Food Engineering Reviews
https://doi.org/10.1007/s12393-023-09353-3

The Application of Optical Nondestructive Testing for Fresh Berry Fruits

Zhujun Chen[1] · Juan Wang[1] · Xuan Liu[1] · Yuhong Gu[2] · Zhenhui Ren[1]

Received: 29 August 2022 / Accepted: 16 July 2023

Abstract

Berry fruits are highly nutritious and possess therapeutic properties, making them popular in various markets including fresh fruit, food, beauty, medical, and health. As people's quality of life continues to improve, the demand for berry fruits is increasing. As a result, farmers must prioritize the quality of berry fruits while also increasing production. In the realm of quality control, berry fruit detection holds great significance. However, traditional detection methods are plagued with major drawbacks such as destructiveness, high cost, and a long detection time. Fortunately, nondestructive testing technology has rapidly developed due to its nondamaging, efficient, and versatile advantages. This method can complete various detection projects and meet the diverse detection requirements of orchard supervision. This paper provides a review of the use of nondestructive testing technology in various types of berry fruits and highlights the progress made in optical nondestructive testing technology for identifying these fruits, as well as detecting their external and internal quality. This article summarizes and analyzes the challenges encountered by nondestructive testing in the same field of berry fruits and explores the potential development directions of nondestructive testing technology in the field. The findings of the study can offer valuable insights and reference for the intelligent management of berry orchards and the enhancement of the berry market system.

Keywords Berry fruit detection · Berry quality · Nondestructive detection · NIR · HSI · CNN

Introduction

A berry is a fleshy fruit developed from ovary or in association with other floral organs; the outer peel of berries consists of thin-walled cells while the peel and inner peel are fleshy and contain abundant juice [1]. Berry fruits are classified into many types, such as blueberry, raspberry, mulberry, grape, strawberry, and cranberry [2, 3], based on their unique characteristics. Berry fruits are highly valued for their medical benefits, as they are rich in nutrients such as anthocyanins, micro-nutrients, and fiber [4]. Due to the growing emphasis on healthcare, the demand for berry fruits has increased significantly in recent years [5–7]. Consequently, there has been a rapid growth in berry plantation areas to meet the market demand. However, with the increase of yield, traditional orchard management methods might not be sufficient to guarantee the quality of fruits [8–10]. The quality requirements for fresh berry fruits are also rising as people's quality of life improves. Despite the variety of berries, there is no uniform international standard for quality inspection, which makes it challenging to develop a consistent grading and quality inspection system [11, 12]. Many countries still rely on manual labor for grading and quality inspections [13]. Therefore, detecting fresh berries for different purposes is needed to enhance the yield and quality of berries and optimize the berries market.

Currently, artificial quality detection is only able to classify and screen the external quality for fruit, with low efficiency, high error, and high cost. However, detecting the internal quality is generally impossible with naked eye. The commonly used chemical methods for fruit detection are destructive and are not suitable for the detecting large-yield berry fruits or for real-time detection of each fruit [14]. Fortunately, nondestructive testing technology has developed rapidly in recent years for the supervision and quality control of agricultural products, with the advantages of nondestructiveness and wide applicability [15]. Nondestructive testing technology is the use of instruments based on X-rays,

Zhujun Chen and Juan Wang contributed equally to this work.

✉ Zhenhui Ren
renzh68@163.com

[1] College of Mechanical and Electrical Engineering, Hebei Agricultural University, Baoding 071001, People's Republic of China

[2] College of Life Sciences, Hebei Agricultural University, Baoding 071001, People's Republic of China

ultrasonic, infrared, electromagnetic, and other principles of technology to obtain the chemical, physical, and other parameters of sample [15, 16]. Optical nondestructive testing technology is based on detecting samples by using the spectral characteristics of visible and invisible light in different electromagnetic wave bands. Common optical nondestructive testing technologies include infrared spectroscopy (IRS), hyperspectral imaging (HSI) technology, machine vision technology, and micro-CT technology [17, 18]. Optical nondestructive testing technology has shown advantages of high efficiency, high precision, and strong applicability in the agricultural field.

This paper presents a review of popular optical testing methods that have been employed in recent years for fresh berry fruits as the research object. Specifically, the research on nondestructive testing of fresh berry fruits that utilizes machine vision technology, visible/infrared spectroscopy (VIS/IRS) technology, and HSI technology is reviewed and analyzed. The related methods and problems are summarized and analyzed, providing a valuable reference for future research and development in optical nondestructive testing of berry fruits and the optimization management of berries orchard.

Berry Fruit Detection Based on Machine Vision

Machine vision technology, which originated in the 1960s [19], is a nondestructive testing technology that uses computers to fully interpret, simulate, and process human visual information [20]. The basic principle applies a camera to acquire images of the physical surface to be measured and uses computer technology instead of human vision to analyze the images for data, extract feature data information, and analyze the feature information to identify the measurement information (Fig. 1). This technique is often applied in the field of classification and inspection of the apparent quality of fruits [21–23].

In the field of classifying and inspecting the apparent quality of agricultural products, machine vision technology embodies the characteristics of noninvasive, efficient, low-cost, and objective. It has been able to achieve many inspection requirements such as shape classification, variety classification, damage detection, quality detection, and classification [24]. The utilization of machine vision technology for nondestructive testing of berries has reached a high level of maturity. This paper provides a comprehensive review and analysis of recent research and related methods in this area (Fig. 2).

Figure 2 illustrates the predominant application of machine vision technology in recent years, with berry fruit yield prediction and ripeness detection being the most common. As a research focus, yield prediction involves object segmentation and object quantification; both of which have a direct impact on the accuracy of yield prediction results. The classification of berry fruit is typically based on the color of the berries, which is an important external feature. Consequently, machine vision for berry maturity classification has been a popular research topic. Moreover, machine vision can detect various diseases on the surface of berry fruits such as fugal decay, shrivel, and mildew.

Berry Fruit Yield Prediction Approach

The positioning and identification of fruit is one of the important fields in the initial stages of agricultural machine vision technology. With the continuous development of machine vision technology, fruit positioning and identification can effectively predict orchard yield

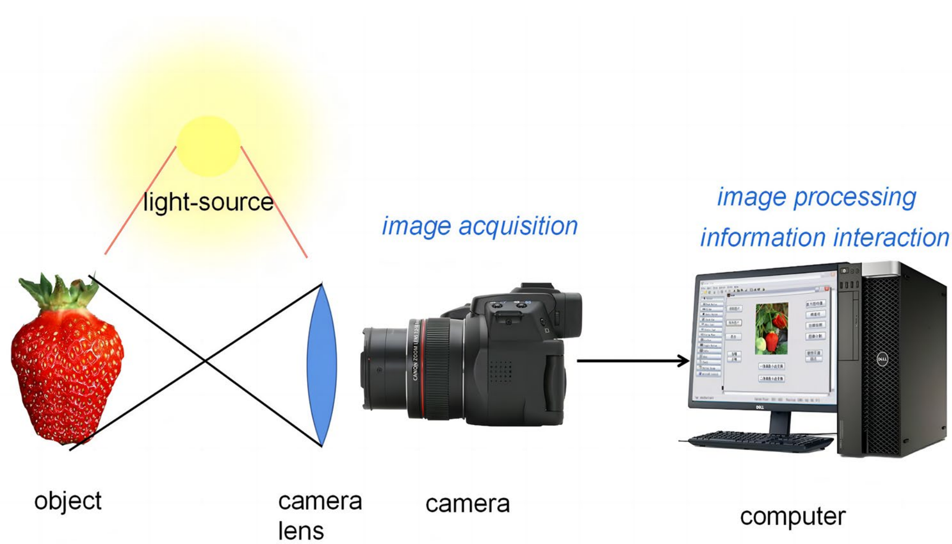

Fig. 1 Working principle of machine vision detecting berry fruits

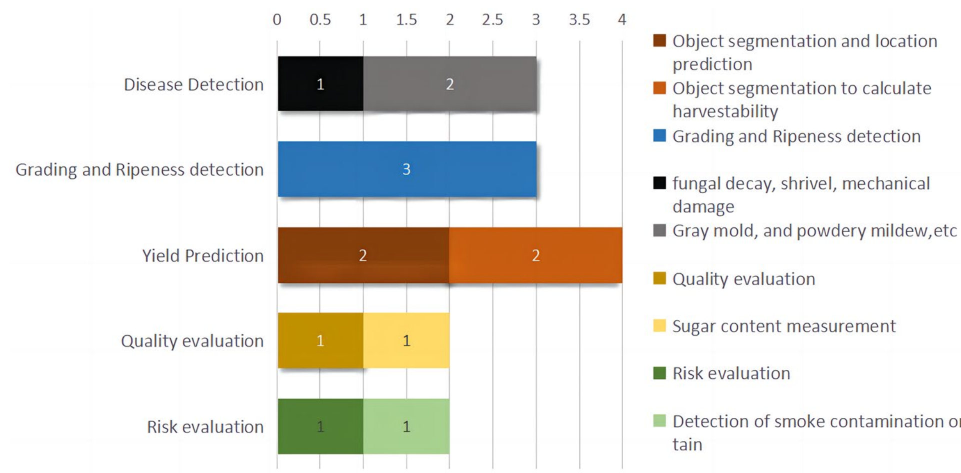

Fig. 2 The main distribution of machine vision researches in this review

and understand the variability of fruit yield in orchards, providing comprehensive orchard information for fruit farmers and facilitating scientific orchard management, thus realizing the fundamental requirements of precision agriculture [24–26]. The integration of machine vision technology into berry yield prediction enables intelligent management of berry orchards. The recent research on berry yield prediction based on machine vision is summarized as Table 1.

Table 1 illustrates that recent studies on different types of berries have predominantly focused on two areas: object segmentation extraction and object detection and quantification. These studies emphasize the significance of extracting feature data information through machine vision technology, which can be accomplished via either automatic or manual feature extraction. The methods employed for automatic feature extraction vary among the mentioned scholars; however, all of them utilize mask region convolutional neural network (Mask-R-CNN) in their research. As such, Mask-R-CNN has emerged as a powerful and advanced tool for yield prediction and target detection in these areas of study.

The deep learning neural networks commonly used in fruit detection, including AlexNet, ZF, VGG, GoogleNet, and ResNet, have been analyzed and evaluated based on their accuracy, convergence, and model detection speed. After careful consideration, ResNet was identified by the scholars as the backbone network for feature extraction. Additionally, the feature pyramid (FPN) was found to effectively capture the multiscale target of berries by layer-by-layer screening of bottom features and merging with the top features. This method allows each layer to independently map the characteristics of the berry fruits, which is particularly beneficial

Table 1 Major contributions of berry detection approach in the field of machine vision

Berry type	Task	Method	Backbone	Feature generation method	Performance indices	Ref.
Strawberry	Object segmentation and location prediction	Mask-R-CNN	ResNet50/101 + FPN	Processes the features extracted by RPN	Accuracy = 95.78%	[123]
Strawberry	Object segmentation and location prediction	Optimized Mask-R-CNN	ResNet50/101	Processes the features extracted by RPN	mPA = 43.85; mI^2oU = 87.27%	[28]
Blueberry	Object detection and quantification	Mask R-CNN	ResNet101/50 or MobileNetV1 + FPN	Processes the features extracted by RPN	mIoU = 0.60, $mAP^{IoU=0.5}$ = 0.76, $mAP^{IoU=0.75}$ = 0.72	[29]
Blueberry	Object detection and quantification	Mask R-CNN	ResNet101 + FPN	Processes the features extracted by RPN	$mAP^{IoU=0.5}$ = 0.72, accuracy = 90.40%	[30]
Grape	Early yield prediction	CNN	SegNet DL	Clustering segmentation	R^2 = 0.54–0.87, NRMSE = 16.74%–39.17%	[31]

Mask-R-CNN mask region convolutional neural network, *RPN* region proposal network, *FPN* feature pyramid network, *mAP* metric average precision, *mIoU* mean intersection over union, R^2 determination coefficients, *NRMSE* normalized root mean squared error for the feature extraction of small berry fruits. Regional proposal network (RPN) is a commonly used approach for feature processing of backbone networks. RPN utilizes a convolution layer to classify input feature anchor points and another convolution layer to set anchor points offsets. With this approach, RPN can effectively remove external environmental regions and is particularly effective in addressing the challenge of overlapping small berry fruits. This approach has been widely adopted due to its significant advantages in berry detection and recognition.

Identifying and counting berry fruits are significant challenges for predicting berry yield [27]. Due to their small size and outdoor growth environment, the complexity of the environmental background, overlap, occlusion, and other factors decreases the accuracy of berry fruit detection, which in turn directly impacts the yield prediction outcome. Therefore, the primary task to enhance the accuracy of yield prediction is to improve the recognition accuracy of berry fruits. Yu et al. [123] addressed this challenge by considering different difficult problems of target recognition under complex growth conditions, such as strawberry fruit overlap and occlusion, and different light intensities. They leveraged various features of the target, including color, shape, and texture, to introduce the mask area convolution neural network and improve the positioning and recognition accuracy of strawberries. The strawberry automatic detector constructed involves multiple target features, however, and Mask-RNN network has a large number of operations, leading to slow model operation. Building on the research team of Yu, the segmentation model proposed by Pérez-Borrero et al. [28] significantly enhances the speed of the model. Based on the traditional Mask-RNN network, Pérez-Borrero et al. [28] designed a new backbone network and mask network architecture while deactivating the target detection and final detection adjustment in the neural network, utilizing the RNP algorithm only to complete the classification of strawberry targets, thereby boosting the operation speed. Furthermore, the algorithm is optimized for the area responsible for filtering, and a new regional grouping and filtering algorithm replaced the traditional one, leading to new strawberry instance segmentation method that meets the requirements of realistic strawberry recognition and positioning under and provides favorable support for fruit yield prediction.

Compared to location recognition, quantitative analysis of berry fruits in image presents more challenges. External factors such as occlusion, size, and light intensity can interfere with the accuracy prediction of fruit number. The segmentation algorithm significantly impacts the segmentation accuracy, with the backbone grid serving as a basis for subsequent algorithm optimization. To address these issues, Gonzalez et al. [29] developed a field blueberry detection, segmentation, and quantitative instance segmentation method based on Mask R-CNN. The authors conducted several experiments and tested three backbone networks (ResNet101, ResNet50, and MobileNetV1) to identify the best parameters for accurately predicting the number of blueberries in the image. The algorithm's performance was evaluated using intersection over union error (IoU) and the competitive mean average precision (mAP) of each image and batch of images. The best results were achieved using the ResNet50 backbone network, with $mIoU = 0.595$ and $mAP^{IoU=0.5} = 0.759$ and $mAP^{IoU=0.75} = 0.724$.

In the realm of berry yield prediction, it is imperative to consider the fact that blueberry fruit mature in batches. Ni et al. [30] devised a data processing pipeline that determines the number of blueberry fruits and assesses their maturity. Through the customized definitions and algorithms of the Mask R-CNN blueberry detection model, three traits are measured. Generally speaking, the Mask R-CNN model is proficient at extracting relevant features, and more precise attribute parameters enhance its accuracy. Drawing from their own experience, Ni et al. [30] recognized the compactness of blueberry fruit as also having a bearing. As such, image recognition is performed on the basis of the diverse clustering compactness characteristics of four different blueberry cultivars. The method of image segmentation developed by Ni et al. [30] for blueberry fruit monitoring and segmentation tasks is efficient in ascertaining relevant information from the image, tracking the growth of blueberry fruit in the field, and predicting blueberry yield. A more complex case in the field of yield prediction is the segmentation of overlapping fruit, where clusters of growing grapes are common. Palacios et al. [31] focused on applying machine vision and machine learning to develop an algorithm for early yield prediction of different grape varieties. They used a SegNet-based architecture to detect six different grape varieties based on visible characteristics of the berries and vines in order to predict the actual yield and quantity of grapes. However, due to the shading of the fruit by grape plant growth, machine vision-based approaches are still limited in accuracy. Thus, further development and improvement of the algorithm are needed to adapt to different grape varieties and growing environments and improve the accuracy of yield prediction.

In recent years, numerous scholars have conducted research on predicting berry fruit yield and have achieved significant progress. However, the prediction of berry yield remains challenging due to the small size of the fruit and the complexity of the growth environment, leading to occlusion and difficulty in identifying the berry target in collected images. Additionally, traditional target detection methods for larger fruit are inadequate for accurately identifying the berry fruit. Thus, the primary challenge in berry yield prediction is target detection, and recognition and location are generally optimized through algorithmic improvements. Although optimization algorithm can greatly enhance predictive accuracy, the angle, distance, and occlusion rate of collected images greatly influence target detection results. Therefore, image collection techniques are also essential for optimizing target detection.

Table 1 illustrates the utilization of convolution neural network (CNN) in berry fruit segmentation in the reviewed studies. It is evident that CNN has achieved significant progress in the recognition and prediction of berry fruits. Moreover, CNN's fundamental architecture can be innovatively improved to further enhance its contribution in the field of machine vision [32]. In addition, when optimizing algorithms, different growth characteristics of various berry fruits must be taken into account to increase selection of feature objectives. For instance, blueberries have different maturity levels [30], while clustered grapes have phenotypic variations, that require consideration of the number of clusters, berry fruits numbers in each cluster, and berry fruit sizes to predict yields [33]. Given the complex growth environment of berry fruits and the unique growth traits of each berry fruit, obtaining 3D image information of berry fruits can significantly improve the accuracy of image segmentation. Recently, studies have investigated 3D fruit detection technology [34], which is superior to 2D image information in providing more comprehensive image details.

An additional challenge in predicting yield for berry fruits is the quantitative analysis of these produce. As of present, the quantitative analysis of berry fruits remains in the research stage. The difficulty lies in the counting small-sized or occluded/overlapped fruits. Even fruit counting for medium-sized produce like apples and citrus is yet to be fully researched. The accuracy of prediction models depends on the fruit size. The larger the fruit, the higher accuracy the prediction models achieve [24, 35]. As such, fruit counting for small berries proves to be more challenging.

Berry Fruit Grading and Ripeness Detection Approach

Berry fruits often show their growth progress through changes in color, which is highly correlated with their quality. As such, color is often used as a preliminary evaluation standard of fruit quality, with farmers generally judging maturity based on the depth of berries' color. However, many berry fruits exhibit batch maturation, with fruit on the same plant maturing at different rates, accurately identifying for estimating fruit yield and optimizing harvest. Combining machine vision technology with traditional methods can be of great significance for realizing precision agriculture. Table 2 displays the results of research on berry ripeness detection based on machine vision technology.

Table 2 displays the method used by scholars in determining characteristic types for maturity detection research. Typically, scholars independently select characteristic factors based on their own experience. Among these factors, color is considered to be the earliest one used in determining the maturity of berry fruits. However, as different types of berry maturity discrimination require different characteristic factors, it is essential to select other varying features during the

Table 2 Major contributions of berry ripeness detection approach in the field of machine vision

Berry type	Task	Color model	Feature type	Feature extraction method	Classification method	Performance indices	Ref.
Blueberry	Ripeness detection	RGB, HSV, YCbCr, YIQ, and EGI	Color	FFSA + SVM/NBC/newly introduced SK-means	KNN/NBC/SK-means	Accuracy (KNN) = 96.00%; accuracy (SK-means) = 90.00%	[37]
Blueberry	Ripeness detection	RGB	Color	HOG + SVM	KNN + TMWE	Accuracy (y) = 86.00%, accuracy (IM) = 94.20%, accuracy (M) = 96.00%	[41]
Mulberry	Ripeness detection	RGB	Geometrical properties, color, and texture	CFS/CONS	ANN + SVM	Accuracy = 98.30%	[36]
Mulberry	Ripeness detection	RGB, CIE Lab, HSV, and YCbCr	Automatically extract features by DL	CNN	CNN	Accuracy (AlexNet) = 98.32%; accuracy (ResNet-18) = 98.65%	[38]

RGB red green blue, *HSI* hue saturation intensity, *YCbCr* luminance blue-difference chroma red-difference chroma, *TIQ* luminance in-phase quadrature-phase, *EGI* excess green index, *CIE Lab* lightness redness yellowness, *DL* deep learning, *HSV* hue saturation value, *FFAS* forward feature selection algorithm, *KNN* K-nearest neighbor, *NBC* naïve Bayesian classifier, *SK-means* supervised K-means clustering classifier using weighted Euclidean distance, *HOG* histogram oriented gradients, *SVM* support vector machine, *TMWE* template matching with weighted Euclidean distance, *CFS* correlation-based feature selection subset, *CONS* consistency subset, *ANN* artificial neural network, *CNN* convolutional neural networks, *Y* young fruit, *IM* intermediate fruit, *M* mature fruit maturity prediction process. Azarmdel et al. [36] selected geometric features, color, and texture features according to his own experience. Alternatively, deep learning (DL) can automatically extract feature factors that impact maturity without the need for prior experience. As maturity detection research has progressed, the application of DL has become more prevalent. Because outdoor lighting conditions can influence the color information captured by images, Li et al. [37] and Ashtiani et al. [38] selected multiple color components to establish a multidimensional color dataset for color extraction information. However, the multidimensional dataset can drastically slow down calculations. Therefore, it is necessary to choose the appropriate algorithm to determine the optimal color component.

Li et al. [37] proposed an algorithm based on color component analysis for outdoor blueberry fruit recognition. The complexity of the classification process was increased by dividing blueberry fruit into four precisions. Li et al. [37] established the first classifier to segment the target fruit in the image, and the other two classifiers were used to divide maturity into four precisions. Traditional maturity segmentation only relies on two classifiers to divide the target fruit into three levels: K-nearest neighbor (KNN) [39], linear discriminant analysis (LDA) [124], and Bayesian classifier. The classification and regression tree (CATR), support vector machine (SVM) classifier, and neural network are the most commonly used classification methods for scholars [40]. Tan et al. [41] classified blueberry fruits into three maturity regions based on the traditional classification method. Tan et al. [41] built a blueberry training set based on the original RGB image. The blueberry region is quickly detected by HOG feature vector and linear SVM classifier. Some non-target regions are first excluded by HOG feature vector, and then, the target regions are divided and selected combined with color features, so as to improve the accuracy of target region segmentation. Tan et al. [41] rely on KNN and independently developed template matching with weighted Euclidean distance (TMWE) classifier maturity distinction, in which TMWE classifier in the case of low computational cost has achieved higher advantages.

The maturity of mulberry fruit can also be distinguished by color features. Color is an important classification feature in the field of maturity classification, but the results obtained by combining multiple feature factors are more accurate. In the classification study of mulberry fruit maturity, Azarmdel et al. [36] selected the color, geometric shape, and texture of mulberry fruit as the classification features and classified the maturity of mulberry fruit based on artificial neural network (ANN) and SVM classification methods. SVM classification effect was more obvious, with the classification accuracy of 98.30% for the test set. It can be seen that the target region segmentation results directly affect the subsequent maturity classification results. The feature extraction method combining multiple feature factors can greatly optimize the target region segmentation results. ANN did not play its advantages in Azarmdel's research because there was no system to optimize the structure, and the more accurate the characteristic parameters can improve the accuracy of the model, which also makes the advantages of SVM.

Among the commonly used classification methods [40] for fruit maturity classification, CNN and its derivatives are the most successful and popular [32, 42]. Miraei Ashtiani et al. [38] developed a computer vision application for the maturity classification of white and black mulberry fruits based on the CNN model. The basic architecture incorporates DenseNet, Inception-v3, ResNet-18, ResNet-50, and AlexNet. To improve the classification accuracy, transfer learning was utilized for model adjustments. Among them, AlexNet and ResNet-18 networks achieved exceptionally high accuracy in the classification and detection of total fruit maturity of white and black mulberry, with accuracies of 98.32% and 98.65%, respectively. The study's difficulty lies in the fact that white mulberry's maturity is difficult to distinguish through color features alone, rendering traditional color-based classification inadequate. Therefore, CNN demonstrates a clear advantage in this study.

The combination of machine vision and image processing methods has become a primary means of measuring the maturity of berry fruits based on their color depth. As shown in Table 2, maturity classification research has achieved high accuracy (above 86.00%). However, color features are easily influenced by changes in light conditions, and early research efforts focused on expanding the color indexing and extracting high-dimensional datasets. Unfortunately, this approach required a reduction in dimension processing, which could directly impact the classification results. In recent years, scholars have optimized the feature extraction method to reduce the color dimension processing. For example, Tan et al. [41] combined the HOG feature vector with color feature to extract target features, while considering the texture and geometric features of berry fruits to reduce the errors caused by color features, thereby improving the classification accuracy. Azarmdel et al. [36] extracted multiple features of mulberry fruit with a final classification accuracy as high as 98.30%. These studies demonstrate the effectiveness of extracting multiple features for fruit maturity classification. DL has also been used to automatically extract features and complete target division without being restricted by sensitive color features. However, the prediction accuracy may be affected by different light intensities and complex background environments in real-world conditions. Thus, researchers have developed different types of classifiers to improve the accuracy of image segmentation and prediction accuracy. Nevertheless, due to the complexity of the maturity classification process, it is difficult to ensure the classification accuracy while saving the classification time. To achieve real-time detection results, the classifier still needs to be optimized. In the field of target segmentation and classification, CNN model and its derivatives have shown significant advantages and achievements. Miraei Ashtiani et al.'s [38] CNN-derived model was significantly better than Li's stepwise recognition algorithm in terms of classification efficiency. Therefore, the use of CNN and its derived models is a considerable development trend in this area.

Berry Fruit Disease Detection Approach

The health of berries can be affected by various factors, with diseases affecting crops during the growth process, resulting in the decline in the quality and yield of berry fruits. Therefore, applying machine vision technology to detect diseases of berry fruits can enhance the intelligence and refinement of orchards [43]. The initial application of machine vision to disease analysis involved logical analysis to study simple characteristics, which then progressed to SVM classification mode. Recently, with the development of DL, CNN and its optimization algorithm have become a research hotspot in the field of machine vision for disease detection, greatly improving detection accuracy [44]. Given that different causes of fruit and vegetable diseases result in various disease locations and different image acquisition locations, only the traits of berry fruits were studied in this research. Hence, this study only detected the diseases evident on the fruit while neglecting leaf diseases and other diseases. The research on berry disease detection based on machine vision is shown as Table 3.

Table 3 summarizes the various diseases found on the surface of berry fruits. With the advancements of machine vision in disease classification, diseases can now be categorized in greater detail, resulting in increased classification types. For instance, Kim et al. [45] classified seven types of strawberry diseases. In terms of predicting the disease type, Leiva-Valenzuela et al. [118] employed six traditional classification algorithms, while Xiao [46] and Kim used DL methods to classify diseases based on two network architectures. The advantages of DL are apparent from the results. However, the evaluation methods used by different scholars and the different disease data obtained by various instruments make it difficult to determine the optimal algorithm for disease classification. Therefore, there is still much work to be done in this field.

Blueberries are berry fruits with dark color, and the external appearance characteristics of fruits under different pathology are also different, but manual screening is not easy to find and distinguish. Early detection of different pathology can provide warning for fruit growers, contribute to the fine management of growth period, provide strong support for fine agriculture, and also provide help for the quality classification and screening of blueberry berries after picking. Leiva-Valenzuela et al. [118] detected three different damage situations of blueberry fruit based on machine vision technology and extracted color and geometric features of blueberry under different damage conditions based on pattern recognition algorithm. Four damage situations (normal, fungal decay, shrivel, and mechanical damage) of blueberry were classified based on six classification algorithms (LDA, QDA, MD, KNN, SVM, PNN). Finally, the analysis results show that three classification methods (LDA, SVM, and PNN) have good accuracy for blueberry

Table 3 Major contributions of berry disease detection approach in the field of machine vision

Berry type	Task	Disease category	Feature type	Method	Performance indices	Ref.
Blueberry	Orientation and disease detection	Fungal decay, shrivel, and mechanical damage	Color and geometrical texture	LDA, QDA, MD, KNN, SVM, PNN	Accuracy (orientation) = 96.82%; accuracy (shrivel) = 96.70%; accuracy (fungal decay) = 100%; accuracy (mechanically damage) = 90.00%	[118]
Strawberry	Detection of strawberry diseases	Disease: gray mold and powdery mildew	Manually trimmed	CNN	Accuracy (original) = 98.06%; accuracy (feature) = 99.60%	[46]
Strawberry	Detection of strawberry diseases	Disease: anthracnose fruit rot, gray mold, powdery mildew fruit, etc.	PlantNet autonomous learning	DNN	PlantNet demonstrated performance superior to the ImageNet training by at least 3.20% mAP	[45]

LDA latent Dirichlet allocation, *QDA* quadratic discriminant analysis, *MD* Mahalanobis distance, *PNN* probabilistic neural network, *DNN* deep neural network direction discrimination, and the average classification accuracy reaches 96.82%. It can be seen that machine vision technology combined with pattern recognition algorithm can classify and discriminate blueberry with different damage. This study lays a foundation for blueberry damage classification and shows a considerable research prospect in the field of berry fruits classification.

The traditional classifier needs to select the feature vector for the classification of berry fruits, and the artificially selected features are generally determined by experience. Single or improper feature selection directly affects the classification accuracy. This shows the advantages of CNN. The advantages of CNN model in image recognition lie in its multilevel structure, which can identify and extract complex visual features and obtain complex semantic information. Therefore, machine vision technology based on DL will show better advantages in theory in the field of disease detection [32, 47]. Xiao et al. [46] created the original image dataset and feature image dataset of strawberry and detected three strawberry diseases, leaf blight, gray mold, and powdery mildew based on CNN. Xiao et al. [46] applied the ResNet50 model for disease detection on their dataset, achieving an accuracy of 100% for Fusarium wilt, 98% for gray mold, and 98% for powdery mildew. It can be seen that the model provides a simple, reliable, and cost-effective detection technology for strawberry diseases. Xiao et al. [46] considered distinguishing three kinds of diseases from feature images, without using any algorithm to distinguish feature regions. Manual segmentation of feature regions is more accurate, but it wastes manpower and reduces work efficiency.

Deep neural networks (DNNs) are a popular topic in DL research, distinguishable from CNNs by their different grid structure. DNN algorithm learns from behavior of the human brain and can extract complex features from multilevel information, making them advantageous for tasks such as image recognition [48]. Kim et al. [45] introduced an improved method for detecting strawberry disease based on DNN and an automated robot system. By incorporating plant domain knowledge and using a human-inspired cascade detection strategy, they achieved high classification accuracy for seven types of diseases. However, computational complexity and long processing times remain challenges, and obtaining sufficient image sets for training DNN models for multiple diseases in berries can be difficult.

The research on machine vision for diseases with recognizable appearance is becoming increasingly mature. In recent years, the detection rates of CNN-based optimization algorithms applied to specific diseases have almost reached their peak. However, few scholars have applied general models to detect a variety of berries or diseases due to the differences in color and texture features of different diseases, as well as the errors introduced by image collection methods [49]. Compared with traditional classification methods, the two algorithms of DL have an advantage in extracting complex features. However, the classification performance of CNN and DNN can be affected by parameters such as initial weights or thresholds. Therefore, due to the characteristics of different berry fruits, the selection of classification algorithm is not unique. At present, a single model cannot be used to determine the problem of berry fruits diseases.

Other Detection Studies' Approach

With the development and application of artificial intelligence technology, machine vision, as one of the important branches, has been widely used in the field of berry nondestructive inspection, which also includes quality assessment, sugar measurement, and risk assessment. These studies are summarized in Table 4.

Quality assessment is a crucial step to ensure the quality of berries and maintain competitiveness in the market. It provides insights into characteristics such as ripeness, sugar content, and aroma to determine whether the berries meet marketing standards. Proper quality assessment can also improve production efficiency and reduce berry losses. For nondestructive quality assessment of grape berries, Cavallo et al. [50] proposed a computer vision system (CVS) that achieved accurate measurements. The authors utilized color reference scenes to fully exploit image analysis and machine learning techniques for quality assessment. The system also has the potential to improve product management and reduce waste in the supply chain. The workflow includes data acquisition and preprocessing, feature extraction, and random forest modeling. The authors evaluated the predictive performance of the system and compared manual and automatic feature selection methods. They also suggested potential improvements such as exploring new feature extraction methods, optimizing parameter settings, expanding the dataset size and grape types, and enhancing algorithm robustness and accuracy.

Sugar content is another important parameter for grape quality assessment. Jia et al. [51] utilized a feature normalized reweighted regression network (FNR) for glucose content measurement. Their new approach, which included feature normalization and reweighting methods, helped to increase sample error weights and improve model accuracy. The study also used high-resolution images for glucose content measurement, with image recognition playing a key role. By using a DL-based method, the authors were able to extract more features from grape images, leading to better accuracy and robustness. Data preprocessing techniques, such as mean normalization and bilateral filter-based image denoising, were also employed. These methods avoided the tedious process of adjusting parameters and manually selecting features used in traditional measurement methods, while better adapting to different data and handling complex image

Table 4 Major contributions of other detection studies in the field of machine vision

Berry type	Task	Image acquisition method	Preprocessing method	Feature extraction method	Approach to modeling	Result	Ref.
Grape	Quality evaluation	High-resolution camera to photograph grapes	Image segmentation, background removal, and grape attribute extraction	Color histogram and morphological processing techniques	Classifiers for machine learning algorithms	Accuracy (Victoria) =92.00%, accuracy (Italy) = 100%	[50]
Grape	Sugar content measurement	High-resolution camera	Image enhancement, denoising, and geometric correction	LBP and GH	Regression networks and FNRR algorithm	R = 0.9599, RMSE = 0.38%	[51]
Cranberry	Risk evaluation	Vegetation index instrument shot in the air	Image cropping, scaling, and vertical flipping	DCNN	DL models for classifiers and logistic regression	The combined system enables overheating risk assessment to inform irrigation decisions	[52]
Grape	Detection of smoke contamination or tain	Remote sensing data are obtained by using satellite and UAV imagery	Image denoising, smoothing, and tone correction	CNN and GH	Classification and regression models	Accuracy = 96%, R = 0.97	[55]

LBP local binary pattern, *GH* gradient histogram, *FNRR* feature normalized reweighting, *R* coefficient of determination, *RMSE* root mean square errors, *DCNN* deep convolutional neural network, *DL* deep learning, *CNN* convolutional neural network

data. Ultimately, the DL approach led to improved accuracy and stability in glucose content measurement, highlighting the benefits of image recognition.

Berries in the field are affected by a range of external factors that can impact their growth and yield, such as light and precipitation. Risk assessment can play an important role in improving the efficiency and quality of fruit production. Machine vision technology can be used to monitor and analyze berry growth and yield in the field, identifying and resolving issues in a timely manner to minimize production risks and losses. Akiva et al. [52] focused on using DL modeling techniques to assess cranberry crop risk. Their innovative approach involved using CNN and recurrent neural networks (RNN) to classify and predict different stages of the crop, based on high-resolution drone images that accurately identified and predicted different crop elements. The authors utilized multiple convolutional and recurrent layers, along with image preprocessing techniques such as image enhancement and background removal, to improve image screening and classification accuracy. They also applied deep learning techniques to cranberry crops in peat bogs, which can be a challenging area. Through their work, Akiva et al. [52] achieved higher classification and prediction accuracy than the benchmark model, demonstrating the effectiveness of their deep learning approach. Future developments could optimize the model even further, for example, by using a more hierarchical network architecture or adding more data samples to improve generalization performance. In addition, the study collected soil and weather data to assess crop risk more accurately, including image data for different dates, spectral bands, and crop stages. Variation in crop risk between rainy and dry seasons could be considered in future research.

Aside from the potential harm to crops caused by soil and climate conditions, smoke pollution is a significant risk factor. Smoke contamination can cause surface contamination of grape berries, affecting texture and taste, diminishing grape quality and value, and posing a health hazard while reducing berry nutritional worth [53, 54]. Conventional ways of detecting grape smoke contamination involve field sampling and analysis, which though accurate and trustworthy require considerable time and expense and may affect vineyards and wine quality. Fuentes et al. [55] pursued a non-destructive testing for smoke contamination using remote sensing technology and machine learning models for vines, berry fruits, and wine. The advantages of machine vision include nonintrusiveness, efficiency, and automation that can enhance accuracy, speed, and stability of smoke contamination detection while decreasing the impact on vineyard and wine production. Compared to traditional methods, machine vision eliminates the need for field sampling and analysis, drastically lessening cost and time overheads and enabling fast and accurate inspections of vast vineyard and grape areas. Moreover, machine vision allows for automated detection and analysis, further enhancing detection accuracy and stability. Fuentes et al.'s [55] innovations include using machine learning models to optimize machine vision and improve detection precision and merging data from multiple drones for smoke pollution detection. Machine vision technology has the potential to expand its applications to smoke pollution monitoring and other areas, proving vital for future research.

In summary, machine vision's application in the berry fruits nondestructive testing field presents promising opportunities. Employing image processing algorithms and machine learning algorithms for analyzing and processing berry products can achieve efficient, accurate quality assessment, yield risk assessment, and other functions. These research results can enhance production efficiency, ensure product quality, and reduce production expenses, serving as a practical tool in promoting a healthy berry industry.

Berry Fruit Detection Based on Infrared Spectroscopy

The visible light spectrum is mainly generated by the electronic transition of molecules, resulting in a molecular spectrum that absorbs varying degrees of light within a specific band (Fig. 3). The absorption degree is different for molecules and ions on the surface of the object being tested, allowing for analysis, determination, and prediction of substance composition, content, and structure. The visible light region is typically defined as 450–750 nm [56–58].

IRS is based on organic molecules in the chemical bonds or functional group vibration will absorb part of the wavelength of infrared light, different chemical bonds or functional group vibration frequency is different absorption wavelength is different, which can be obtained from different positions in the infrared spectrum of organic different effective information[59]. The infrared light band is 750–3000 nm, and the infrared spectrum can be generally divided into three regions according to different wavelengths (Fig. 3): near-infrared (750–2500 nm), mid-infrared (2500–25000 nm), and far-infrared (25,000–10^6 nm) [60–62]. Spectral technology has been widely applied for nondestructive testing of fruits. Since hydrocarbons have different absorption intensities in infrared light, characteristic models can be developed and implemented for different nondestructive testing research projects on berries, based on this theory.

Fourier transform infrared spectroscopy (FTIRS) is an analysis method based on the combination of Fourier transform mathematical function computer technology and IRS technology. The principle is that there is a Fourier function relationship between the intensity of the IR spectrum and the two coherent beams of light that are formed. Therefore, the Fourier transform of the collected interferogram can obtain the full-band IR spectral curve, and the characteristics of FTIR spectra of different factors are unique [63, 64]. The infrared absorption frequency can reflect the corresponding chemical characteristics. Therefore, FTIR provides more comprehensive wavelength information, which offers more specific and comprehensive analysis characteristics compared to the visible spectrum and infrared spectrum [65]. It aims to analyze the problem from the whole band curve, rather than the characteristic information of specific peaks. The measurable spectral range is 10,000–10 cm^{-1} (1000 nm–10^6 nm) [63].

Spectral technology has been widely employed in the field of nondestructive testing for fruits. By exploiting the differentia absorption intensities of hydrocarbons under infrared light, various characteristic models can be established and applied to different research projects on nondestructive testing for berry fruits. NIR (near-infrared) spectroscopy is one of the fastest growing and most widely used research methods in recent years. Its advantages are strong adaptability, simple operation, and wide application. FTIR spectroscopy can analyze areas that cannot be analyzed by simple spectral analysis technology, such as the determination of components in fruits and vegetables rich in multiple components. The spectral characteristics obtained by the diversification of chemical components are obtained by the accumulation of a single component and the overlap of frequency bands. Therefore, it is necessary to combine

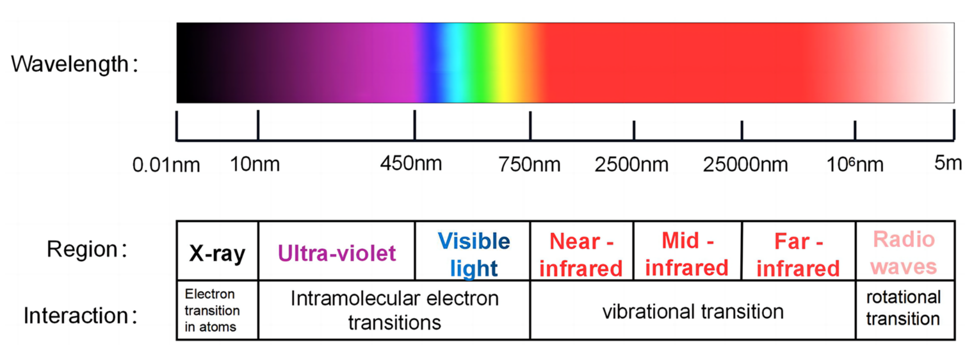

Fig. 3 Infrared multirange options

complex chemical computer technology to calculate and analyze the spectral characteristic curve [66]. FTIR spectroscopy is still in the development stage, and its application in the field of berry fruit detection is not as extensive as that of Vis/NIR (visible/near-infrared) spectroscopy. This review summarizes the research progress and research direction of infrared spectroscopy in nondestructive testing of berry fruits (Fig. 4).

Figure 4 shows that the number of studies on berry variety and quality detection by Vis/IRS is relatively large. Among them, the study on internal detection of berry fruit has always been a hot field. This paper only selects four articles that are more consistent with the correlation of this paper for review. Vis/IRS is a widely applied technology. According to the characteristics of berry fruits, the damage degree, hardness, and pesticide residues of berry fruits are also studied. The application of Vis/IRS technology on berry fruits is still continuing. This paper only selects three articles with high correlation to describe.

Berry Variety Discrimination Approach

The traditional method of variety identification is based on the phenotypic characteristics of leaves, berries, and flowers [67]. However, visually distinguishing between similar berry fruits can be challenging. NIR spectroscopy can accurately detect total sugar, total acid, soluble compounds, and vitamins in berry fruits [68, 69]. These characteristics can reflect the berries varieties. The variety of berry fruits has a great influence on the berry market, and the quality of the variety cannot be judged by the naked eye, which leads to the phenomenon of inferior filling in the market so that the rights and interests of consumers cannot be guaranteed. Therefore, the adoption of variety identification technology is necessary to ensure the orderly circulation of the market

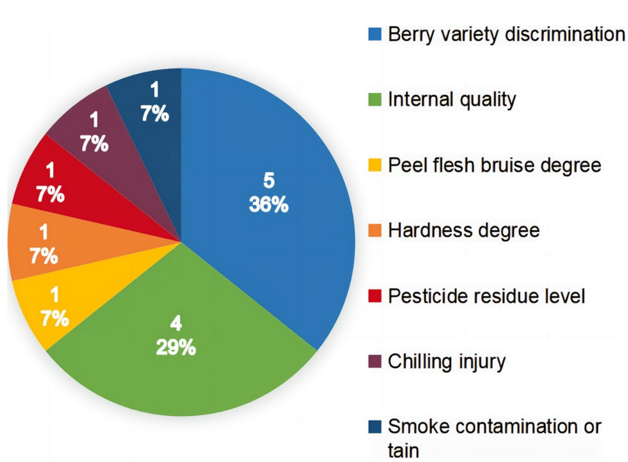

Fig. 4 The main application of Vis/infrared spectroscopy in this review

and accurately identify varieties. Therefore, in view of this problem, it is necessary to identify berry fruits varieties. The identification of berry fruits based on IRS is shown in Table 5.

Table 5 indicates that there are many studies focusing on the identification of wolfberry berries in the berry variety identification field. The reason is that the price of wolfberry varies greatly in the berry market, and wolfberry varieties directly influence the market value of wolfberry. NIR technology is widely used in the study of variety identification, and Kim's study stands out because he employed FT-IR technology and used genotype as a crucial indicator for variety identification instead of a specific chemical parameter. In terms of algorithm research, earlier scholars selected a single algorithm, but since Tingting et al. [120], researchers have optimized the model with various statistical methods, making algorithm research an optimization focus.

Li et al. [70] studied the variety identification of berry fruits using Vis/IR spectroscopy technology relatively early on, which provide strong support for later scholars to identifying berry fruits. Li et al. [70] measured the reflectance spectral curve (325 nm–1025 nm) of four different varieties of bayberry fruit. Generally, after acquiring spectral data, preprocessing is required to remove spectral noise and enhance effective spectral information [68]. Based on the traditional algorithm, Li proposed PCA-ANN algorithm. PCA (principal component analysis) was utilized to reduce the dimensions of spectral data matrix and extract relevant characteristic information. ANN algorithm was employed to establish classification model based on the extracted feature information. The PCA-ANN model exhibited a high identification rate of 95.00% for bayberry varieties, and the most significant wavelengths contributed to the discrimination were 530 nm and 720 nm. Li's study provided fundamental support for the identification of berry varieties. However, selecting only a few varieties of bayberry fruit may not fully showcase the strengths of the classification model.

The identification of commercial strawberry varieties relays on gene fingerprinting technology, as these berry fruits often result from hybridization to produce new varieties. As a result, genotype has become an important factor in variety identification. Many genetic fingerprinting techniques for identification varieties have been studied by scholars [71]. Berry fruits can also be chemically classified to determine their quality. For example, Kim et al. [67] classified and discriminated five strawberry varieties using preprocessed spectral information based on the PCA algorithm and then used the Fisher LDA for classification model. The results obtained from the spectral information of fruits and leaves were consistent with the chemical classification and genetic relationship between strawberry varieties. Therefore, Kim et al. [45] suggested that the FT-IR method could replace the current research method for determining

Table 5 Major contributions of berry variety discrimination approach in the field of infrared spectroscopy

Berry type	Attribute assessed	Spectroscopy	Wavelength range (nm/cm^{-1})	Statistical method	Performance indices	Ref.
Bayberry	Relationship between the reflectance spectra and bayberry varieties	Vis/NIRS	325–1025 nm	PCA-ANN	Accuracy (recognition) = 95%	[70]
Strawberry	Chemotaxonomical relationship among varieties	FT-IR	40,000–4000 cm^{-1} (250–2500 nm)	PCA, LDA	Accuracy (accounting) = 93.48%	[67]
Goji berry (wolfberry)	Geographical origin and flavonoid content	NIR	10,000–4000 cm^{-1} (1000–2500 nm)	LS-SVM, BP-ANN, KNN, Si-PLS	Accuracy = 96.67%; RMSEP = 0.38 mg/g; Rp = 0.91	[120]
Black wolfberry	Geographical origin and anthocyanin content	NIR	10,000–4000 cm^{-1} (1000–2500 nm)	LS-SVM, BP-ANN, KNN, LDA, Si-PLS	Accuracy = 98.18%; RMSEP = 0.60 mg/g; Rt = 0.90	[121]
Black wolfberry	Geographical origin and polysugar content	NIR/MIR	10,000–4000 cm^{-1} (1000–2500 nm); 4000–500 cm^{-1} (2500–20,000 nm)	LS-SVM, Si-PLS	Accuracy = 99.17%; RMSEP = 2.57%; Rt = 0.95	[122]

Vis/NIRS visible and near-infrared reflectance spectroscopy, *FT-IR* Fourier transform infrared spectroscopy, *MIR* mid-infrared spectroscopy, *PCA* principal component analysis, *LS-SVM* least squares support vector machines, *BP-ANN* back propagation artificial neural network, *Si-PLS* synergy interval partial least squares

the genetic relationship between hybrid genotypes of plants such as strawberries.

Wolfberry is a type of nutritious berry that varies in price depending on the growth environment and variety. Unfortunately, some merchants may try to pass off inferior wolfberry as high quality in order to improve its market value. To combat this issue, researchers have used chemometrics and NIRS to predict the sources and chemical elements of wolfberry. Tingting et al. [120] and Li et al. [72, 122] measured anthocyanin and polysaccharide content. Both studies used various recognition models to determine the origin and quality of wolfberry, with the LS-SVM model consistently performing the best. Yahui et al. [122] expanded on the research of Tingting et al. [120] by fusing the near-infrared and mid-infrared spectral information and expanding the spectral information database to extract more useful information. This led to an increased accuracy rate for determining the source and category of wolfberry, reaching as high as 98.18%. However, the need for more data and improved algorithms remains, as expanding the dataset can lead to slower model calculation speeds. In conclusion, the use of chemometrics and NIRS has proven to be effective in determining the quality and origin of wolfberry. Future research should focus on improving calculation speeds and data processing methods to further enhance the accuracy of this method..

Since 2007, research has been conducted on the identification of berry varieties, indicating that spectral analysis for this purpose started earlier, but fewer studies have been conducted recently. This is due to the dominance of electronic nose technology in the field of variety identification, but it does not diminish the significance of spectral analysis technology in this area. Spectral analysis technology is widely used, and different berry fruit information can be analyzed using a spectral curve. Thus, the study of berry fruit traits in this paper reflects its wide application. In the future, a series of berry fruit-related parameters can be obtained through spectral data. Genetic fingerprint technology is generally used in commercial fruit variety identification, but Kim's experimental analysis found that spectral technology can also accomplish the work of genetic fingerprint technology, with the advantages of higher efficiency.

In addition, no scholars have established classification models for distinguishing different types of berries, although such models have been widely used in the field of fruit, vegetables, and popular berries like grape [73]. Raspberry, blueberry, mulberry, strawberry, and other minority berry fruits have different varieties but are difficult to identify based on appearance alone. Currently, the market supervision system of minority berry fruits is not as complete as that for fruit and vegetable markets. However, increased market demand and improvements in the berry market system necessitate the classification of varieties. Hence, the classification method of wolfberry varieties should be widely applied to different berry fields.

Berry Internal Quality Detection Approach

The quality of fruit directly impacts its value in the market. Berries have garnered significant attention from consumers due to their richness in nutrition. Chemical composition detection in berries plays a critical role in evaluating their quality, categorizing berries according to their quality in the market, and improving their market presence. Different chemical components have distinct absorption spectra, and therefore, the application of IRS technology in predicting the internal chemical components of berries can potentially assist in evaluating their internal quality. The present review aims at exploring the research on berry fruit internal quality detection based on IRS technology as listed in Table 6.

Table 6 illustrates the diverse chemical components that researchers have measured in recent years, including total phenolic content (TPC), antioxidant activity (AOA), total soluble solid (TSS), and ascorbic acid (AA). This demonstrates how spectral analysis technology can measure different chemical elements and highlights the wide applicability of this technology; NIR technology was initially utilized in research. However, as the study of berry quality detection has progressed, there has been an increase in research which incorporates FT-NIR (Fourier-transform near-infrared) technology. These studies have shown that FT-NIR technology has certain advantages in the field of quality detection. With regard to algorithm selection, Gajdoš was the first to use the PCA algorithm for predicting chemical components. In subsequent studies, the PLS algorithm demonstrated relative advantages, and the derivative algorithm based on PLS algorithm has been widely employed in the field of quality detection. This has led to some research advancements.

Polyphenols are known to be strong antioxidants, which contribute to human health [74]. Modern science has confirmed that berry fruits are rich in chemical elements such as anthocyanin, which are also known as polyphenols and have antioxidant properties that promote human health [75]. Therefore, polyphenols can be used as an essential measure of the quality of berry fruits. Jasenka et al. [78] conducted quality testing on blackberry, wild blueberry, raspberry, gooseberry, strawberry, and other berry fruits. Jasenka analyzed the feasibility of using TPC and AOA index of these berries. PCA was employed to distinguish the varieties of berries, and the prediction model of PLS was used to predict berries' parameters.

It is not accurate to use a single chemical parameter to describe the quality of berry fruits. The selection of multiple factors can effectively improve the prediction model for quality screening. Therefore, Soltanikazemi et al. [119] predicted four chemical parameters of TSS, TA, AA, and TAC in mulberry fruit. A correlation model was established between mulberry chemical parameters and absorbance spectra using multivariate calibration analysis of PLS, and the most effective spectral range was selected by GA-PLS. The results showed that the spectral range applied by Soltanikazemi effectively evaluates the growth quality of mulberry. The traditional wavelength selection is based on genetic algorithm, which can automatically and effectively obtain the optimal wavelength. The genetic algorithm selected by Esteki et al. [40] was combined with PLS to select the effective wavelength so that the model could combine the advantages of GA and PLS. This optimization model is also one of the most widely used methods for processing NIR spectral data [76].

Soltanikazemi's study exemplifies the importance of choosing an effective wavelength. Selecting excellent algorithm to extract characteristic wavelength can not only improve the prediction accuracy but also take into account the prediction

Table 6 Major contributions of berry fruit internal quality detection approach in the field of infrared spectroscopy

Berry type	Determination parameters	Spectrum types	Wavelength range (nm)	Statistical method	Result	Ref.
Blackberry, blueberry, raspberry, red currants, strawberry	TPC; AOA	NIR	904–1699 nm	PCA + PLS	$R^2 > 0.86$; RPd = 1.80–3.10	[78]
Black mulberry	Tss; AA; AC	UV-IR	300–1100 nm	SVN + GA-PLS	TSS:RMSEV = 0.06, $r = 0.98$; AA:RMSEV = 0.04, $R = 0.98$; RMSEV (AC) = 0.0006, $R = 0.96$	[119]
Goji berry (wolfberry)	GBTS	FT-NIR	1149.43–2500 nm	PLS	$R^2 > 0.90$; RMSEV = 0.70	[72]
Goji berry (wolfberry)	TFC; TAC; TCC; TS; TA	FT-NIR	1000–2500 nm	Si-PLS Bi-PLS GA-PLS	$0.88 \le R^2 \le 0.97$, $0.87 \le r^2 \le 0.94$, $1.75 \le \text{RPD} \le 4.00$	[77]

TPC total phenolic content, *AOA* antioxidant activity, *TSS* total soluble solid, *AA* ascorbic acid, *AC* total anthocyanin content, *UV-IR spectra* ultraviolet-infrared reflectance spectroscopy, *SVN* standard normal variate, *PLS* partial least squares, *Si-PLS* synergy interval-PLS, *Bi-PLS* backward interval PLS, *GA-PLS* genetic algorithm-PLS, R^2 determination coefficients, *RPd* regression point displacement, *RMSE* root mean square errors efficiency. Li et al. [72] for the first time based on FT-NIR spectroscopy combined with chemometrics to measure the content of Goji berry total sugar (GBTS) in 2017, combined with x-load weight and RT to select characteristic wavelengths, and based on PLS to establish a prediction model. And the RMSE of calibration validation set prediction is 0.406 and 0.695, respectively. Therefore, using FT-NIR spectroscopy to achieve rapid determination of GBTS is feasible. The optimization of the prediction model is another way to improve the prediction accuracy. Arslan et al. [77] predicted the chemical elements of wolfberry, measured other chemical components of wolfberry based on FT-MIR spectroscopy combined with chemistry, such as TFC, AC, carotenoid content (CC), total sugar (TS), and total acid (TA). Based on the classical PLS combined with improved Si-PLS, backward interval partial least squares (Bi-PLS), and genetic algorithm partial least square (sGA-PLS), the prediction model was established. The evaluation results of the model showed that all the developed model with high prediction strength. It can be seen that in the field of berry fruit quality detection, PLS derivative models show certain advantages, and all models show high prediction strength. With the development of research in the field of quality detection, the types of chemical elements detected by scholars rely on spectral technology are also growing, which is another manifestation of algorithm optimization.

The nondestructive detection of fruit internal quality through NIRS is currently a hot topic in research. Many scholars have applied this method to identify the quality of berry fruits due to the increasing attention of consumers to such fruits in recent years. The prediction of internal chemical elements can evaluate berry fruit quality, distinguish between varieties [78], determine maturity [77], and study inherent biological variability [79]. The chemical elements measured and the quality problems they reflect differ, resulting in a diversified detection purpose.

Berries and other fruits have essential differences. Berry fruits have a juicy peel and inner peel, giving them a better spectral transmittance than other fruits such as apple, citrus, and pear. Additionally, the peel and endocarp of berries are both juicy, contributing to their favorable spectral transmittance. However, due to the large number of berry varieties and differences in planting environments and equipment used across various studies, research results are not standardized or easily referenced, limiting the marketability of berries. Therefore, the creation of a unified detection standard is a key issue that needs to be addressed.

Overall, nondestructive detection methods for fruit internal quality through NIRS offer great potential for evaluating and improving fruit quality. However, further research is needed to establish standardized detection methods and overcome the challenges posed by the multitude of berry varieties and environmental factors.

Other Detection Studies' Approach

In recent years, scholars have applied Vis/IRS to explore various fields and solve different berry fruits analysis problems. These factors include damage, hardness, and pesticide residues in berry fruits. These studies are shown in Table 7.

Table 7 shows that Vis/IR spectroscopy technology in the field of berry fruits damage, hardness, and pesticide residues have also been studied. It can be seen that the application of this technology can be reflected in different fields, and more technical applications need to be explored in depth according to the characteristics of different berry fruits. In the above three studies, due to the different spectral bands, different algorithms, and different research directions, there is no method to compare them in various aspects. This study makes a simple analysis of its research direction.

The crushing of berry fruits directly affects the quality of the fruit. The fruit with bruises is more likely to rot. If not screened in time, it will accelerate the decay rate of other fruits and reduce the market value of the fruit. However, manual screening can only screen the characterization of the injured fruit, and it is unable to screen the fruit with subcutaneous crush. Therefore, it is also of great significance to identify such fruits based on NIRS. Fresh blueberry is the most vulnerable to crush during harvest and packaging, which directly affects the quality of blueberry fruit and reduces the profit of farmers and consumers. Zhang et al. [80] studied the optical properties of blueberry peel and pulp with different degrees of bruise. Three spectral bands were selected to analyze the absorption coefficient (μ_a), scattering coefficient (μ_s), and scattering anisotropy (g) of blueberry peel and pulp, and the degree of bruise was detected by Monte Carlo multilayer (MCML) model. The comparison results show that the NIR spectrum (930 nm–1400 nm) is the best spectral range for reflectance or transmittance method to verify the degree of blueberries bruising, which can provide theoretical support for nondestructive monitoring technology of blueberries bruising.

Hu et al. [81] proposed a scheme to classify the hardness of blueberry and then transport it according to the characteristics of blueberry that is easy to be crushed. So Hu et al. [81] classified the hardness of blueberry fruit based on NIR spectroscopy. Due to the internal structure of blueberry (the macroscopic characteristic is hardness) will lead to different incident light paths and different spectral effects, the extraction of blueberry spectral characteristics can also reflect the hardness information.

With the increase of berries planting area, the problems of pests and diseases caused by different ecology are also increasing, so the use of pesticides is essential. The increase in the demand for pesticides, along with the nonstandard use of pesticides, has led to food safety problems in berries. In order to ensure the edible safety of berry fruits, it

Table 7 Major contributions of other detection studies in the field of infrared spectroscopy

Berry type	Attribute assessed	Spectrometers	Spectrum types	Wavelength range (nm)	Statistical method	Result	Ref.
Blueberry	Peel flesh bruise degree	Antaris II FT-NIR spectrophotometer	Vis–NIR	350–2400 nm	MCML	μa (mm^{-1}) = 0.15–0.04, μs′ (mm^{-1}) = 2.70–0.22	[80]
Blueberry	Hardness degree	Visible-NIR spectrometer, model USB2000+; NIR spectrometer, model SNIR0018	NIR	1000 – 2500 nm	RT	Rp = 0.94, Rc = 0.85, RMSEp = 51.76 g, MSEc = 62.19 g	[81]
Strawberry	Pesticide residue level	Nicolet IS50 with NIR module containing Ge coated KBr beamsplitter and InGaAs	NIR	930 nm–1400 nm	PLSR	RPD = 2.28; RPD = 2.31	[82]
Kiwifruit	Chilling injury	Broadband light source and a diode array spectrometer	NIR	400–2500 nm	iPLS-DA	Self-created low-temperature detection method outperforms traditional methods	[83]
Grape	Smoke contamination or tain	ASD FieldSpec, Analytical Spectral Devices, Boulder, CO, USA	Visible-NIR	350 ~ 2500 nm	Machine learning fitting modeling	Accuracy = 96%, R = 0.97	[55]

MCML Monte Carlo multilayered, *RT* random frog variable selection, *PLSR* partial least squares regression, *μa* absorption coefficient, *μs′* reduced scattering coefficient, *Rp* prediction, *Rc* calibration

is necessary to carry out nondestructive testing of pesticide residues on the surface of berry fruits. Yazici et al. [82] predicted and evaluated the pesticide residue level of strawberry based on IRS. In order to abandon the traditional pesticide determination method, a rapid, efficient, and nondestructive method was proposed to establish a pesticide residue prediction model. The PLSR model established by Yazici can effectively predict the pesticide residue level.

Low-temperature injury is a common issue in kiwifruit production and distribution, leading to decreased sugar and vitamin content and reduced quality. To address this, Wang et al. [83] aimed to explore a nondestructive, efficient, and reliable method to reduce the risk of low-temperature injury in kiwifruit. The researchers collected a large amount of spectral data from kiwifruit samples using near-infrared spectroscopy. To develop a low-temperature injury detection model, Wang et al. [83] employed a chemometric approach to construct a predictive model. The modeling methods, including iPLS-DA, were combined with traditional quality detection techniques, ultimately leading to a more accurate method for low-temperature injury detection. The innovation of this study lies in the utilization of novel metrological methods for spectral analysis and the provision of a new, efficient, and reliable solution for low-temperature injury detection in kiwifruit. NIR spectroscopy and chemometric methods enable nondestructive and efficient detection and prediction of low-temperature injury in kiwifruit, providing a new and reliable quality detection method for kiwifruit production and transportation. Future trends in this field are likely to focus on standardization and practicality to better meet market requirements.

Vis-NIR spectroscopy was utilized in a study by Fuentes et al. [55], as detailed in "Other Detection Studies' Approach" of this review. This technology offers several advantages for analyzing smoke contamination in vines, grapes, and wine, including its nondestructive nature, rapidity, efficiency, and practicality. By employing spectroscopic techniques and machine learning modeling methods, various levels of contamination and impacted areas can be identified, enabling targeted measures to prevent and mitigate quality losses. The future of this field is likely to focus on professional and comprehensive grape quality detection using intelligent methods for identification and management, to better meet market demands.

IRS can predict the internal chemical composition of berries. Therefore, NIRS has attracted much attention in the field of fruit quality detection and classification. In recent years, with the increasing maturity of IRS, many scholars have begun to apply this technology to solve more problems due to its strong detection ability. Some achievements have also been made in the fields of berry hardness classification, bruise detection, and pesticide residue prediction. Since the transmittance of berries is better than that of other fruits, it is more obvious to study the spectral characteristics of berries by using the transmission infrared camera. At present, there are differences in the equipment for collecting IRS information of berry fruits by various scholars, which leads to the lack of reference for the accuracy of each model and the inconsistency of detection methods.

The IRS technology is a point measurement technique that lacks the ability to provide spatial characteristics of the object under investigation. This approach is based on the light intensity curve that is acquired from the diffuse reflection or transmission of light on the surface of the target object. However, the information collected is highly dependent on the configuration and parameter settings of the instrument, probe, light source, and other factors, making the data source unstable and the spectral information difficult to interpret. As a result, it is crucial to choose the appropriate instrumental and operational conditions when employing IRS technology. In summary, while IRS is a powerful tool for nondestructive evaluation of berry fruit quality, it does have some limitations. To reduce potential errors in experimentation, future research should consider more demanding experimental conditions or focus on optimization of the modeling algorithms.

Berry Fruit Detection Based on Hyperspectral Imaging Technology

Since the 1980s, HSI technology has been applied by NASA for the first time [84]. In the past four decades, HSI technology has matured and expanded its application fields. Recently, with the rapid advancements of hyperspectral technology, the market of hyperspectral imaging equipment is growing popular, and more high-quality algorithms are emerging. As a result, the utilization of hyperspectral technology in agriculture has become deeper in recent years.

The typical hyperspectral imaging acquisition system consists of light source, camera, camera lens, wavelength dispersion equipment, computer, and control device (shown as Fig. 5).

The difference between hyperspectral image information and near-infrared spectral information is that hyperspectral image information includes spatial information in addition to spectral information. Its storage structure is a three-dimensional structure (Fig. 6). The first two-dimensional is the two-dimensional spatial information of the object to be measured. The third dimension is the full-wavelength spectral information [85–87]. Therefore, each point in the spatial region can extract a certain wavelength of spectral information, and the obtained spectral information is more intuitive and continuous. Hyperspectrum can be divided into four regions according to the wavelength: visible region, visible-near infrared region, near-infrared region, and short-wave infrared region [88].

In recent years, HSI technology has been used to measure the internal chemical composition of berries in the growth process and to identify the maturity. It can also be used to monitor the safety of harvested berries and to identify bruises. This paper summarizes the application of HSI technology in nondestructive testing of berries as shown in Fig. 7.

The most widely adopted classification of HSI technology pertains to the detection of internal quality and damage, which are closely related to the characteristics of various berry fruits. The value of each type of berry fruits is reflected in its internal chemical elements, and soluble solid content (SSC) can be utilized as a parameter indicator of maturity. Compared to other types of fruit, berry fruits possess certain unique characteristics, such as a juicy inner

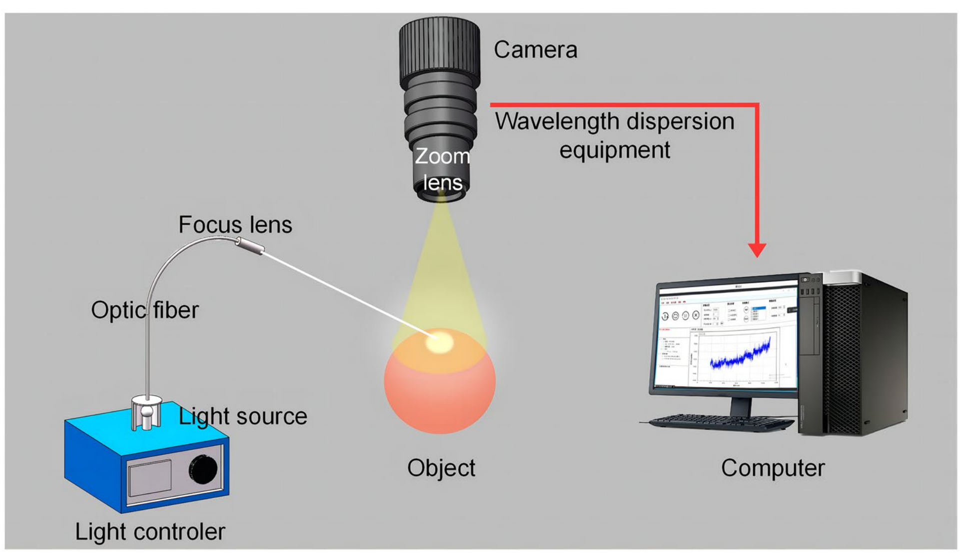

Fig. 5 Working principle of hyperspectral imaging spectrometer for detecting berry fruits

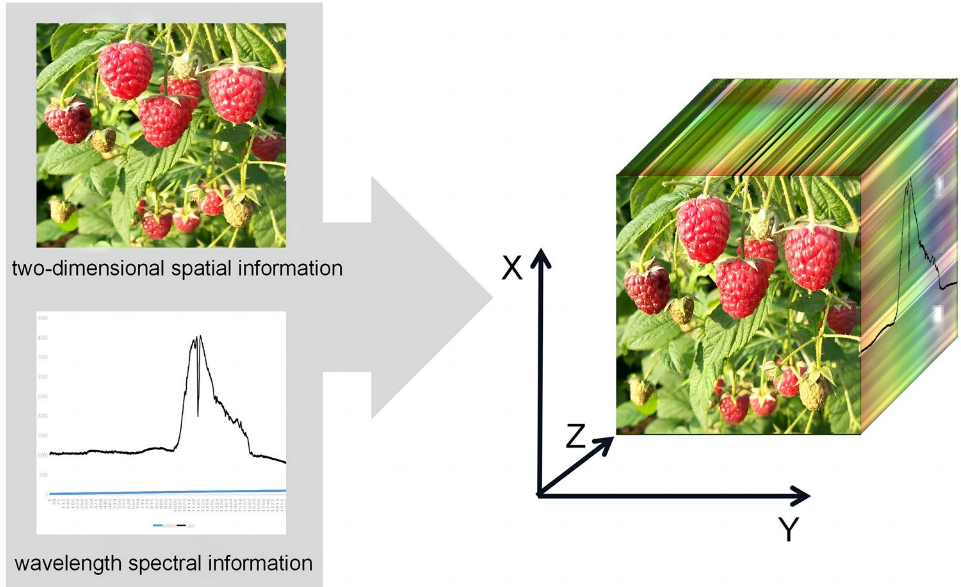

Fig. 6 Hyperspectral information cube

and outer flesh, which makes them more susceptible damage, including crush and mildew. As a result, internal quality, maturity, damage, and safety monitoring have become widely studied areas of research when it comes to berry fruits. Soft hardness, storage time, and variety monitoring are especially appropriate for individual berry fruits. Notably, the field of VIS/IRS monitoring has already achieved considerable progress in the research of variety identification, but HSI technology is more expensive than visible and IRS detection technology, with more complex data analysis.

Berry Internal Quality Detection and Evaluation Approach

The quality evaluation of berry fruits is a crucial factor in determining their market value. The use of hyperspectral analysis technology to determine the chemical composition can accurately evaluate the internal quality of berry fruits, making it a vital component in the classification of their quality. However, this technology alone cannot provide spatial information. Spectral technology has proven to be an effective technique for detecting internal quality factors [89]. To detect the internal quality of berry fruits and obtain accurate spatial information of the internal chemical elements, it is essential to utilize HSI technology, as shown in Table 8. We kindly request that you check and correct any syntax and formatting errors and polish the language to improve clarity and readability.

In studies evaluating the internal quality of berry fruits using hyperspectral imaging (HSI) technology, various scholars have applied different algorithms for feature extraction. This is because the data obtained through HSI technology is complex, resulting in fuzzy modeling information and decreasing the accuracy of the evaluation model. Multidimensional coincidence information also contributes to reduced accuracy, making the selection of characteristic parameters and multidimensional data dimension reduction important methods to improve model accuracy. Therefore, selecting effective feature extraction methods is currently a hot research topic in HSI technology. Algorithm optimization

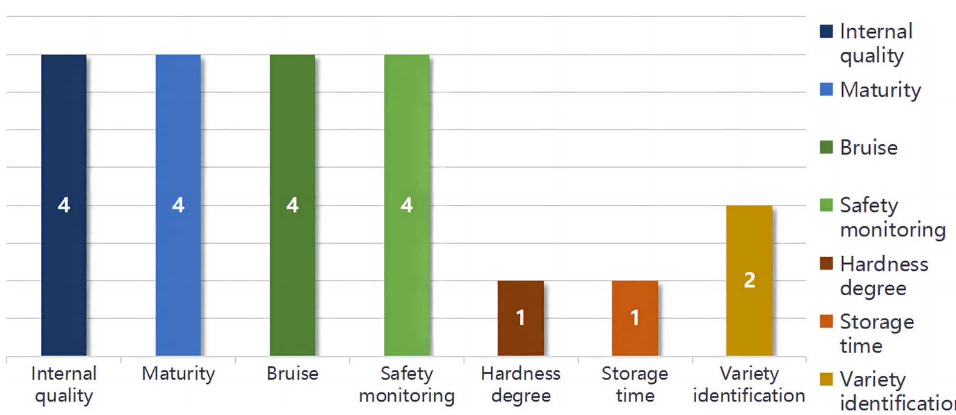

Fig. 7 The main application of HSI technology in this review

Table 8 Major contributions of berry internal quality detection in the field of hyperspectral technology

Berry type	Wavelength range (nm)	Determination parameters	Feature extraction	Modeling method	Result	Ref.
Mulberry	380–1030 nm	TSS	RF	PLSR, LS-SVM	RF-LS-SVM: Rp = 0.956; RMSEP = 0.430	[90]
Mulberry	380–1030 nm, 874–1734 nm	TA, AA	SPA, UVE, UVE-SPA, and CARS	PLSR, LS-SVM	TA: R^2val = 0.959, RPD = 4.964; AA: R^2val = 0.995, RPD = 14.255	[91]
Strawberry	374–1020 nm	SSC, pH, VC	CARS, UVE	PLSR, SVR, LWR	SSC: Rp^2 = 0.9370, RMSEP = 0.1145; PH: Rp^2 = 0.8493, RMSEP = 0.0501; VC: Rp^2 = 0.8769, RMSEP = 0.0279	[93]
Goji berry (wolfberry)	874–1734 nm	TP, TF, TA	PCA, WT	PLSR, LS-SVM	TP (PAE): Rp^2 = 0.836–0.862; TP (CNN): Rp^2 = 0.841–0.849; TF (PAE): Rp^2 = 0.779–0.834; TF (CNN): Rp^2 = 0.839–0.838; TA (PAE): Rp^2 = 0.886–0.897; TA (CNN): Rp^2 = 0.876–0.881	[94]

SSC soluble solid content, *VC* vitamin C, *TP* total phenolics, *TF* total flavonoids, *TA* total anthocyanins, *SPA* successive projection algorithm, *UVE* uninformative variable elimination, *CARS* competitive adaptive reweighted sampling, *WT* wavelet transform

for establishing models is another important method that directly affects evaluation accuracy. Early research in the Vis/IRS technology field has yielded promising results. It is important to note that this literature review should be written in third person and adhere to the format of a journal article. If there are any grammatical or formatting errors, please let me know, and I can make the necessary corrections.

Table 8 presents the application of HSI technology in detecting the internal quality of berry fruits. As quality detection technology has advanced, researchers have started to measure various chemical elements. The inclusion of multiple chemical elements allows for a comprehensive evaluation of berry fruit quality from different perspectives. However, it is worth noting that the chemical element information derived from spectral information reactions varies across different wavelength bands. Consequently, to gain additional chemical element information, subsequent studies by scholars have expanded the range of spectral wavelengths. In the summary of feature information extraction, the feature extraction methods of scholars are different, but in the method of model establishment, PLSR and LS-SVM methods are widely used. Thus, in HSI technology, feature extraction research is more valued by scholars than modeling research, and there is more room for improvement.

TSS in mulberry fruit is an important indicator to measure quality. Zhao et al. [90] predicted the SSC in mulberry fruit based on HSI technology. Random frog algorithm is an effective variable selection algorithm. Zhao et al. [90] selected the characteristic wavelength based on RF algorithm and established the TSS prediction model of mulberry by combining PLSR and LS-SVM algorithm. The PLSR model showed the best prediction accuracy, and the spatial distribution of TSS in blueberry was visualized to reflect the TSS concentration. According to the research results, HSI technology provides favorable support for predicting the spatial distribution of TSS content in mulberry fruits. Zhao et al. [90] provide an effective method for nondestructive testing of the internal quality of mulberry fruits. The research also laid a good foundation for HSI technology in the field of berries internal quality detection.

Nevertheless, the uneven surface of mulberry fruit can impact the reflectivity of light, consequently affecting the accuracy of the model. Furthermore, distinct C-H bonds are associated with different bands that directly reflect diverse chemical elements. Therefore, broadening the wavelength range can allow for the measurement of more chemical elements, thereby enhancing the overall assessment. Huang et al. [91] improved the regular information collection method by using Si and InGaAs probes to collect spectral information in different hyperspectral regions (380–1030 nm and 874–1734 nm). Huang uses successive projection algorithm (SPA), uninformative variable elimination (UVE), and competitive adaptive reweighted sampling (CARS) to select the characteristic wavelength. Effective selection of characteristic wavelength can simplify the elimination of redundant invalid information and greatly improve the robustness of the model. It can be seen that the extended spectral information data and multivariate modeling method can effectively, rapidly, and accurately predict the chemical composition of mulberry.

The high-dimensional data information of HSI technology can not only reflect the spatial distribution of a chemical element concentration but also explore the content information of various chemical elements. In order to explore the application of HSI technology in the field of internal quality, Weng et al. [92, 93] extracted color and texture features of strawberry from the spectral region of 374–1020 nm hyperspectral image and predicted SSC, pH, and vitamin C (VC) content of strawberry. Three feature models based on PLSR, support vector regression (SVR), and local weighted regression (LWR) were established to predict the three feature information of strawberry. This study can effectively and nondestructively detect the quality of strawberry. Weng et al. [92, 93] also proposed that this method can be extended to nondestructive testing of more quality parameters.

The optimization of feature extraction and model establishment directly affects the accuracy of the evaluation model. The traditional methods of feature selection and model establishment have made some achievements, and DL method has also shown its relative advantages in the field of spectral technology. Therefore, Zhang et al. [94] designed and developed a CNN to predict the chemical constituents of black wolfberry based on near infrared HSI technology. The main chemical components measured include total phenolics (TP), total flavonoids (TF), and total anthocyanins (TA). Zhang et al. [94] measured many chemical compositions and optimized the method of establishing prediction model. Compared with the prediction model established by traditional methods, it was found that the model obtained by DL method as modeling method and feature extraction method with higher accuracy. Therefore, in the process of determining the chemical composition by hyperspectral analysis technology, DL as a feature extraction method shows greater advantages.

Zhao et al. [90] studied the quality of mulberry fruit and determined the TSS content. However, due to the uneven surface of mulberry fruit and other factors, the collected spectral information will have certain errors. Therefore, Huang et al. [91] expanded the collected spectral information and obtained the spectral information of two bands by combining two different probes. The expansion of multi-source spectral information can effectively reduce the acquisition error of single-band spectral information. With the improvement of high-spectral analysis technology, in the research after 2020, scholars have more accurate analysis of berry fruit quality and more measurement objectives. In order to further improve the quality detection results, the method of independently developing convolution neural network and combining multiple algorithms for calculation is more popular in the past two years. It can be seen that in the research of HSI technology in recent years, it is generally correct to improve the prediction model accuracy by means of spectral data preprocessing, wavelength selection, feature extraction, various modeling methods, and model parameter optimization [89, 95, 96].

Berry Fruit Maturity Detection and Grading Approach

Judging the maturity of berry fruits is an indispensable and important link in the berry market. The results of berries maturity determination directly affect the accuracy of berry fruits quality classification and picking period determination in fresh berries market. Detection of SSC in internal quality testing can also preliminarily predict the maturity of berry fruits. However, one of the predictive characteristics of berries maturity is SSC. In order to improve the prediction accuracy of maturity, the selection of multiple characteristic parameters is extremely important. The research on berry fruit maturity detection and classification based on HSI technology is summarized as shown in Table 9.

In the first chapter of this paper, the introduction to the detection method of outdoor berries mentioned that, regardless of the application purpose, the target fruit needs to be identified and segmented. The difficulty lies in removing external interference, which is also an important and complex part of machine vision. Generally, the study of quality detection or maturity prediction based on hyperspectral technology will avoid the interference of external environmental factors and obtain berry fruit information in the laboratory. The HSI technology for outdoor berry fruit information acquisition also needs to eliminate

Table 9 Major contributions of berry maturity detection in the field of HSI technology

Berry type	Wavelength range (nm)	Feature extraction	Modeling method	Result	Ref.
Blueberry	396–1010 nm	NDVI	SAM, MLR, decision tree	Accuracy = 82.10% ~ 89.80%	[97]
Strawberry	400–1000 nm	CARS, SPA, PCA	PLS-DA, LS-SVM	Accuracy = 91.70% ~ 96.70%	[98]
Strawberry	370–1015 nm	SFS	SVM, CNN	Accuracy = 98.60%	[99]
Grape	400–1000 nm	PCA, PLS-DA	PLSR	Accuracy = 86.00%–91.00%	[100]

GLCM gray-level co-occurrence matrix, *NDVI* normalized difference vegetation index, *SFS* sequential feature selection the interference of complex environment. Ma et al. [97] collected spectral information of blueberry fruits grown indoor and outdoor based on HSI technology. In order to eliminate the influence of complex environmental background on fruit identification, Ma et al. [97] established a normalized index based on the optimal spectral bands of blueberry fruits at different mature stages. Based on two spectral angle mapping (SAM), multiple logistic regression (MLR) and decision tree, the maturity detection model of blueberry was established. And the decision tree model combined with normalization index had the highest accuracy, and the accuracy rate reached 89.8%. Thus, HSI technology can be used to identify the maturity of blueberry grown in outdoor and indoor environments, and the normalization spectral index can effectively improve the accuracy of the model. Therefore, the maturity prediction accuracy can also be optimized by selecting effective modeling methods and optimizing model parameters.

Shao et al. [98] also evaluated the maturity of berry fruits in both environments. In order to evaluate the maturity of strawberries in the field and indoor, Shao et al. [98] mainly optimized the accuracy of the model by selecting effective feature bands and established the maturity discriminant model based on PLS-DA (partial least squares discriminant analysis) and LS-SVM by selecting three algorithms (x load, CARS, and SPA). Similarly, Gao et al. [99] focused on the maturity classification method for strawberry. Gao et al. [99] applied AlexNet convolutional neural network (CNN) to classify the maturity of strawberry samples with different maturity. The accuracy of the discriminant model was evaluated based on the classification results, and the accuracy of the testing dataset was as high as 98.6%. Thus, Zongmei Gao team combined with CNN real-time HSI system can complete indoor and outdoor strawberry maturity evaluation, which provides a strong foundation for future real-time maturity evaluation. Therefore, HSI technology can be used to identify strawberry maturity in field and indoor environment. Among them, Shao et al. [98] selected feature extraction methods (using three different algorithms to select feature bands) and selected excellent classification model to optimize the maturity evaluation model. Gao et al. [99] established a discriminant model based on CNN algorithm. Both of them start from the perspective of algorithm and model to optimize the model accuracy.

Traditional methods for monitoring grape ripeness often require destructive sampling and chemical analysis, which can be costly and inefficient. However, the use of hyperspectral imaging technology can allow for nondestructive, real-time, and wide-area ripeness testing during the grape growing process, improving production efficiency, reducing costs, and allowing for more effective control of grape growth and harvest timing. The advantage of hyperspectral imaging technology is that it enables comprehensive longitudinal analysis and comparison of grape varieties, growing seasons, growing environments, and other factors by collecting large amounts of data, further facilitating the assessment of grape growth optimization and ripening capacity. Benelli et al. [100] conducted a study using hyperspectral imaging data to build a predictive model of grape ripening, which was validated and adjusted in the field. The innovation in their study was the application of different data preprocessing methods and analytical techniques to obtain more accurate and reproducible results. The optimization point of the study was in further adjusting and improving the model performance and accuracy of the prediction model through sample data collected in the field.

In the field of berry maturity research, HSI technology has shown more advantages, and it can be seen from Table 9 that the accuracy of maturity discriminant model has obtained excellent results. At present, the most widely used maturity detection technology is machine vision technology, and there are also high classification results by distinguishing colors. However, the maturity of berries is not only judged by color, so HSI technology shows its advantages in the field of maturity, which can be combined with more maturity spectral characteristic parameters to classify and be more accurate. There are variations in berry fruits maturity levels between indoor and outdoor growth methods, and successful identification of berry fruits maturity necessitates taking into account both indoor and outdoor factors. Moreover, the hyperspectral information acquired is intricate and arduous to compute. Ma et al. [97] combined with a variety of algorithms to establish a maturity classification model, Shao et al. [98] combined with three algorithms to extract the characteristic bands, and Gao et al. [99] combined with CNN to classify the maturity of berry fruits. These methods effectively improve the development of hyperspectral technology in the field of berries maturity classification.

The optimization of the algorithm is still under continuous attention. The powerful function of HSI technology is far more than the existing research results. At present, with the development of precision agriculture, the demand for detection technology is also increasing, especially real-time detection is particularly important, and HSI technology is not perfect to meet the demand of real-time detection. Therefore, the study of feature extraction and effective band selection is necessary. Optimizing the computational model and improving the computational efficiency of the model is also one of the key directions of current research.

Berry Fruit Bruise Detection Approach

The external quality of the berry fruit is essential to determine their market value [101]. Bruises are a common problem that damages the subcutaneous tissue of the fruit, leaving a visible scar. The appearance of dark scars at the site of the bruise is due to phenolic compound and oxidase mixing [102, 103], leading to a darker coloration at the bruise site. While the bruising of most berry fruits can be observed with the naked eye, some berry fruits, such as blueberries, are difficult to identify their appearance scars [104]. Hyperspectral technology has shown promise in detecting and grading the maturity of berry fruits, as presented in Table 10. The thin, juicy skin of berry fruits makes them susceptible to extrusion, which can lead to bruises. According to Table 10, the research on bruise detection of berry fruits generally focuses on blueberries. This approach is because bruises on most berry fruits can be solved using machine vision, while bruises on blueberries, such as dark berries, are difficult to detect. Therefore, the application of hyperspectral imaging technology to detect bruises reflects its relative advantage.

Table 10 presents that blueberry fruit is a common research object in the field of bruise detection of berry fruits. Due to the dark color of blueberries, it is challenging to detect bruises using naked eyes, making the use of machine vision technology limited. The use of HSI technology for detecting bruises in blueberry fruit is particularly significant. In the field of siltation damage identification, there are two main areas: siltation quantitative identification and siltation time prediction. Researchers have primarily focused on traditional algorithm classification and deep learning classification, using the SVM classifier in early research. However, deep learning is now being introduced and applied to the field of bruise detection. Scholars have optimized the bruise discrimination model in the field of blueberry bruise detection by adding a spectral information database and choosing an optimized model. Specifically, optimization algorithms have been researched more, indicating that there is much potential and ample opportunity for further optimizing model algorithms.

External damage is inevitable for blueberry fruit in the market, and the degree of bruising affects its value. Typically, fruit is considered bruised when the degree of bruising exceeds 20%. Currently, the quantification of blueberry bruising requires slicing and measuring the total value of the color change area of the section. Therefore, nondestructive testing technologies like HSI are advantageous for quantitative detection of bruising. Jiang et al. [105] proposed the application of HSI technology to study blueberry bruises. They developed a quantitative analysis method for nondestructive testing of blueberry bruises and established the blueberry bruise ratio index based on HSI technology, stiffness measurement, and artificial evaluation. By using a SVM classifier, they separated the bruised parts of blueberries from healthy tissues with 94% accuracy for the training set, 92% accuracy for the test set, and 96% accuracy for the verification set. Jiang et al.'s [105] research provides a feasible quantitative scheme for

Table 10 Major contributions of berry external quality detection in the field of HSI technology

Berry type	Attribute assessed	Wavelength range (nm)	Feature extraction	Modeling method	Result	Ref.
Blueberry	Quantitative determination of bruise	950–1650 nm	Manually select ROIs	SVM	Testing set accuracy = 92%	[105]
Blueberry	Prediction of bruise time and bruise degree	950–1650 nm	CARS	LS-SVM	Accuracy (30 min) = 77.5%; accuracy (2 h) = 83.80%; accuracy (6 h) = 92.50%; accuracy (12 h) = 95.00%	[106]
Blueberry	Prediction of bruise time and bruise degree	400–1000 nm, 965–1650 nm	Manually select	PLS-DA, SVM	Accuracy (PLS-DA) = 87.1–87.30%; accuracy (SVM) = 87.3–87.500%	[107]
Blueberry	Prediction of bruise time and bruise degree	328.82–1113.54 nm	Morphologic processing methods	SMO, LR, RF, bagging, MLP, ResNet, ResNeXt	Accuracy (ResNet) = 0.88; accuracy (ResNeXt) = 0.88; accuracy (SMO) = 0.80; accuracy (LR) = 0.76; accuracy (RF) = 0.73; accuracy (bagging) = 0.71; accuracy (MLP) = 0.78;	[108]

SMO sequential minimal optimization, *LR* linear regression, *MLP* multilayer perceptron blueberry bruise detection and offers a valuable technical direction for subsequent berry bruise research. Additionally, their research has direct market implications.

In addition to the quantitative analysis of blueberry bruising, predicting the time course of bruising is also a valuable research direction. After blueberry fruits are subjected by external pressure, bruising may not immediately appear. Over time, pigments from damaged cells accumulate and the bruised area becomes more visible [103]. Fan et al. [106] investigated the use of HSI to detect blueberry bruises at various time points following mechanical damage 30 min, 2 h, 6 h, and 12 h. The authors used the CARS method to select characteristic wavelengths and then used the wavelengths and full spectral information in combination with LS-SVM classifiers to predict the damage time for each blueberry. Classification accuracy was 77.5%, 83.8%, 92.5%, and 95.0% for the four damage time intervals, respectively. These results demonstrate the effectiveness of using near-infrared hyperspectral technology to detect blueberry bruises 30 min after mechanical damage. To further improve prediction accuracy and reduce environmental interference, Fan et al. [107] combined two HSI systems to collect complementary spectral information and address internal bruising in blueberries. Using the two sets of hyperspectral data and various processing techniques, the authors extracted features and made classification decisions to achieve more accurate bruise prediction. The results showed that multisource data fusion led to more accurate classification than single HSI analysis alone. This approach can therefore be effective for improving prediction accuracy of internal blueberry fruit bruises. Regarding response parameters, blueberry bruising can be evaluated using various quantitative indicators such as productivity, quality, reliability, efficiency, power consumption, and environmental impact. However, the key response parameter in this study was the time course of bruising, which is influenced by several factors including external pressure, blueberry ripeness, and other environmental conditions. By characterizing the temporal changes in bruising using hyperspectral imaging, the authors were able to predict the time since mechanical damage with high accuracy.

The above scholars optimize the siltation model by increasing the amount of spectral information, selecting feature extraction methods, and selecting model establishment methods. In the field of model optimization, CNNs are also generally used to study. Wang et al. [108] studied the problem of blueberry bruises combine with convolution neural network. Two CNN (ResNet and its improved version ResNeXt) were selected to detect the blueberry damage, and five classification algorithms (SMO, LR, RF, bagging, and MLP) were selected to classify the mechanical damage of blueberry and compare the classification results. The average clarity and *f*1 score of the fine-tuned ResNet/ResNeXt reached 0.8844/0.8784 and 0.8952/0.8905, respectively, and the classification calculation time of the two models was 5.2 ms and 6.5 ms, respectively. It can be seen that the deep learning framework has a good development prospect in classification, which can greatly improve the calculation speed and provide strong support for real-time detection. HSI technology can identify and detect the internal wear of blueberry within 30 min of mechanical impact on blueberry fruit. Compared with the traditional SVM classification method, the CNN method is more effective in predicting blueberry bruises, and the model has superiority.

In the early stage, Jiang et al. [105] detected and quantitatively analyzed the bruises of blueberry fruits and proposed that hyperspectral technology was feasible to study the bruises of blueberry fruits. The severity of abrasion is proportional to the increase of time after mechanical injury. Jiang et al.'s [105] research mainly focuses on quantitative analysis of blueberry bruise degree, which can meet the market demand for blueberry quality judgment. In the following year, Fan et al. [106, 107] carried out research on blueberry at different time intervals after mechanical injury and had objective discriminant results for early siltation measurement. In order to further improve the discriminant accuracy, Fan et al. [106, 107] expanded the amount of information collection and added different algorithms for siltation judgment. Wang et al. [108] combined with CNN to study the internal bruising problem of blueberry and obtained considerable judgment results. It can be seen that CNN network application in deep learning has considerable prospects for hyperspectral analysis of blueberry bruising problem.

The above research indicates that HSI technology is effective in predicting the time interval of blueberry fruit bruising, but it cannot predict the exact time after the bruise occurs based on the degree of blueberry fruit bruising. The accuracy of predicting and discriminating within 2 h of blueberry fruit bruises does not yet reach the ideal prediction level, and thus, predicting the specific time after bruises is even more challenging. Therefore, at this stage, it is necessary to optimize the prediction model of bruising time within 4 h after bruising to improve the prediction accuracy. CNN and its derivative models have shown certain advantages in this direction. In future studies, the focus should be placed on further optimizing CNN and its derivative frameworks to solve the problem of low prediction accuracy of berry bruising in a short time. It is recommended to conduct research that speculates on the specific time after bruising. In conclusion, there is a need for further optimization of the prediction model to improve the accuracy of berry bruising prediction, and CNN and its derivative models show promise for improving the accuracy of bruising prediction within 4 h.

Berry Safety Monitoring Approach

Ensuring the safety and quality of berry fruits in the market requires effective safety detection methods. In particular, safety monitoring of berry fruits focused on identifying fungal and bacterial infections, as well as pesticide residues. HSI technology has shown promising results in this regard. Table 11 provides an overview of recent research on safe monitoring of berry fruits using hyperspectral technology.

Table 11 shows that HSI technology in the field of safety monitoring mainly consists of two directions: mildew infection and pesticide residues. The research of pesticide detection is not much, because the NIRS technology has been able to effectively identify pesticide residues. In contrast, HSI technology is accompanied by complex data and high cost characteristics, so it is not the best detection technology in the field of pesticide residues. In the study of mildew infection, scholars focus on algorithm optimization. In the later studies, CNN and its derivative structures are applied to feature extraction and classification model establishment. It can be seen that the advantages of CNN are also reflected in the field of security detection.

The characteristics of juicy berry fruits make them prone to mildew. If the berry fruits infected by fungi are not timely detected and processed, they will spread and lead to fungal infection of healthy berry fruits around them, which will cause a certain degree of waste for fruit farmers. The berry fruits infected by fungi can produce mycotoxins, and eating can lead to allergic reactions or canceration, thus endangering human health [109–111]. Siedliska et al. [112] applied HSI technology to detect fungal infection of strawberry. Two varieties of strawberry were selected to be inoculated with *Botrytis cinerea* and *Colletotrichum acutatum*, respectively, as the comparative analysis of fruit without fungi. The prediction accuracy obtained by the BNN model was the best, and the identification accuracy of the comparison fruit and the inoculated fruit reached 97%. It can be seen that HSI technology is feasible to distinguish strawberry infected by fungi. The infection characteristics of strawberry inoculated within 24 h were not obvious. In view of the fact that the early symptoms of fungal and bacterial infection are not obvious, Qiao et al. [113] proposed the feasibility of hyperspectral technology to detect early decayed blueberry fruit and optimized and improved the CNN framework to obtain deep residual three-dimensional convolutional neural network (3D-CNN) to identify early decayed blueberry fruit. This model can effectively extract the feature spectrum and feature image region from the complete spectrum information module. In order to verify the performance of the network, the comparative analysis with AlexNet and GoogleNet shows that the grid effectively improves the classification accuracy. The results showed that 3D-CNN greatly reduced the calculation amount, reduced the operation time, improved the detection accuracy of early decay of blueberry fruit, and could effectively complete the early decay detection of blueberry fruit. This proves again that the optimization and improvement of CNN have strong ability and potential in the field of berry nondestructive testing.

Pesticide residues present a significant concern for the safety of berries as they are often subjected to contamination during growth. Hyperspectral imaging technology can facilitate rapid and nondestructive detection of pesticide residues in berries, thereby enhancing the quality and safety of the fruit. Hyperspectral imaging provides rich image information and enables analysis of reflectance spectral data across different wavelength bands, thereby enabling accurate detection of pesticide residues. Ye et al. [114] used hyperspectral imaging in conjunction with machine learning to identify different levels of pesticide residue in grapes. The study aimed to explore the spectral differences between various grape varieties and different concentrations of pesticide residue levels by comparing the hyperspectral imaging performance in two distinct spectral regions. The study utilized LR, SVM, RF, CNN, and ResNet models

Table 11 Major contributions of berry safety monitoring in the field of hyperspectral technology

Berry type	Wavelength range (nm)	Attribute assessed	Feature extraction	Modeling method	Result	Ref.
Strawberry	400–1000 nm, 1000–2500 nm	Detection of fungal infections	Spectral differences	Bnn, RF, SVM	BNN accuracy = 97.00%	[112]
Blueberry	450–1000 nm	Detection and classification of decay	3D-CNN	3D-CNN, AlexNet, GoogleNet	Accuracy (AlexNet) = 89.12%; accuracy (GoogleNet) = 91.88%; accuracy (3D-CNN) = 92.15%	[113]
Grape	376–1044 nm, 915–1699 nm	Pesticide residue level	DL	LR, SVM, RF, CNN, ResNet	Best accuracy (LR) = 97%	[114]
Mulberry	270–850 nm, 400–1000 nm, 900–1700 nm	Detection of pesticide residues	Spectral differences	PCA, PLSR	LIBS-HSI-PLSR: RPD = 2.585, RMSEP = 7.09×10^{-4}	[115]

to establish a pesticide residue level classification model. The results indicate that hyperspectral imaging combined with machine learning is highly effective in detecting pesticide residue levels in grapes, with the overall accuracy of NIR spectra being greater than that of Vis-NIR spectra, and the deep learning approach outperforming traditional machine learning techniques. The innovation of the study lies in employing hyperspectral imaging in combination with machine learning to facilitate fast and accurate pesticide residue detection. Furthermore, the study optimizes the detection process by comparing the performance of different models and identifying the contributing spectral features. Since multisource information fusion can also effectively improve the model accuracy, Wu et al. [115] proposed for the first time the application of laser-induced breakdown spectroscopy (LIBS) and HSI technology to study pesticide residues in berry fruits. The results showed that the prediction results of single LIBS and single HSI model for pesticide residues in mulberry fruit were not ideal, and the PLSR detection model with LIBS-HSI fusion information obtained the best prediction results, RPD value was 2.585, RMSEP value was 7.09×10^{-4}. Wu et al. [115] confirmed that LIBS and HSI nondestructive testing technology can effectively detect pesticide residues in berries, and the detection accuracy of multisource information fusion model is better than that of single model. However, due to the completely different information processing methods between LIBS and HSI, there is a great degree of complexity in data processing. Therefore, it is necessary to further study the data processing, information fusion, and later model establishment of both information. Therefore, in the follow-up study, multisource information processing has certain advantages and will become the trend of future research. However, the research on solving the problem of pesticide residues by high spectral information is relatively less. The main reason for the analysis is that NIRS has made some research results on pesticide residues, and the cost of HSI is too expensive. As spectroscopic technology advances and the cost of using spectroscopic instruments decreases, improvements in the model algorithm and model adaptability can also result in the extension of the above research methods to the detection of other fruits and agricultural products in the field, ultimately leading to a wider range of applications.

Hyperspectral techniques have been extensively studied in the field of berry safety monitoring, particularly for the detection of fungal infections. Fungal infections pose a significant threat to fresh berry preservation due to the short storage period and susceptibility to decay. However, it is also critical to monitor the presence of pesticide residues, which can affect the safety of berries for consumption. For instance, Wu et al. [115] applied a multisource information fusion method to study the detection of pesticide residues, resulting in improved monitoring accuracy. Hyperspectral techniques also prove to be effective in detecting rotten berries. Anna Siedliska's study found that hyperspectral techniques can distinguish four types of molds that infect strawberries and identify fungal infections through analyzing the characteristic hyperspectral wavelengths. Similarly, Qiao et al. [113] successfully constructed 3D-CNN to study blueberry fruit decay, significantly enhancing the speed and accuracy of detection. Further optimization of information processing methods could improve the effectiveness and efficiency of hyperspectral techniques in monitoring berry safety. Overall, hyperspectral techniques have significant potential in ensuring the safe consumption of fresh berries, and future research could continue to explore more advanced applications.

It can be seen from the above studies that the research on HSI technology in the field of berry safety monitoring is far less than that in other fields, mainly because the field of safety monitoring is a very important research direction. Early studies have applied different technologies to study various safety monitoring methods of fruits, and some research results have been achieved. HSI technology started relatively late, so the application of this technology in the field of safety monitoring research is less. However, the research on berry safety monitoring based on HSI technology with great significance. The reason is analyzed because of the powerful function of HSI. In the future, after obtaining a certain amount of spectral information, it is an ideal goal to analyze and calculate the berry fruit information in different fields. Therefore, the subsequent research should carry out more research on HSI technology in the field of berry safety monitoring and provide support for the extensive analysis function of HSI technology in the future.

Other Detection Studies' Approach

HSI technology has also been applied in the field of berry variety identification and other fields. The research on other detection based on HSI technology is shown as Table 12.

Hu et al. [104] first applied HSI technology to study the soft and hard degree of blueberry and combined with RF algorithm to extract characteristic spectral information. The reflectance and transmittance characteristic spectral information were combined to predict the soft and hard degree of blueberry. The results showed that the mechanical properties of blueberry could be evaluated by hyperspectral technology combined with RF method. The selection of reflectivity and transmittance will also affect the evaluation results. However, the selection of reflectance or transmittance spectral information by scholars often depends on equipment factors. At present, many studies compare the results of reflectance spectrum and transmittance spectrum data under different research objects.

Table 12 Major contributions of other detection studies in the field of HSI technology

Berry type	Wavelength range (nm)	Attribute assessed	Feature extraction	Modeling method	Result	Ref.
Blueberry	410–1113 nm	Detection of soft and hard degree	RF	LS-SVM	Hardness: Rc = 0.85, Rp = 0.76, RPD = 1.52	[104]
Strawberry	400–1000 nm	Detection of storage time	CARS, SPA, UVE, CARS-SPA	PLSR, SVM, RF	PLSR: R^2 = 0.10, RMSE = 0.75 SVM: R^2 = 0.10, RMSE = 1.36	[92]
Wolfberry	900–1700 nm	Variety identification	SPA	SVM, ELM, RF	Accuracy (RF) = 100%	[117]
Grape	493.80–1001.61 nm	Variety identification	CARS-SPA	SVM	SVM accuracy = 99.32%	[116]

The thin and juicy peel characteristics of fresh berry fruits restrict their storage period. Exceeding the recommended storage period can result in mold growth and subsequent losses. Therefore, it is crucial to develop methods for predicting the storage period to minimize these risks. Moreover, with the increase of storage time, berries internal nutrients will also be lost. Therefore, it is necessary to predict the storage period of berry fruits quickly, accurately, and without damage to the fruit. Taking strawberry as the research object, Weng et al. [92, 93] conducted a prediction study on its storage time combined with hyperspectral analysis technology, collected fresh strawberry, and calculated the storage time. SVM and RF were used to establish strawberry classification models with different storage time, and the SVM classification accuracy reached 100%. In order to predict the storage time more accurately, Weng et al. applied CARS, SPA, UVE, and CARS-SPA methods to extract the characteristic wavelength information and predicted the storage time based on PLSR, SVM, and RF algorithms. The research proved that HSI technology was feasible to predict the storage time of berry fruits.

Variety identification is a relatively mature and important application research. Fan et al. [117] identified wild and cultivated wolfberry by high spectral analysis technology. In previous studies, many scholars have studied the identification of wolfberry varieties. Fan et al. [117] first solved the identification of wolfberry varieties based on HSI technology. The variety identification model of wolfberry fruit was established based on the SVM, extreme learning machine (ELM), and RF algorithm. Among the three models, the accuracy of RF model was the best and the accuracy reached 100%. It can be seen that the HSI technology can effectively and accurately identify wild wolfberry. Xu et al. [116] utilized HSI techniques and machine learning algorithms to rapidly and accurately identify grape varieties in a nondestructive manner. Hyperspectral data are complex and varied, therefore, Xu et al. [116] proposed an enhanced denoising algorithm based on ensemble empirical modal decomposition (EEMD) and discrete wavelet transform (DWT) to reduce noise in hyperspectral data. CARS-SPA was then utilized to select key wavelengths, and a SVM was employed to construct a discriminative model. The method proved to have outstanding discrimination accuracy (99.3125%), indicating the feasibility of combining hyperspectral imaging and machine learning for grape variety identification. The innovation of this study lies in the use of hyperspectral imaging and machine learning algorithms, with optimization achieved through the proposed enhanced denoising algorithm to reduce data noise and the use of CARS-SPA to select key wavelengths, improving prediction accuracy. The study outcomes are important for grape grading and promotion of high-quality varieties, while also offering guidance for berry industry producers in quickly and accurately identifying berry varieties.

In recent years, HSI technology has been increasingly used to detect berry fruits in various aspects such as their hardness, storage time prediction, and variety identification, thanks to the rapid development of image processing, computer, and spectral analysis technologies. The technology can provide accurate and informative measurements of the external quality of berry fruits and enable their recognition, classification, prediction, and quantitative analysis. However, it requires processing hyperspectral data from an information cube, which can be complex and time-consuming and may not be suitable for real-time online detection. Despite this limitation, hyperspectral analysis technology holds significant value and significance for future research. Firstly, it has a broad application range that continues to expand with the advancement of research. Secondly, the process from information collection to model establishment includes many flexible and diverse processes that can provide strong support for the study of optimization models in the future. Lastly, hyperspectral analysis technology can be applied to various fields, creating more possibilities for its future development. However, challenges such as the selection and extraction of feature bands still need to be addressed to improve the accuracy of predicted parameters. Please note that the text has been modified to conform to the format of a literature review and avoid using the first person. Also, minor changes were made to enhance readability, coherence, and grammar.

Development and Prospects

At present, nondestructive testing of berries primarily utilizes machine vision technology and spectral analysis technology. While machine vision technology has been used for longer, spectral analysis technology has become more widely used in the past seven years. Hyperspectral analysis technology, which combines the features of both machine vision technology and spectral analysis technology, has a broad range of applications that can address various problems, such as variety identification, encounter detection, maturity classification, safety monitoring, and hardness. Other promising technologies for application development include electronic nose technology and NMR technology.

Currently, despite the advantages discussed in this review, nondestructive testing of berry fruits faces various challenges. These include limited detection accuracy and poor model applicability, which significantly impede the practical implementation of such testing. The main findings can be summarized as follows:

1. Research on machine vision detection of berry fruits has focused on algorithm development to improve detection accuracy. However, variations in different types of berries, geographical location, experimental environments, equipment, and lighting methods limit the generalizability of detection algorithms. Currently, there is no universally applicable algorithm that can achieve high-precision results for fruit location, maturity classification, or quality detection.

In the process of nondestructive testing, various algorithms have been employed to address different detection issues. However, the operation process is complex and the interrelatedness of each detection problem needs to be considered. Despite efforts to optimize the detection module, highly precise calculation models are still too complex. Compared to spectral technology, machine vision technology has been applied to nondestructive testing of berry fruits earlier and has achieved relative maturity. It has been applied to orchard berry fruit intelligent management as well as berries' market planning.

2. Research on NIRS detection of berry fruits: the differences in berry fruits, NIRS equipment, selected spectral bands, and lighting methods selected by researchers from various countries have led to the limitations of prediction models.

The spectral information obtained by the NIRS is relatively single and can only obtain the spectral information of a certain point of the berry fruit. Therefore, in the determination of the quality information of the berry fruit, pesticide residues, bruising detection, etc., only the part to be studied can be determined, and the spectral information of the entire berry fruit cannot be obtained, and the problem cannot be fully reflected, especially the fruit quality detection, which can only explain the quality problem of a certain point. This is also the deficiency of spectral analysis technology itself.

Moreover, NIRS equipment is expensive and maintenance is complex, which makes it difficult to be widely used in the production and management of berry fruits. However, the development of portable spectrometers using VIS/IRS technology has made nondestructive testing of fruits and vegetables practical. This technology has been applied to berry fruits such as grapes and strawberries to improve the development of intelligent agriculture. As demand for berries increases, different types of berry fruits may also be included in its application range.

Currently, the small differences between berry fruits make data processing challenging, and traditional algorithms have limitations in processing the data. However, deep learning algorithms, such as CNN and its derivative structure, have the potential to make significant advancements in data processing. This will improve the quality and maturity prediction models for nondestructive testing of berry fruits.

Overall, while NIRS has limitations, its potential use in detecting berry fruit quality and its applications in the future make it an area of continued research and development.

3. Research on HSI technology detection of berry fruits: the information obtained by HSI technology is the information block that integrates the spectral information and image information. Therefore, the data source is too rich and complex, and only a very small part of the spectral information is applied in the analysis and research process, which greatly reduces the detection speed. The data screening process still needs to be optimized.

At present, the cost of HSI technology is more expensive than that of VIS/IR spectrometer. The spectral phase instruments from different manufacturers are also different. At present, machine vision and spectral technology are more popular in the practical application of fruit farmers and market management. However, the strength of HSI technology is still in the research stage. At present, the analysis and application only select a small part of spectral information, so data dimension reduction has been an indispensable part of data processing in imaging technology. With the complete information of the data, different results can be analyzed, such as maturity, content of various compounds, damage degree, mildew, and pesticide residues. Therefore, from the perspective of future development, HSI technology has more advantages than the other two technologies. At present, the research on CNN algorithm and optimization has developed rapidly, showing great advantages in the field of data processing. In the future, the hyperspectral cube information block obtained by HSI technology can obtain the prediction results of different information at the same time.

This study did not make direct comparisons of algorithms since suitability depends on different evaluation indexes selected by scholars. However, optimized convolutional neural network (CNN) shows advantages over traditional algorithms in deep learning. Nonetheless, the CNN structure may not be the most suitable for nondestructive testing of berries, and traditional algorithms have their own advantages. CNN and its derivative structures have stronger applicability, and deep learning is a driving force behind the development of nondestructive testing technology.

This study did not make direct comparisons of the algorithms since suitability depends on different evaluation indexes selected by scholars. However, optimized CNN shows advantages over traditional algorithms in DL. Nonetheless, the CNN structure may not be the most suitable for nondestructive testing of berries, and traditional algorithm have their own advantages. CNN algorithm and its derivative structures have stronger applicability, and DL is a driving force behind the development of nondestructive testing technology.

Conclusion

This study aims to review the optical technology used in nondestructive testing of berry fruits, including machine vision technology, VIS/IRS, and HSI technology. These techniques have been widely used in predicting yield, detecting maturity, identifying varieties, evaluating internal quality, monitoring safety, and detecting diseases. Machine vision technology is the oldest technology used in the detection of berry fruits. This study summarizes the recent applications of machine vision technology in predicting yield, detecting maturity, and identifying diseases. VIS/IRS can be used to detect various parameters of berry fruits, such as internal quality, external damage, pesticide residues, and hardness prediction. HSI technology combines the advantages of machine vision technology and VIS/IRS, which makes it have broader application prospects. This study also summarizes the research on HSI technology in nondestructive testing of berry fruits, such as internal quality evaluation, maturity testing, silting detection, safety monitoring, variety identification, hardness testing, and storage period prediction.

The research in the field of berry fruit maturity detection, internal quality detection, external damage, and safety monitoring is relatively popular. Machine vision technology is extensively used in maturity detection. However, HSI technology is currently the most accurate technology for predicting maturity, while VIS/IRS technology is the most suitable for practical applications. HSI technology is chosen because the color feature is the most straightforward and related features complement it, allowing more precise predictions of maturity degree. For internal quality detection and external damage, HSI technology is also advantageous as it can predict a specific chemical element's spatial concentration, which is not achievable with VIS/IRS technology. Consequently, HSI technology is the most promising and developing technology. In this research field, HSI technology's full functionality can be explored, and the application range of nondestructive testing of berry fruits can extend beyond the current research field. However, the selection of data processing algorithms presents a significant challenge. Currently, CNN algorithms and their derivative structures are the hot research directions for imaging technology. While CNN algorithms and their derivative structures show promising applications and lower costs, VIS/IRS technology is currently more practical for many applications. Portable spectral measuring instruments exist already and can detect spectral information in real time. Consequently, the research on the CNN algorithm also propels the development of nondestructive testing technology.

In conclusion, optical technology is being extensively researched for nondestructive testing of berry fruits with machine vision technology, VIS/IRS and HSI technology having widespread applications for predicting yield, detecting maturity, identifying varieties, evaluating internal quality, monitoring safety, and detecting diseases. While HSI technology offers more precise results in most applications, VIS/IRS technology is still more practical for many applications. The research on CNN algorithms and their derivative structures promises significant developments in this field.

Author Contribution Zhujun Chen collected and analyzed references and drafted the manuscript; Zhenhui Ren and Juan Wang offered much help in the process of revision. All authors read and approved the final manuscript.

Funding The authors are grateful for the financial support from the Hebei Provincial Department of Science and Technology (Grant number: 20326338D) and Agricultural Machinery And Equipment Technology Innovation Center for Hilly Areas of Hebei Province (No. 2021019).

Declarations

Competing Interests The authors declare no competing interests.

References

1. Kumar S, Baghel M, Yadav A, Dhakar, MK (2018) Postharvest biology and technology of berries. Postharvest Biol Technol Temp Fruit 349–370.
2. Manganaris GA, Goulas V, Vicente AR, Terry LA (2014) Berry antioxidants: small fruits providing large benefits. J Sci Food Agric 94(5):825–833. https://doi.org/10.1002/jsfa.6432

3. Salo HM, Nguyen N, Alakärppä E, Klavins L, Hykkerud AL, Karppinen K, Jaakola L, Klavins M, Häggman H (2021) Authentication of berries and berry-based food products. Compr Rev Food Sci Food Saf 20(5):5197–5225. https://doi.org/10.1111/1541-4337.12811
4. Miller K, Feucht W, Schmid M (2019) Bioactive compounds of strawberry and blueberry and their potential health effects based on human intervention studies: a brief overview. Nutrients 11(7):1510. https://doi.org/10.3390/nu11071510
5. Golovinskaia O, Wang C (2021) Review of functional and pharmacological activities of berries. Molecules 26(13):3904. https://doi.org/10.3390/molecules26133904
6. Neri-Numa IA, Soriano Sancho RA, Pereira APA, Pastore GM (2018) Small brazilian wild fruits: nutrients, bioactive compounds, health-promotion properties and commercial interest. Food Res Int 103:345–360. https://doi.org/10.1016/j.foodres.2017.10.053
7. Tourte L, Bolda M, Klonsky K (2016) The evolving fresh market berry industry in Santa Cruz and Monterey counties. Calif Agric (Berkeley, Calif.) 70(3):107–115. https://doi.org/10.3733/ca.2016a0001
8. Jingbo P (2007) Develop small berry industry and open up international market. North Fruit Tree (03):77–78. https://doi.org/10.3969/j.issn.1001-5698.2007.03.047
9. Lan C (2003) Small berries will become a new economic growth point. Yunnan Agric (04):37. CNKI:SUN:YNNY.0.2003–04–048
10. Miina J, Pukkala T, Kurttila M (2016) Optimal multi-product management of stands producing timber and wild berries. Eur J Forest Res 135(4):781–794. https://doi.org/10.1007/s10342-016-0972-9
11. Doerflinger FC, Pagay V (2018) Objective assessment of dried sultana grape quality using digital image analysis. Aust J Grape Wine Res 24(2):234–240. https://doi.org/10.1111/ajgw.12316
12. Liu X, Wang H, Huang X, Guo M, Yang Z, Zhang K, Liu J, Wang M, Gong Y, Wei J, Di D (2020) Quality assessment and classification of goji berry by an hplc-based analytical platform coupled with multivariate statistical analysis. Food Anal Methods 13(12):2222–2237. https://doi.org/10.1007/s12161-020-01827-y
13. Xisheng T (2015) Study on quality detection and grading of blueberry based on machine vision and visible/near infrared spectroscopy. Master degree Thesis
14. Pathmanaban P, Gnanavel BK, Shanmuga SA (2019) Recent application of imaging techniques for fruit quality assessment. Trends Food Sci Technol 94
15. El-Mesery H, Mao H, Abomohra A (2019) Applications of non-destructive technologies for agricultural and food products quality inspection. Sensors 19(4):846. https://doi.org/10.3390/s19040846
16. Magwaza LS, Ford HD, Cronje PJR, Opara UL, Landahl S, Tatam RP, Terry LA (2013) Application of optical coherence tomography to non-destructively characterise rind breakdown disorder of 'nules clementine' mandarins. Postharvest Biol Technol 84:16–21. https://doi.org/10.1016/j.postharvbio.2013.03.019
17. Fei X (2013) Key technologies and applications of automatic optical inspection based on computer vision. Doctorate Thesis, Nanjing University
18. Li L, Chen S, Deng M, Gao Z (2022) Optical techniques in non-destructive detection of wheat quality: a review. Grain Oil Sci Technol 5(1):44–57. https://doi.org/10.1016/j.gaost.2021.12.001
19. Baxes GA (1994) Digital image processing: principles and applications. Wiley, New York, p 452
20. Xuejun Z, Shenming G, Bin L (2019) Application of machine vision technology in agricultural production. Rural Econ Technol 30(23):55–56. CNKI:SUN:NCJI.0.2019–23–026
21. Hemamalini V, Rajarajeswari S, Nachiyappan S, Sambath M, Devi T, Singh BK, Raghuvanshi A (2022) Food quality inspection and grading using efficient image segmentation and machine learning-based system. J Food Qual 2022:1–6. https://doi.org/10.1155/2022/5262294
22. Kumar RA, Rajpurohit VS, Gaikwad N (2021) Image dataset of pomegranate fruits (Punica granatum) for various machine vision applications. Data Br 37:107249. https://doi.org/10.1016/j.dib.2021.107249
23. Nithya R, Santhi B, Manikandan R, Rahimi M, Gandomi AH (2022) Computer vision system for mango fruit defect detection using deep convolutional neural network. Foods 11(21):3483. https://doi.org/10.3390/foods11213483
24. Mavridou E, Vrochidou E, Papakostas GA, Pachidis T, Kaburlasos VG (2019) Machine vision systems in precision agriculture for crop farming. J Imaging 5(12):89. https://doi.org/10.3390/jimaging5120089
25. Häni N, Roy P, Isler V (2020) A comparative study of fruit detection and counting methods for yield mapping in apple orchards. J Field Robot 37(2):263–282. https://doi.org/10.1002/rob.21902
26. Tang Y, Chen M, Wang C, Luo L, Li J, Lian G, Zou X (2020) Recognition and localization methods for vision-based fruit picking robots: a review. Front Plant Sci 11:510. https://doi.org/10.3389/fpls.2020.00510
27. Maheswari P, Raja P, Apolo-Apolo OE, Pérez-Ruiz M (2021) Intelligent fruit yield estimation for orchards using deep learning based semantic segmentation techniques—a review. Front Plant Sci 12. https://doi.org/10.3389/fpls.2021.684328
28. Pérez-Borrero I, Marín-Santos D, Gegúndez-Arias ME, Cortés-Ancos E (2020) A fast and accurate deep learning method for strawberry instance segmentation. Comput Electron Agric 178:105736. https://doi.org/10.1016/j.compag.2020.105736
29. Gonzalez S, Arellano C, Tapia JE (2019) Deepblueberry: quantification of blueberries in the wild using instance segmentation. IEEE Access 7:105776–105788. https://doi.org/10.1109/ACCESS.2019.2933062
30. Ni X, Li C, Jiang H, Takeda F (2020) Deep learning image segmentation and extraction of blueberry fruit traits associated with harvestability and yield. Hortic Res 7(1). https://doi.org/10.1038/s41438-020-0323-3
31. Palacios F, Diago MP, Melo-Pinto P, Tardaguila J (2023) Early yield prediction in different grapevine varieties using computer vision and machine learning. Precision Agric 24(2):407–435. https://doi.org/10.1007/s11119-022-09950-y
32. Bhatt D, Patel C, Talsania H, Patel J, Vaghela R, Pandya S, Modi K, Ghayvat H (2021) Cnn variants for computer vision: history, architecture, application, challenges and future scope. Electronics 10(20):2470. https://doi.org/10.3390/electronics10202470
33. Aquino A, Barrio I, Diago M, Millan B, Tardaguila J (2018) Vitisberry: an android-smartphone application to early evaluate the number of grapevine berries by means of image analysis. Comput Electron Agric 148:19–28. https://doi.org/10.1016/j.compag.2018.02.021
34. Chaudhury A, Ward C, Talasaz A, Ivanov AG, Brophy M, Grodzinski B, Huner NPA, Patel RV, Barron JL (2019) Machine vision system for 3d plant phenotyping. IEEE/ACM Trans Comput Biol Bioinf 16(6):2009–2022. https://doi.org/10.1109/TCBB.2018.2824814
35. Dorj U, Lee M, Yun S (2017) An yield estimation in citrus orchards via fruit detection and counting using image processing. Comput Electron Agric 140:103–112. https://doi.org/10.1016/j.compag.2017.05.019
36. Azarmdel H, Jahanbakhshi A, Mohtasebi SS, Muñoz AR (2020) Evaluation of image processing technique as an expert system in mulberry fruit grading based on ripeness level using artificial neural networks (anns) and support vector machine (svm). Postharvest Biol Technol 166:111201. https://doi.org/10.1016/j.postharvbio.2020.111201
37. Li H, Lee WS, Wang K (2014) Identifying blueberry fruit of different growth stages using natural outdoor color images. Comput

Electron Agric 106:91–101. https://doi.org/10.1016/j.compag.2014.05.015
38. Miraei Ashtiani S, Javanmardi S, Jahanbanifard M, Martynenko A, Verbeek FJ (2021) Detection of mulberry ripeness stages using deep learning models. IEEE Access 9:100380–100394. https://doi.org/10.1109/ACCESS.2021.3096550
39. Sun B, Chen H (2021) A survey of k nearest neighbor algorithms for solving the class imbalanced problem. Wirel Commun Mob Comput 2021
40. Deng X, Li Y, Weng J, Zhang J (2019) Feature selection for text classification: a review. Multimed Tools Appl 78(3):3797–3816. https://doi.org/10.1007/s11042-018-6083-5
41. Tan K, Lee WS, Gan H, Wang S (2018) Recognising blueberry fruit of different maturity using histogram oriented gradients and colour features in outdoor scenes. Biosys Eng 176:59–72. https://doi.org/10.1016/j.biosystemseng.2018.08.011
42. Zhang Y, Lian J, Fan M, Zheng Y (2018) Deep indicator for fine-grained classification of banana's ripening stages. Eurasip J Image Video Process 2018(1). https://doi.org/10.1186/s13640-018-0284-8
43. Rauf HT, Saleem BA, Lali MIU, Khan MA, Sharif M, Bukhari SAC (2019) A citrus fruits and leaves dataset for detection and classification of citrus diseases through machine learning. Data Br 26:104340. https://doi.org/10.1016/j.dib.2019.104340
44. Wang Q, Qi F, Sun M, Qu J, Xue J (2019) Identification of tomato disease types and detection of infected areas based on deep convolutional neural networks and object detection techniques. Comput Intell Neurosci 2019:1–15. https://doi.org/10.1155/2019/9142753
45. Kim B, Han Y, Park J, Lee J (2021) Improved vision-based detection of strawberry diseases using a deep neural network. Front Plant Sci 11. https://doi.org/10.3389/fpls.2020.559172
46. Xiao JR, Chung PC, Wu HY, Phan QH, Yeh JA, Hou MT (2020) Detection of strawberry diseases using a convolutional neural network. Plants (Basel) 10(1). https://doi.org/10.3390/plants10010031
47. Zheng C, Abd-Elrahman A, Whitaker V (2021) Remote sensing and machine learning in crop phenotyping and management, with an emphasis on applications in strawberry farming. Remote Sens 13(3):531. https://doi.org/10.3390/rs13030531
48. Albanese A, Nardello M, Brunelli D (2021) Automated pest detection with dnn on the edge for precision agriculture. IEEE J Emerg Sel Top Circuits Syst 11(3):458–467. https://doi.org/10.1109/JETCAS.2021.3101740
49. Iqbal Z, Khan MA, Sharif M, Shah JH, Ur Rehman MH, Javed K (2018) An automated detection and classification of citrus plant diseases using image processing techniques: a review. Comput Electron Agric 153:12–32. https://doi.org/10.1016/j.compag.2018.07.032
50. Cavallo DP, Cefola M, Pace B, Logrieco AF, Attolico G (2019) Non-destructive and contactless quality evaluation of table grapes by a computer vision system. Comput Electron Agric 156:558–564. https://doi.org/10.1016/j.compag.2018.12.019
51. Jia M, Li J, Hu T, Jiang Y, Luo J (2022) Feature normalization reweighting regression network for sugar content measurement of grapes. Appl Sci 12(15):7474. https://doi.org/10.3390/app12157474
52. Akiva P, Planche B, Roy A, Oudemans P, Dana K (2022) Vision on the bog: cranberry crop risk evaluation with deep learning. Comput Electron Agric 203:107444. https://doi.org/10.1016/j.compag.2022.107444
53. Kennison KR, Wilkinson KL, Pollnitz AP, Williams HG, Gibberd MR (2009) Effect of timing and duration of grapevine exposure to smoke on the composition and sensory properties of wine. Aust J Grape Wine Res 15(3):228–237. https://doi.org/10.1111/j.1755-0238.2009.00056.x
54. Kennison KR, Wilkinson KL, Pollnitz AP, Williams HG, Gibberd MR (2011) Effect of smoke application to field-grown merlot grapevines at key phenological growth stages on wine sensory and chemical properties. Aust J Grape Wine Res 17(2):S5–S12. https://doi.org/10.1111/j.1755-0238.2011.00137.x
55. Fuentes S, Tongson EJ, De Bei R, Gonzalez Viejo C, Ristic R, Tyerman S, Wilkinson K (2019) Non-invasive tools to detect smoke contamination in grapevine canopies, berries and wine: a remote sensing and machine learning modeling approach. Sensors 19(15):3335. https://doi.org/10.3390/s19153335
56. Duncan MA (2000) Frontiers in the spectroscopy of mass-selected molecular ions. Int J Mass Spectrom 200(1):545–569. https://doi.org/10.1016/S1387-3806(00)00366-3
57. Gómez AH, He Y, Pereira AG (2006) Non-destructive measurement of acidity, soluble solids and firmness of satsuma mandarin using vis/nir-spectroscopy techniques. J Food Eng 77(2):313–319. https://doi.org/10.1016/j.jfoodeng.2005.06.036
58. Walsh KB, Blasco J, Zude-Sasse M, Sun X (2020) Visible-nir 'point' spectroscopy in postharvest fruit and vegetable assessment: the science behind three decades of commercial use. Postharvest Biol Technol 168:111246. https://doi.org/10.1016/j.postharvbio.2020.111246
59. Bin L (2019) Application of infrared spectroscopy in food detection. Food Saf Guide (Z2):64–65. CNKI:SUN:SPAQ.0.2019-Z2–033
60. Cortés V, Blasco J, Aleixos N, Cubero S, Talens P (2019) Monitoring strategies for quality control of agricultural products using visible and near-infrared spectroscopy: a review. Trends Food Sci Technol 85:138–148. https://doi.org/10.1016/j.tifs.2019.01.015
61. Jiajia M, Keqiang W (2021) Advances in optical nondestructive testing of fruit quality. Technol Food Ind 42(23):1–15. https://doi.org/10.13386/j.issn1002-0306.2020110235
62. Soriano-Disla JM, Janik LJ, Viscarra Rossel RA, Macdonald LM, McLaughlin MJ (2014) The performance of visible, near-, and mid-infrared reflectance spectroscopy for prediction of soil physical, chemical, and biological properties. Appl Spectrosc Rev 49(2):139–186. https://doi.org/10.1080/05704928.2013.811081
63. Balan V, Mihai C, Cojocaru F, Uritu C, Dodi G, Botezat D, Gardikiotis I (2019) Vibrational spectroscopy fingerprinting in medicine: from molecular to clinical practice. Materials 12(18):2884. https://doi.org/10.3390/ma12182884
64. Ling S, Shao Z, Chen X (2014) Application of synchrotron ftir imaging for cells. Prog Chem (Beijing) 26(1):178–192. https://doi.org/10.7536/PC130662
65. Song Y, Cong Y, Wang B, Zhang N (2020) Applications of Fourier transform infrared spectroscopy to pharmaceutical preparations. Expert Opin Drug Deliv 17(4):551–571. https://doi.org/10.1080/17425247.2020.1737671
66. Bureau S, Cozzolino D, Clark CJ (2019) Contributions of Fourier-transform mid infrared (ft-mir) spectroscopy to the study of fruit and vegetables: a review. Postharvest Biol Technol 148:1–14. https://doi.org/10.1016/j.postharvbio.2018.10.003
67. Kim SW, Min SR, Kim J, Park SK, Kim TI, Liu JR (2009) Rapid discrimination of commercial strawberry cultivars using Fourier transform infrared spectroscopy data combined by multivariate analysis. Plant Biotechnol Rep 3(1):87–93. https://doi.org/10.1007/s11816-008-0078-z
68. Liu Y, Chen X, Ouyang A (2008) Nondestructive determination of pear internal quality indices by visible and near-infrared spectrometry. LWT Food Sci Technol 41(9):1720–1725. https://doi.org/10.1016/j.lwt.2007.10.017
69. Lu HS, Fu XP, Xie LJ, Ying YB (2007) Estimation of soluble solids content of intact citrus fruit by vis/nir spectroscopy. Guang Pu Xue Yu Guang Pu Fen Xi 27(9):1727–1730

70. Li X, He Y, Fang H (2007) Non-destructive discrimination of Chinese bayberry varieties using vis/nir spectroscopy. J Food Eng 81(2):357–363. https://doi.org/10.1016/j.jfoodeng.2006.10.033
71. Kunihisa M, Fukino N, Matsumoto S (2003) Development of cleavage amplified polymorphic sequence (caps) markers for identification of strawberry cultivars. Euphytica 134(2):209–215. https://doi.org/10.1023/B:EUPH.0000003884.19248.33
72. Li Q, Yu X, Gao J (2017) A novel method to determine total sugar of goji berry using ft-nir spectroscopy with effective wavelength selection. Int J Food Prop 20(sup1):S478–S488. https://doi.org/10.1080/10942912.2017.1299759
73. Rong D, Wang H, Ying Y, Zhang Z, Zhang Y (2020) Peach variety detection using vis-nir spectroscopy and deep learning. Comput Electron Agric 175:105553. https://doi.org/10.1016/j.compag.2020.105553
74. Saura-Calixto F, Serrano J, Goñi I (2007) Intake and bioaccessibility of total polyphenols in a whole diet. Food Chem 101(2):492–501. https://doi.org/10.1016/j.foodchem.2006.02.006
75. Luís Â, Duarte AP, Pereira L, Domingues F (2018) Interactions between the major bioactive polyphenols of berries: effects on antioxidant properties. Eur Food Res Technol 244(1):175–185. https://doi.org/10.1007/s00217-017-2948-5
76. Stefansson P, Liland KH, Thiis T, Burud I (2020) Fast method for ga-pls with simultaneous feature selection and identification of optimal preprocessing technique for datasets with many observations. J Chemom 34(3). https://doi.org/10.1002/cem.3195
77. Arslan M, Xiaobo Z, Tahir HE, Xuetao H, Rakha A, Basheer S, Hao Z (2018) Near-infrared spectroscopy coupled chemometric algorithms for prediction of antioxidant activity of black goji berries (lycium ruthenicum murr.). J Food Mea Charact 12(4):2366–2376. https://doi.org/10.1007/s11694-018-9853-x
78. Jasenka GK, Mariya G, Kiril M, Senka D, Ivana B, Ivana P, Želimir K (2016) Near-infrared spectroscopic analysis of total phenolic content and antioxidant activity of berry fruits. Food Technol Biotechnol 54(2)
79. Zheng W, Bai Y, Luo H, Li Y, Yang X, Zhang B (2020) Self-adaptive models for predicting soluble solid content of blueberries with biological variability by using near-infrared spectroscopy and chemometrics. Postharvest Biol Technol 169:111286. https://doi.org/10.1016/j.postharvbio.2020.111286
80. Zhang M, Li C, Yang F (2019) Optical properties of blueberry flesh and skin and Monte Carlo multi-layered simulation of light interaction with fruit tissues. Postharvest Biol Technol 150:28–41. https://doi.org/10.1016/j.postharvbio.2018.12.006
81. Hu M, Zhai G, Zhao Y, Wang Z (2018) Uses of selection strategies in both spectral and sample spaces for classifying hard and soft blueberry using near infrared data. Sci Rep 8(1). https://doi.org/10.1038/s41598-018-25055-x
82. Yazici A, Tiryaki GY, Ayvaz H (2020) Determination of pesticide residual levels in strawberry (fragaria) by near-infrared spectroscopy. J Sci Food Agric 100(5):1980–1989. https://doi.org/10.1002/jsfa.10211
83. Wang Z, Künnemeyer R, McGlone A, Burdon J (2020) Potential of vis-nir spectroscopy for detection of chilling injury in kiwifruit. Postharvest Biol Technol 164:111160. https://doi.org/10.1016/j.postharvbio.2020.111160
84. Hao M (2015) Application of spectral and hyperspectral imaging technology in crop characteristic information extraction. Doctor Thesis
85. Ben-Xue MA, Ying YB, Rao XQ (2009) Advance in nondestructive detection of fruit internal quality based on hyperspectral imaging. Spectros Spect Anal 6:5. https://doi.org/10.3964/j.issn.1000-0593(2009)06-1611-05
86. Feng YZ, Sun DW (2012) Application of hyperspectral imaging in food safety inspection and control: a review. Crit Rev Food Sci Nutr 52(11):1039–1058
87. Lorente D, Aleixos N, Gómez-Sanchis J, Cubero S, García-Navarrete OL, Blasco J (2012) Recent advances and applications of hyperspectral imaging for fruit and vegetable quality assessment. Food Bioprocess Technol 5(4):1121–1142. https://doi.org/10.1007/s11947-011-0725-1
88. Lu Y, Huang Y, Lu R (2017) Innovative hyperspectral imaging-based techniques for quality evaluation of fruits and vegetables: a review. Appl Sci 7(2):189. https://doi.org/10.3390/app7020189
89. Ben-Xue MA, Guo-Wei YU, Wen-Xia W, Xiu-Zhi L, Yu-Jie LI, Xiao-Zhan LI, Sheng-Yuan L (2020) Recent advances in spectral analysis techniques for non-destructive detection of internal quality in watermelon and muskmelon: a review. Spectrosc Spect Anal 40(7):2035–2041. https://doi.org/10.3964/j.issn.1000-0593(2020)07-2035-07
90. Zhao Y, Yu K, He Y (2015) Hyperspectral imaging coupled with random frog and calibration models for assessment of total soluble solids in mulberries. J Anal Methods Chem 2015:1–11. https://doi.org/10.1155/2015/343782
91. Huang L, Zhou Y, Meng L, Wu D, He Y (2017) Comparison of different ccd detectors and chemometrics for predicting total anthocyanin content and antioxidant activity of mulberry fruit using visible and near infrared hypers. Food Chem 224:1–10. https://doi.org/10.1016/j.foodchem.2016.12.037
92. Weng S, Yu S, Dong R, Pan F, Liang D (2020) Nondestructive detection of storage time of strawberries using visible/near-infrared hyperspectral imaging. Int J Food Prop 23(1):269–281. https://doi.org/10.1080/10942912.2020.1716793
93. Weng S, Yu S, Guo B, Tang P, Liang D (2020) Non-destructive detection of strawberry quality using multi-features of hyperspectral imaging and multivariate methods. Sensors 20(11):3074. https://doi.org/10.3390/s20113074
94. Zhang C, Wu W, Zhou L, Cheng H, Ye X, He Y (2020) Developing deep learning based regression approaches for determination of chemical compositions in dry black goji berries (Lycium ruthenicum murr.) Using near-infrared hyperspectral imaging. Food Chem 319:126536. https://doi.org/10.1016/j.foodchem.2020.126536
95. Fatchurrahman D, Nosrati M, Amodio ML, Chaudhry MMA, de Chiara MLV, Mastrandrea L, Colelli G (2021) Comparison performance of visible-nir and near-infrared hyperspectral imaging for prediction of nutritional quality of goji berry (lycium barbarum l.). Foods 10(7):1676. https://doi.org/10.3390/foods10071676
96. Guan X, Liu J, Huang K, Kuang J, Liu D (2019) Evaluation of moisture content in processed apple chips using nirs and wavelength selection techniques. Infrared Phys Technol 98:305–310. https://doi.org/10.1016/j.infrared.2019.01.010
97. Ma H, Zhao K, Jin X, Ji J, Qiu Z, Gao S, College Of Agricultural Equipment Engineering HUOS, Collaborative Innovation Center Of Machinery Equipment Advanced Manufacturing Of Henan Province LC (2019) Spectral difference analysis and identification of different maturity blueberry fruit based on hyperspectral imaging using spectral index. Int J Agric Biol Eng 12(3):134–140. https://doi.org/10.25165/j.ijabe.20191203.4325
98. Shao Y, Wang Y, Xuan G, Gao Z, Hu Z, Gao C, Wang K (2020) Assessment of strawberry ripeness using hyperspectral imaging. Anal Lett 54(10):1547–1560. https://doi.org/10.1080/00032719.2020.1812622
99. Gao Z, Shao Y, Xuan G, Wang Y, Liu Y, Han X (2020) Real-time hyperspectral imaging for the in-field estimation of strawberry ripeness with deep learning. Artificial Intelligence in Agriculture 4:31–38. https://doi.org/10.1016/j.aiia.2020.04.003

100. Benelli A, Cevoli C, Ragni L, Fabbri A (2021) In-field and non-destructive monitoring of grapes maturity by hyperspectral imaging. Biosys Eng 207:59–67. https://doi.org/10.1016/j.biosystemseng.2021.04.006
101. Tong L, Toppinen A, Wang L, Berghäll S (2023) How motivation, opportunity, and ability impact sustainable consumption behaviour of fresh berry products. J Clean Prod 401:136698. https://doi.org/10.1016/j.jclepro.2023.136698
102. Hussein Z, Fawole OA, Opara UL (2020) Harvest and postharvest factors affecting bruise damage of fresh fruits. Hortic Plant J 6(1):1–13. https://doi.org/10.1016/j.hpj.2019.07.006
103. Mohsenin NN (1986) Physical properties of plant and animal materials. J Biomed Mater Res B Appl Biomater 11(1):83–89
104. Hu M, Dong Q, Liu B, Opara UL, Chen L (2015) Estimating blueberry mechanical properties based on random frog selected hyperspectral data. Postharvest Biol Technol 106:1–10. https://doi.org/10.1016/j.postharvbio.2015.03.014
105. Jiang Y, Li C, Takeda F (2016) Nondestructive detection and quantification of blueberry bruising using near-infrared (nir) hyperspectral reflectance imaging. Sci Rep 6(1). https://doi.org/10.1038/srep35679
106. Fan S, Li C, Huang W, Chen L (2017) Detection of blueberry internal bruising over time using nir hyperspectral reflectance imaging with optimum wavelengths. Postharvest Biol Technol 134:55–66. https://doi.org/10.1016/j.postharvbio.2017.08.012
107. Fan S, Li C, Huang W, Chen L (2018) Data fusion of two hyperspectral imaging systems with complementary spectral sensing ranges for blueberry bruising detection. Sensors 18(12):4463. https://doi.org/10.3390/s18124463
108. Wang Z, Hu M, Zhai G (2018) Application of deep learning architectures for accurate and rapid detection of internal mechanical damage of blueberry using hyperspectral transmittance data. Sensors 18(4):1126. https://doi.org/10.3390/s18041126
109. Kepner C, Swett CL (2018) Previously unrecognized diversity within fungal fruit rot pathosystems on vitis vinifera and hybrid white wine grapes in mid-atlantic vineyards. Australas Plant Pathol 47(2):181–188. https://doi.org/10.1007/s13313-017-0538-4
110. Shankar J (2021) Food habit associated mycobiota composition and their impact on human health. Front Nutr 8. https://doi.org/10.3389/fnut.2021.773577
111. Zalewski ZD, Page R, Lankau RA, McManus PS (2021) Role of yeasts in the cranberry fruit rot disease complex. Plant Dis 105(8):2141–2148. https://doi.org/10.1094/PDIS-11-19-2303-RE
112. Siedliska A, Baranowski P, Zubik M, Mazurek W, Sosnowska B (2018) Detection of fungal infections in strawberry fruit by vnir/swir hyperspectral imaging. Postharvest Biol Technol 139:115–126. https://doi.org/10.1016/j.postharvbio.2018.01.018
113. Qiao S, Wang Q, Zhang J, Pei Z (2020) Detection and classification of early decay on blueberry based on improved deep residual 3d convolutional neural network in hyperspectral images. Sci Program 2020:1–12. https://doi.org/10.1155/2020/8895875
114. Ye W, Yan T, Zhang C, Duan L, Chen W, Song H, Zhang Y, Xu W, Gao P (2022) Detection of pesticide residue level in grape using hyperspectral imaging with machine learning. Foods 11(11):1609. https://doi.org/10.3390/foods11111609
115. Wu D, Meng L, Yang L, Wang J, Fu X, Du X, Li S, He Y, Huang L (2019) Feasibility of laser-induced breakdown spectroscopy and hyperspectral imaging for rapid detection of thiophanate-methyl residue on mulberry fruit. Int J Mol Sci 20(8):2017. https://doi.org/10.3390/ijms20082017
116. Xu M, Sun J, Zhou X, Tang N, Shen J, Wu X (2021) Research on nondestructive identification of grape varieties based on eemd-dwt and hyperspectral image. J Food Sci 86(5):2011–2023. https://doi.org/10.1111/1750-3841.15715
117. Fan Z, Zhaoru Y, Jianxin X, Bing X (2021) Hyperspectral nondestructive identification of wild and cultivated black wolfberry. Spectrosc Spect Anal 41(01):201–205. www.gpxygpfx.com/CN/Y2021/V41/I01/201
118. Leiva-Valenzuela GA, Aguilera JM (2013) Automatic detection of orientation and diseases in blueberries using image analysis to improve their postharvest storage quality. Food Control 33(1):166–173. https://doi.org/10.1016/j.foodcont.2013.02.025
119. Soltanikazemi M, Abdanan Mehdizadeh S, Heydari M (2017) Non-destructive evaluation of the internal fruit quality of black mulberry (morus nigra l.) Using visible-infrared spectroscopy and genetic algorithm. Int J Food Prop 20(11):2437–2447. https://doi.org/10.1080/10942912.2016.1238930
120. Tingting S, Xiaobo Z, Jiyong S, Zhihua L, Xiaowei H, Yiwei X, Wu C (2016) Determination geographical origin and flavonoids content of goji berry using near-infrared spectroscopy and chemometrics. Food Anal Methods 9(1):68–79. https://doi.org/10.1007/s12161-015-0175-x
121. Yahui L, Xiaobo Z, Tingting S, Jiyong S, Jiewen Z, Holmes M (2017) Determination of geographical origin and anthocyanin content of black goji berry (Lycium ruthenicum murr.) Using near-infrared spectroscopy and chemometrics. Food Anal Methods 10(4):1034–1044. https://doi.org/10.1007/s12161-016-0666-4
122. Yahui L, Yanxiao L, Weilong T, Xiaoxia S, Jiyong S, Xiaobo Z, Junjun Z, Caiping J (2020) Judgment of origin and quality information of black wolfberry based on fusion of near and middle infrared spectroscopy. Spectrosc Spectr Anal 40(12):3878–3883
123. Yu Y, Zhang K, Yang L, Zhang D (2019) Fruit detection for strawberry harvesting robot in non-structural environment based on mask-rcnn. Comput Electron Agric 163:104846. https://doi.org/10.1016/j.compag.2019.06.001
124. Esteki M, Shahsavari Z, Simal-Gandara J (2018) Use of spectroscopic methods in combination with linear discriminant analysis for authentication of food products. Food Control 91:100–112. https://doi.org/10.1016/j.foodcont.2018.03.031