSEP = 1.63° Brix	[28]
Melon	SSC	USB2000+, Ocean Optics, USA	Diffuse reflection	550–950 nm	UVE-SPA-PLS	RMSEP = 0.8359° Brix	[20]
Melon	SSC	USB2000+, Ocean Optics Inc., Dunedin, FL, USA	Diffuse reflection	750–950 nm	CARS-PLS	RMSEP = 0.67–0.78° Brix	[19]
Melon	TSS	DA-7000, Perten Instruments North America, Inc., Springfield, IL, USA	Diffuse reflection	400–1700 nm	MPLS	SECV = 0.96° Brix	[31]
Pineapple	SSC	USB4000, ORNET Sdn. Bhd., Selangor, Malaysia	Diffuse reflection	650–1000 nm	PCA-ANN	RMSEP = 0.87° Brix	[32]
Pineapple	SSC	USB4000, ORNET Sdn, Bhd, Selangor, Malaysia	Diffuse reflection	662–1005 nm	PCR	RMSECV = 0.81° Brix	[14]
Watermelon	Lycopene Moisture SSC	K-BA100R, Kubota Co., Osaka, Japan	Diffuse reflection	500–1010 nm	MC-UVE-PLS	RMSEP = 0.439 mg/100 g RMSEP = 0.276% RMSEP = 0.717%	[33]
Watermelon	Lycopene TSS β Carotene	DA7200, Perten Instruments, Hägersten, Sweden	Diffuse reflection	950–1650 nm	PLSR	SEP = 3.58 ugg^{-1} SEP = 0.1° Brix SEP = 1.4 ugg^{-1}	[15]
Watermelon	Lycopene TSS β Carotene	NIR-OnlineX-One, Buchi, Flawil, Switzerland	Diffuse reflection	900–1700 nm	PLS	RMSEP = 16.19 mg/kg RMSEP = 1.4% RMSEP = 0.98 mg/kg	[34]
Watermelon	Maturity	MicroNIR Pro 1700, VIAVI Solutions, Inc., San Jose, CA, USA	Diffuse reflection	908–1676 nm	PLS-DA	CCR = 66.4–82.2%	[17]
Watermelon	Maturity	commercial miniature fiber optic spectrometer, Ocean Optics Inc., USA	Diffuse transmission	200-1110 nm	RPP	CCR = 88.1%	[30]
Watermelon	Maturity	Self-developed	Diffuse reflection	700–1900 nm		CCR = 76.7%	[35]
Watermelon	Moisture SSC	K-BA100R, Kubota Co., Osaka, Japan	Diffuse transmission	-	PLS	RMSEP = 0.766% RMSEP = 0.732° Brix	[27]
Watermelon	SSC	commercial miniature fiber optic spectrometer, Ocean Optics Inc., USA	Diffuse transmission	680–950 nm	MC-UVE-PLS	RMSEP = 0.512° Brix	[29]

Table 1. *Cont.*

Fruits	Detection Properties	Equipment	Data Acquisition Modes	Spectral Range	Models	Results	References
Watermelon	SSC	commercial miniature fiber optic spectrometer Ocean Optics, Ocean Optics Inc., USA	Diffuse transmission	687–920 nm	MC-UVE-SMLR	RMSEP = 0.328° Brix	[36]
Watermelon	TSS	DA-7000, Perten Instruments North America, Inc., Springfield, IL, USA	Diffuse reflection	400–1700 nm	MPLS	SECV = 0.93° Brix	[31]

3.2. Acoustic Technique

Acoustic detection technology can utilize the transmission characteristics, scattering characteristics, absorption characteristics, reflection characteristics, attenuation coefficient, propagation speed, and its own acoustic impedance and natural frequency of fruits under the action of sound waves to analyze fruit quality [37]. This technology is mainly divided into two types, namely contact and non-contact. The contact detection method needs a sensor attached to the surface of the fruit. Wei et al. [38] used six acceleration sensors attached to different positions on the surface of a watermelon to evaluate the internal quality. Taniwaki et al. [39] used an acceleration sensor to detect the second resonance rate of melon and determined the elasticity index (EI). The study found that EI could evaluate the shelf life of melon to ensure the quality of fruit during the sales period. Ikeda et al. [40] calculated the shear elasticity of watermelon by using the velocity of surface elastic waves at different positions of watermelon according to Poisson's ratio. This method had a better accuracy in detecting the hardness of large-sized fruits. Choe et al. [41] studied the transmission velocity of sound in the watermelon sample based on the piezoelectric transducers (used as a transmitter and a receiver) to evaluate the maturity of watermelon, in which sugar content was used as an indicator of watermelon maturity. The results indicated that the determination coefficients of sound velocity and sugar content of samples used in the experiment could reach 0.987 and 0.975, respectively.

Unlike contact detection, non-contact acoustic detection technology requires the use of microphones to detect acoustic impulse response signals. The detection system is shown in Figure 3. The system mainly includes a test bench, a multi-channel signal conditioner, a vibration control, and a dynamic signal acquisition analyzer and software system. Mao et al. [42] used three kinds of balls made of stainless steel, glass, and rubber to impact fruit samples placed in plastic trays and rubber trays. The experimental results showed that the resonance frequency obtained by the stainless-steel ball was the most stable, and the plastic tray had a lower standard deviation than the rubber tray. Abbaszadeh et al. [43] tried to find the best frequency excitation position of watermelon based on ANSYS finite element modeling. The results showed that the best location for excitation and detection of the response was the equator of watermelon. On this basis, the experiment was carried out to establish a regression model between the vibration response detected and the hardness of watermelon. The determination coefficient R^2 could reach 0.9998. Baki et al. [44] constructed a multi-layer perceptron (MLP) model to determine the maturity of watermelon and obtained a classification accuracy of 77.25%. Terdwongworakul et al. [45] evaluated coconut hardness based on acoustic characteristics. The PLSR model based on coconut resonance frequency achieved a result of R^2 = 0.927. Chen et al. [46] presented an approach to detecting watermelon maturity based on wavelet multi-resolution decomposition and a statistical hypothesis test. By employing this approach, the training and testing accuracies achieved rates of 91.67% and 91.76%, respectively. This method avoided complex feature extraction and classification modeling and provided a reference for online detection of watermelon maturity.

In addition to the use of a single acoustic detection technology, some attempts have been made to integrate acoustic technology with other technologies to detect the internal quality attributes of large-size and thick-skinned fruits. Phuangsombut et al. [47] determined the maturity of pomelo according to the sugar/acid ratio (SSC/TA). The PLS-DA model was constructed by combining the visible light reflectance and resonance frequency of the pomelo epidermis and achieved an 83.9% classification accuracy. Chawgien et al. [48] used the knocking sound signal, watermelon peel pattern, and weight as the characteristics for measuring watermelon maturity and used machine learning to classify watermelon maturity. The experimental results showed that the classification accuracy of the gradient enhancement tree model (GBDT) could reach 92%. In the non-contact acoustic detection device, the laser Doppler vibrometer is a measuring instrument that uses the principles of laser Doppler effect and optical heterodyne interference to measure the vibration of objects. It has high accuracy in detecting fruit hardness and can be used to detect the maturity of large-size and thick-skinned fruits. In the study of laser Doppler vibrometer, Abbaszadeh et al. [49] used the correlation between phase shift frequency and the color of the watermelon to detect the content of lycopene in the watermelon, and a R^2 of 0.86 was obtained. Abbaszadeh et al. [50,51] constructed stepwise multiple linear regression (SMLR) and partial least squares regression (PLSR) models based on amplitude and phase information to predict watermelon hardness. Among them, the SMLR model combined with the phase spectrum obtained the best performance, and the RMSEP values were 0.0116 N and 0.0346 N, respectively. In another study, Abbaszadeh et al. [52] used a laser Doppler vibrometer combined with the amplitude spectrum of the fast Fourier transform (FFT) to construct a KNN model to determine the maturity of watermelon, and the maturity classification accuracy was 95%. In order to use a laser Doppler vibrometer(Model OmetronVH1000-D, Denmark) to accurately judge the internal quality of watermelon, Abbaszadeh et al. [53] constructed SMLR and PLS models based on vibration spectrum to predict TA, total soluble solids (TSS) and TSS/TA of watermelon. The results showed that the SMLR model was superior to the PLS model, and the R^2 values of the three indicators were 0.9976, 0.9985, and 0.9542, respectively. Table 2 summarizes the typical applications of acoustic detection technology in large-size and thick-skinned fruits.

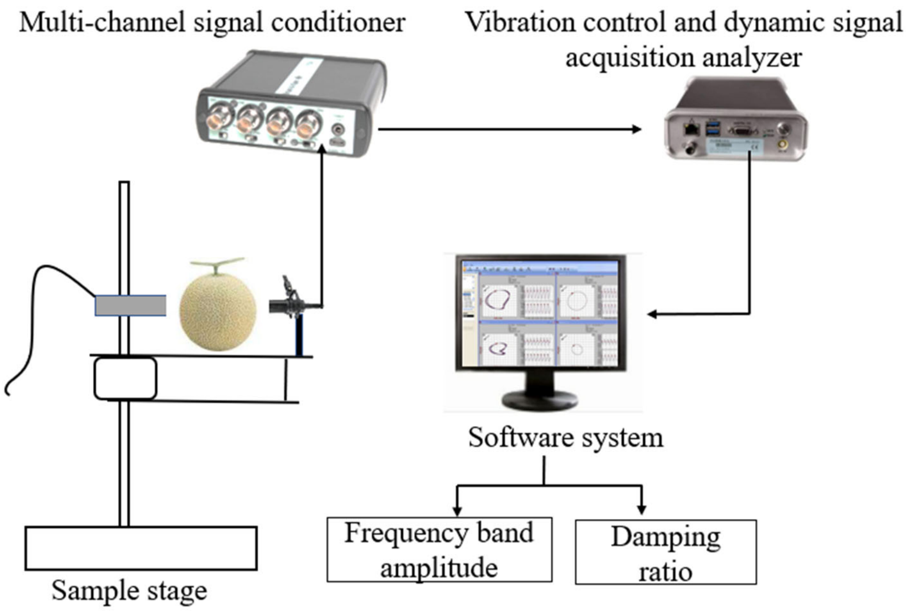

Figure 3. Internal quality detection system of muskmelon based on acoustic pulse response signal.

Table 2. Applications of acoustic detection technology in the internal quality detection of fruits with large size and thick peel.

Fruits	Detection Properties	Data Acquisition Mode	Models	Results	References
Coconut	Hardness	Contactless microphone senses and acoustic pulse response signals	PLSR	R^2 = 0.927	[45]
Pineapple	Maturity	Contactless microphone senses and acoustic pulse response signals	Discriminant function	82.8%	[54]
Shaddock	Maturity	Contactless microphone senses and acoustic pulse response signals	PLS-DA	83.9%	[47]
Watermelon	Flesh color	Contactless laser Doppler vibrometer	MLR	RMSEP = 2.16–5.59	[49]
Watermelon	Hardness	Contactless laser Doppler vibrometer	MLR	RMSEP = 0.0294 kgf	[43]
Watermelon	Hardness	Contactless laser Doppler vibrometer	SMLR	RMSEP = 0.0116 N	[50]
Watermelon	Hardness	Contactless laser Doppler vibrometer	SMLR	RMSEP = 0.0346 N	[51]
Watermelon	Hardness	Contactless microphone senses and acoustic pulse response signals	BPANN	RMSEP = 1.861 N/mm	[42]
Watermelon	Maturity	Contactless laser Doppler vibrometer	KNN	95%	[52]
Watermelon	Maturity	Contactless microphone senses and acoustic pulse response signals	GBDT	92%	[48]
Watermelon	Maturity	Contactless microphone senses and acoustic pulse response signals	MLP	77.25%	[44]
Watermelon	SSC	Contact acceleration sensor	Linear regression	R^2 = 0.8124	[55]
Watermelon	SSC	Contact piezoelectric transducer	BPANN	R^2 = 0.987	[41]
Watermelon	TA TSS TSS/TA	Contactless laser Doppler vibrometer	SMLR	RMSEP = 0.0006% RMSEP = 0.0518% RMSEP = 9.8557%	[53]

3.3. Other Technologies

In addition to the most commonly used Vis-NIR spectroscopy and acoustic technology, other technologies, such as machine vision [56], electromagnetic technology [57], hyperspectral imaging [58], laser backscatter imaging [59], and thermal imaging, were also used for the non-destructive testing of internal quality of large-size and thick-skinned fruits. Table 3 summarizes the typical applications of these techniques.

Table 3. Applications of other technologies in the internal quality detection of fruits with large size and thick peel.

Detection Technologies	Fruits	Detection Properties	Models	Results	References
Electromagnetic technology	Melon	SSC	ELM, PLS	RMSEP = 0.986–1.085° Brix	[60]
Electromagnetic technology	Melon	SSC	PCA-GA-BPANN	RMSEP = 0.762° Brix	[61]
Hyperspectral imaging	Durian	DM Maturity	PLSR LDA	RMSEP = 1.22–1.55% 100%	[62]
Hyperspectral imaging	Melon	Hardness	PLS, SMLR, PCR	RMSEP = 6.4–8.13 N	[63]
Hyperspectral imaging	Melon	Hardness SSC TA	PLS	RMSEP =20.5 g/cm^2 RMSEP = 0.38168° Brix RMSEP = 0.0263 g/kg	[64]
Hyperspectral imaging	Melon	SSC	PLS, SMLR	RMSEP = 0.727–0.873° Brix	[65]
Laser backscatter imaging	Watermelon	Hardness Moisture pH SSC	PCA-PLS	RMSEP = 0.079–0.085 N RMSEP = 0.492–0.557% RMSEP = 0.089–0.167 RMSEP = 0.175–0.223%	[66]
Laser backscatter imaging	Watermelon	Maturity	LDA	94%	[67]
Machine vision	Watermelon	Maturity	ANN	77.3%	[68]
Machine vision	Watermelon	Maturity	ANN	86.51%	[69]
Machine vision	Watermelon	Maturity	KNN	86.66%	[70]
Machine vision	Watermelon	Maturity	LDA	93%	[71]
Thermal imaging	Durian	Maturity	LDA, KNN, SVM	95–97%	[72]

Machine vision uses image sensors to obtain images of fruits and then converts the images into data matrices and analyzes them with computers instead of the brain to complete processing and analysis. Machine vision is mainly used to detect the external quality of fruits, especially defects. Studies have found that fruit maturity can be detected based on external features [73]. Based on machine vision, Syazwan et al. [68] studied the effect of different parts of watermelon peel characteristics on the detection of watermelon maturity. The study showed that different detection positions could affect the classification results, and the skin with yellow spots had the highest classification accuracy of 77.3%. Gupta et al. [60] used machine vision to study the correlation between peel color characteristics (L*, a*, and b*) and fruit internal quality parameters (SSC, TA, hardness, β-carotene, pH) for determining the pomelo maturity. The results showed that hardness, acidity, and sugar content had the highest correlation with maturity, and the coefficient of determination could reach 0.90.

Additionally, electromagnetic technology has great potential in the non-destructive testing of large-size and thick-skinned fruits. Tantisopharak et al. [74] used electromagnetic scattering characteristics to track the natural frequency of durian fruit over time to determine maturity. The results showed that the maturity classification accuracy of durian could reach 70% when the resonance frequency of durian was lower than 100 MHz, indicating that electromagnetic technology could effectively predict the stage of maturity of durian. The most commonly used method in electromagnetic technology is to evaluate the maturity based on the dielectric properties of fruits. Dielectric properties refer to the properties of fruits showing storage and loss of electrostatic energy under the action of an electric field, which are usually expressed by dielectric constant and dielectric loss. Liu et al. [66] compared the performance of PLS and extreme learning machine (ELM) models in evaluating the SSC of four melons based on the dielectric properties. The results showed that both models had accurate effects, and the RMSEP values ranged from 0.986 to 1.085° Brix.

Laser backscatter imaging is a technique for detecting the internal quality of fruit based on the relationship between light scattering and the physical properties of fruit tissue. Ali et al. [67] used laser backscatter imaging to detect the internal quality of watermelon and explored the feasibility of evaluating watermelon during storage based on the PCA multivariate statistical method. The results showed that the laser backscatter imaging could classify the seven types of storage days (0, 4, 8, 12, 15, 18, and 21 d) of watermelon, and the classification accuracy could reach 94%. Furthermore, Ali et al. [71] compared the performance of laser backscatter imaging and machine vision technology in evaluating watermelon maturity. The classification accuracies of the two technologies were 94% and 93%, respectively.

Thermal imaging is a non-contact and non-destructive detection technology. This technology converts the detected infrared energy into an electrical pulse signal and converts it into thermal image information, which can be used to detect the maturity of fruits. Ali et al. [72] used thermal imaging to detect the maturity of durian, obtained the mapping of thermal parameters using PCA, and also obtained the physical and chemical characteristics of durian by constructing a PLS model. This study indicated that the SVM model had the best performance, and the overall accuracy of durian maturity detection was 97%.

Hyperspectral imaging combines traditional two-dimensional image and spectral technology, which has rich spectral information and can achieve effective and accurate characterization of fruit quality. Ma et al. [65] and Li et al. [63] observed the feasibility of using hyperspectral imaging to predict the sugar content and hardness of melon. The results showed that the RMSEP values of the PLS models were 0.873° Brix and 6.4 N, respectively. Sharma et al. [62] employed this technology to conduct experiments focused on maturity stage classification and DM prediction of durian pulp. They found that the five classification models of SVM, random forest (RF), LDA, PLS-DA, and KNN could achieve accurate results in evaluating the DM of durian. A classification accuracy of 100% was obtained for maturity using full specter or characteristic wavelengths. In subsequent investigations, Sharma et al. [75] discovered that the GA-PLSR model yielded an accurate predictive outcome for dry matter (DM) in durian pulp (R^2 and RMSEP were 0.97 and 1.12%, respectively).

4. Online Detection and Grading System

The purpose of the research is to face the actual production. Many scholars have also been committed to developing an online rapid detection system suitable for the real-time evaluation of the internal quality of large-size and thick-skinned fruits. To achieve practical commercial implementation, the real-time detection system must meet specific demands for detection speed while maintaining accuracy. Tamburini et al. [34] developed an online system for internal quality detection of watermelon based on Vis-NIR spectroscopy. The system had three different detection speeds (2100, 2400, and 2700 rpm) and could systematically compare and analyze the watermelons, which were positioned on four different sides. The PLS model was constructed to predict the sugar content, lycopene, and β-carotene content of watermelon. It was found that the RMSEP values of the model for lycopene, β-carotene, and sugar content were 16.19 mg/kg, 0.96 mg/kg, and 1.4%, respectively. Jie et al. [36] developed an online detection system, as shown in Figure 4, to analyze the SSC of watermelon based on Vis-NIR spectroscopy. The model was constructed, and the influence of watermelon moving speed on the detection accuracy of SSC was evaluated. The results showed that the detection performance was the best with RMSEP of 0.328° Brix for the SMLR model when the conveyor belt speed was 0.3 m/s.

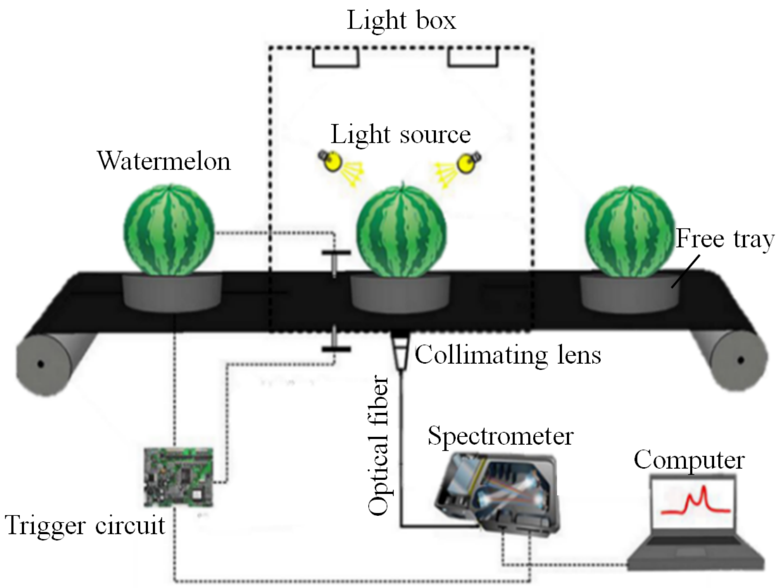

Figure 4. The online detection system for the internal quality of watermelon [36].

In addition to the prototype system from the laboratory, some commercial sorting systems for non-destructive testing of the internal quality of large-size and thick-skinned fruits have also gradually been developed. For example, Japan's FANTEC company has developed a watermelon online detection system based on diffuse transmission NIR spectroscopy, which can detect the SSC of watermelon in real time, and the detection speed is two watermelons per second. The Italian company SACMI successfully developed a sorting system that can detect the internal quality of small watermelons, such as sugar content, acidity, and hollowness. The detection speed is two watermelons per second. Based on NIR spectroscopy, machine vision, and acoustic technology, OMI Weighing Machine Company developed watermelon online detection equipment, which can effectively detect the sugar content and the degree of hollowness of watermelon. The online detection speed is six watermelons per second. In recent years, some commercial watermelon quality detection equipment has also been successfully developed in China, mainly for the detection of the weight and sugar content of watermelons.

5. Suggestions and Thoughts

In terms of the non-destructive testing of the internal quality of large-size and thick-skinned fruits, there are some suggestions and thoughts. Firstly, fusion technology can make up for the limitations of a single technology. For example, the laser Doppler vibrometer combines optical technology and acoustic vibration technology to improve the adaptability of acoustic detection to the environment [76,77]. Hyperspectral imaging can detect the external and internal quality of large-size and thick-skinned fruits by combining spectral technology and machine vision. Although fusion can achieve advantages between technologies, it usually takes more time to collect abundant data, which inevitably affects the speed and real-time performance of quality detection. Therefore, it is necessary to further develop more efficient detection and data processing methods to deal with abundant data. Secondly, the full transmission spectrum detection mode needs to be further studied. At present, Vis-NIR spectroscopy mainly involves two modes (reflection and diffuse transmission), which cannot effectively collect the information of deep pulp of large-size and thick-skinned fruits. Therefore, it is possible to try to develop a Vis-NIR spectral detection technology based on full transmission mode, but it is necessary to develop a more sensitive spectral acquisition system to obtain full transmission spectral data with a high signal-to-noise ratio in real time. Thirdly, it is necessary to further study the internal quality detection model or algorithm for large-size and thick-skinned fruits. Because of the thick skin, the accuracy of the internal quality prediction model is affected. The large size poses a challenge for the effective acquisition of comprehensive fruit information. The construction of models and algorithms with higher prediction accuracy, wider applicability, and more objective evaluation is a challenge. The advantages and disadvantages of these reviewed non-destructive testing techniques for the quality analysis of large-size and thick-skinned fruits are shown in Table 4.

Table 4. Advantages and disadvantages of the reviewed non-destructive testing technologies for internal quality of fruits with large size and thick peel.

Detection Technologies	Advantages	Disadvantages
Vis-NIRS	Fast operation, simple equipment, low cost, especially suitable for online detection of internal components	Limited light penetration ability, model accuracy is easily affected by peel, detection location, and spectral acquisition method
Acoustic technology	Fast, simple, and low-cost, especially suitable for hollow and hardness detection	Sound signals susceptible to environmental interference
Laser backscatter imaging	High detection accuracy and the potential for online detection	Difficult to distinguish between fruits with similar density and maturity
Hyperspectral imaging	Rich data information, especially suitable for simultaneous analysis of internal and external quality	Slow detection speed, high cost, not suitable for online detection
Machine vision	Fast detection speed, low cost, and online implementation	Unable to effectively analyze the internal quality of fruits
Electromagnetic technology	Fast and low-cost	Susceptible to temperature and relative humidity
Thermal imaging	Low cost and high sensitivity	Susceptibility to ambient temperature effects, low applicability, weak anti-interference ability, and accelerated fruit decay

6. Conclusions

This article reviews the latest progress of seven techniques used for the non-destructive detection of the internal quality of five types of large-size and thick-skinned fruits. The literature over the past decade has shown that each technique can effectively evaluate the internal quality of large-size and thick-skinned fruits with its unique advantages. Vis-NIR spectroscopy can effectively analyze the internal components of fruits, such as sugar content, acidity, lycopene, moisture, and β-carotene. Acoustic detection technology has good performance in classifying fruit maturity. Other advanced technologies, such as electromagnetic technology, hyperspectral imaging, laser scattering imaging, and thermal imaging, have also been gradually applied to the internal quality detection of large-size and thick-skinned fruits and showed certain potential. In addition to the technology itself, the development of advanced algorithms is also crucial to promote the practical application of detection technology. In the commercial application of online detection, it is necessary to give priority to four important aspects: system cost, detection speed, accuracy, and stability. Therefore, although some technologies are worth recommending, there are still many problems to be solved. Overall, this review provides a valuable reference for the industry to carry out research and practical application of the internal quality detection of large-size and thick-skinned fruits based on non-destructive sensing technology.

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