Hyperspectral imaging and deep learning for quality and safety inspection of fruits and vegetables: A systematic review

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Hyperspectral imaging and deep learning for quality and safety inspection of fruits and vegetables: A systematic review

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Short title: DL in HSI imaging Inspection of Food

Abstract

Quality inspection of fruits and vegetables linked to food safety monitoring and quality control. Traditional chemical analysis and physical measurement techniques are reliable, they are also time-consuming, costly, and susceptible to environmental and sample changes. Hyperspectral imaging technology combined with deep learning methods can effectively overcome these problems. Compared with human evaluation, automated inspection improves inspection efficiency, reduces subjective error, and promotes the intelligent and precise fruit and vegetable quality inspection. This paper reviews reports on the application of hyperspectral imaging technology combined to deep learning methods in various aspects of fruits and vegetables quality assessment. In addition, the latest applications of these technologies in the fields of fruit and vegetable safety, internal quality and external quality inspection are reviewed, and the challenges and future development directions of hyperspectral imaging technology combined with deep learning in this field are prospected. Hyperspectral imaging combined with deep learning has shown significant advantages in fruit and vegetable quality inspection, especially in improving inspection accuracy and efficiency. Future research should focus on reducing costs, optimizing equipment, personalizing feature extraction, and model generalizability. In addition, the development of lightweight models and the balance of accuracy, the enhancement of the database and the importance of quantitative research should also be brought to attention. These efforts will promote the wide application of hyperspectral imaging technology in fruit and vegetable inspection, improve its practicability in the actual production environment, and bring important progress for food safety and quality management.

Keywords： Food quality and safety; Hyperspectral imaging; Deep learning;

Convolutional neural network; Nondestructive inspection

1. Introduction

Fruits and vegetables are an indispensable source of energy and nutrients in human life, and an accurate assessment of their composition is essential to ensure food quality and authenticity. Traditional inspection methods are usually used to evaluate food ingredients, but for the analysis of fruits and vegetables, common methods include high performance liquid chromatograph for sugar and vitamin content, and UV-visible spectrophotometry for evaluating antioxidant substance (Patle et al., 2022; Nikzad et al., 2021). While traditional methods have been effective in food composition analysis, their low throughput and high costs limit their applicability for large-scale sample analysis. A comprehensive evaluation of food testing encompasses safety, visual inspection, and internal quality evaluation. Fruits and vegetables are susceptible to microbial contamination such as fungi and bacteria infection, leading to rotting, deterioration or foodborne illnesses. Appearance defects, such as mechanical damage, blemishes, and irregular shape, can significantly reduce perceived food quality, leading to economic losses. Internal characteristics such as soluble solids content and acidity, which are closely related to the aroma and taste of the product, are key factors in quality assessment.

Traditional food quality sorting systems usually rely on manual inspection, which is laborious and time-consuming, as well as prone to subjective biases. To improve the efficiency of classification and reduce human error, researchers have devoted themselves to developing rapid, accurate and non-destructive food inspection technology in recent years. Computer vision technology, utilizing image analysis, can extract gray-scale or RGB values from samples, making it a widely used method for food quality inspection (Jia et al., 2023). While, computer vision technology effectively evaluates the quality of food based on external characteristics such as shape, size, color and texture, its reliance on color changes limits its ability to accurately analyze the internal attributes that exhibit minimal change in appearance. Currently, spectroscopic analysis methods (such as reflection, transmission, fluorescence and Raman measurement) have been widely used in food quality inspection. These methods assess the quality by evaluating the spectral characteristics of functional groups such as C-H, N-H and O-H within food sample (Feng et al., 2021). However, these single-point inspection methods have limitations when applied to heterogeneous samples.

Hyperspectral imaging technology (HSI) combines imaging and spectral scanning, which can provide spectral spatial distribution information of samples and effectively detect internal characteristics, thus overcoming the limitations of traditional spectral inspection. Near-infrared light has limited penetration, but its response at specific wavelengths during reflection and scattering can still provide important information. Although light cannot penetrate deep into the core of the sample, the texture and composition of the sample can still be inferred through spectral data from surface reflection and local scattering. HSI can indirectly reflect internal characteristics by collecting reflectance spectra at different wavelengths, and can provide more comprehensive and accurate data support for changes in internal quality parameters of certain fruits and vegetables, such as moisture content and sugar content. This indirect detection method is difficult to achieve in traditional spectral analysis, and provides ideas and methods for quality evaluation.

HSI has been successfully applied to evaluate the internal and external attributes of different foods by combining the advantages of spectroscopy and imaging (Xuan et al., 2022). Although the HSI system has certain limitations in image acquisition and analysis, which affects its effectiveness in real-time industrial applications, the introduction of deep learning (DL) algorithms can significantly improve data processing speed and decision accuracy. DL effectively extracts useful information from high-dimensional hyperspectral data and addresses challenges such as sensor noise, illumination changes, and sample heterogeneity. Using advanced DL techniques such as convolutional neural network (CNN), researchers can further optimize HSI data processing and improve the robustness and efficiency of fruit and vegetable quality inspection (Roy et al., 2021).

The combination of DL and HSI, offers promising prospects for the future of food quality inspection. Furthermore, this combined approach has achieved remarkable results in solving the quality and safety problems associated with fruits and vegetables (Guo et al., 2023； He et al., 2024). DL can automatically extract complex spectral features and achieve accurate evaluation of the appearance and internal quality of fruits and vegetables through its powerful data processing capabilities (Wang et al., 2024). In this context, this paper aims to review the latest applications of HSI technology combined with DL in non-destructive evaluation of fruit and vegetable safety, and external and internal quality. This review specifically focuses on: (1) Introducing the basic principles and key data analysis steps of HSI technology and DL; (2) Summarizing the current application status of fruit and vegetable inspection, analyzed from three perspectives: safety, external and internal quality. (3) Discussing the challenges of HSI technology combined with DL in fruit and vegetable quality inspection, and exploring future research trends.

2. Hyperspectral imaging systems

2.1 Principles and System components

2.1.1 HSI principles

HSI technology combines mechanical vision and spectral technology, which can detect the two-dimensional spatial and one-dimensional spectral information of targets, obtaining continuous and narrow band image data with high spectral resolution, and thus complete the recognition and inspection process of objects of interest (Saha et al., 2021).

In HSI systems, hyperspectral image sensors serve as spatial sensing devices that capture multiple digital images in different spectral wavelengths. When a substance is exposed to a known spectral band, specific spectral reflections, absorption, or emissions occur based on its structure, and this reaction is defined as the spectral characteristics of the substance. This feature information describes the storage method of data in HSI technology, where each spectral band is "stacked" according to its wavelength in a cubic data structure. Compared to traditional spectral inspection techniques, HSI technology has similar spectral resolution and range, but can provide more detailed and accurate information contained in the spatial domain, suitable for non-destructive testing of fruit quality (Mahanti et al., 2022).

By integrating imaging and spectral technology, HSI can extract important external features (such as size, geometry, appearance, and color) of the measured object. Additionally, the physiological characteristics of fruits and other objects can also be detected by spectral analysis thereby determining the nature or chemical composition of the object (Min et al., 2023). The technology can be divided into reflection imaging (Weng et al., 2021), fluorescence imaging (Fu et al., 2022), and transmission imaging (Li et al., 2022). Among these, reflection imaging technology is the most widely employed.

2.1.2 HSI System components

Hyperspectral images may cover a wavelength range of 200 to 2500 nanometers, including ultraviolet (200-400 nm), visible and near-infrared (400-1000 nm), and shortwave infrared (1000-2500 nm) spectral bands. To effectively detect the quality of fruits and vegetables, visible light/near-infrared spectroscopy is the most used, followed by shortwave infrared spectroscopy. It should be noted that most commercial HSI systems do not cover the entire wavelength range, which may affect their performance in different applications. Choosing and configuring hardware is crucial for obtaining high-quality hyperspectral information. Different wavelengths have different penetration depths: near-infrared light can effectively penetrate the skin of samples such as fruits, usually up to 2-3 mm; while short-wave infrared light can obtain important internal information in some samples, but its penetration depth is small, about 1-2 mm. In addition, the penetration depth of ultraviolet light is usually only tens of microns, and is mainly used for the analysis of surface features. An HSI system typically includes light sources, wavelength dispersive devices, area detectors, and computers (Fig.1A) (Jo et al., 2023). These components work together to collect and analyze spectral information of objects at different wavelengths. Therefore, when establishing a hyperspectral image system, it is necessary to ensure that the selection and configuration of various hardware components can work together to provide accurate and high-resolution hyperspectral data.

The HSI system sensing modality is mainly due to the absorption and reflection of light emitted by the light source upon the surface of an object (Fig.1B) (Tang et al., 2023). After passing through the lens and entrance slit, different degrees of light undergo bending and diffusion phenomena, and converge on the collimating lens, decomposing the light with different degrees of wavelength. Then, a three-dimensional data cube containing image and spectral information is obtained. As a key part of the imaging system, the light source should be considered to illuminate the object and weaken the influence of the background when selecting the light source. Commonly used light sources include halogen lamps, light-emitting diodes, or lasers, which are important components in optical inspection systems (Ram et al., 2024). For example, halogen lamps, as broadband lighting sources involving the Vis/NIR region, are commonly used in HSI systems for food trait analysis (reflection and transmission modes) (Vejarano et al., 2017).

The different acquisition and formation methods of hyperspectral images can be divided into three methods: point scanning, line scanning, and area scanning (Fig1C). Among them, line scanning is a widely used scanning mode in the food industry, as its advantage lies in the ability to achieve continuous unidirectional scanning on the conveying system, making it more suitable for practical applications (Özdoğan et al., 2021). When collecting images, the key is to ensure that each layout in the hyperspectral system is reasonable and set to corresponding parameters based on the object being tested. These include ensuring that the light source distribution is evenly distributed on the test object, as well as adjusting and analyzing parameters such as the exposure time set by the camera, distance between the lens and the moving platform, and scanning speed according to the application (Rehman et al., 2020).

2.2 Data analysis methods

HSI technology offer multi-channel, high resolution, and continuous band coverage. By analyzing hyperspectral images and extracting useful spatial information, the external quality and internal attribute features of the test sample can be obtained, thereby achieving target inspection and classification. However, due to the high correlation of adjacent band information in hyperspectral images, it will be affected or interfered by factors such as noise, diffuse reflection and specular reflection from non-planar surfaces. Therefore, when analyzing spectral data, a series of image preprocessing methods and algorithms are involved for image calibration. Image enhancement and segmentation are necessary to reduce anomalies and improve the quality of images acquired (Li et al., 2023).

2.2.1 Spectral pre-processing

Because the measurement equipment is influenced by factors such as temperature, light, experimental environment, and the shape of the sample itself, hyperspectral data collection include problems such as data differences, uneven illumination, pixel anomalies, and noise (Yoon et al., 2020). These different changes and interference factors introduce irrelevant or incorrect spectral signals, which affect the reliability and accuracy of subsequent data analysis. The main purpose of hyperspectral preprocessing is to reduce the influence of uneven illumination and noise in the acquisition process, obtain high-quality spectral images and non-mixed spectral signals, and increase the feasibility of data (Cozzolino et al., 2023). Preprocessing methods usually include smoothing, scattering, baseline correction, derivatives. Convolution smoothing, derivatives can reduce the effects of noise and other effects during the data collection process. Recently, S-G convolution smoothing has been a widely used spectral processing method (Li et al., 2021). To measure the influence of sample morphology and determine the influence of instrument errors, algorithms such as multivariate scattering correction, standard normal variable transformation, and detrending can be used to eliminate the influence of uneven sample distribution and factors such as illumination and temperature. Preprocessing methods can be used individually or in combination with processing analysis. Preprocessing methods are broadly versatile for different types of spectral data. Although hyperspectral instruments are primarily used in laboratories, there are still many interfering factors in practical applications. Therefore, for samples to be tested in different application scenarios, preprocessing selections must be made based on the uniqueness of the samples to be tested and the inspection environment. There are no fixed rules when it comes to choosing a preprocessing method.

Image preprocessing involves eliminating the effects of sensor, environmental and background noise, while image segmentation enhances the relationship between the target object and the background in the image. The contrast makes the target more visible. For example, the threshold segmentation method (Yin et al., 2022), region segmentation (Wang et al., 2022) and watershed algorithm (Tian et al., 2021) have been widely used in the preprocessing stage of hyperspectral data. Threshold segmentation helps separate redundant and abnormal areas in hyperspectral images while also reducing noise for better analysis. In addition, dark current noise may affect imaging quality due to hardware device limitations and changes in environmental conditions during HSI. The black-and-white correction method is widely used to eliminate dark current noise in hyperspectral instruments, and enhancing image reliability.

The image information obtained by hyperspectral systems is a two-dimensional image in terms of spatial dimensions and distribution. Therefore, classic denoising methods can be used to denoise information in each band. These methods include but are not limited to median filtering, mean filtering and wavelet transform, etc. They can effectively remove spatial noise, retain the details and edge information of the image, and improve the visual effect and analysis accuracy of the image. At the same time, in the spectral dimension, Savitzky-Golay filtering can be used to remove digitizing errors, high-frequency noise whilst retaining spectral information and main features (Zhang et al., 2021).

2.2.2 Feature wavebands extraction

HSI systems contain the visible spectrum and in addition, hundreds of spectral bands, each pixel covers hundreds of spectral bands (Zaman et al., 2023). Compared with traditional imaging systems, HSI systems provide rich spectral information and images, enabling more accurate identification of external and internal characteristics of the sample. However, due to the dense spectral band spacing in the spectral imaging systems, which contains a lot of redundant information and high-dimensional data, the unnecessary amount of calculation increases and classification accuracy is adversely affected. (Sawant et al., 2020). Some specific bands can reveal key information about sample attributes, but this band information may not provide corresponding key data for other objects.

Currently, there are two main dimensionality reduction methods, namely feature extraction and feature selection (Hongjun et al., 2022). The feature extraction algorithm mainly uses the idea of a transformation matrix to scale, compress and rotate the spatial distribution of spectral data of the original image. Commonly used feature extraction methods include algorithms such as principal component analysis (Tian et al., 2020), linear discriminant analysis (Fabiyi et al., 2021), and partial least squares (Chen et al., 2021). These methods have unique advantages in hyperspectral data analysis and can retain actual features and key information during application. For example, principal component analysis maps the original data into a new low-dimensional space through linear transformation to maximize the explanation of data variance. In addition, to select and effectively reduce the dimensionality of spectral data, the most discriminative frequency band information needs to be recognized. Common optimization algorithms include the genetic algorithm (Singh et al., 2022), particle swarm optimization algorithm (Wei et al., 2024) and ant colony optimization algorithm (Wang et al., 2022). At the same time, instead of gradually processing the data of each band with point features, effective wavelength interval selection methods can also be applied, including interval partial least squares, moving window partial least squares, variable size moving window partial least squares, directional partial least squares, post-margin partial least squares, and co-margin partial least squares. For example, the backward interval partial least squares algorithm uses reverse selection to exclude intervals with low correlation with the target variable from the entire wavelength range, reducing the number of bands in the early stage of data processing, thereby greatly reducing the calculation time and cost of storage (Que et al., 2023).

3. Deep learning techniques

3.1 DL principles

The application of artificial intelligence in the field of fruits and vegetables quality assessment has a long-standing history. Although initially artificial intelligence was regarded as a cognitive system that mimics human reasoning and representation, it did not fully meet the expected goals of developers and practitioners in its early stages. With the development of advanced algorithms, the rapid increase of big data, and the support of advanced computer capabilities such as GPU and TPU, modern artificial intelligence has been able to effectively complete complex tasks (Shi et al., 2023). These tasks previously required human expertise and cognitive ability to make judgments and decisions.

At present, artificial intelligence technology has a higher level of "intelligence" than previous technologies. The advancement of these technologies has highlighted the importance and increased the adoption of artificial intelligence in the field of fruits and vegetables quality assurance. DL, as the core technology of modern artificial intelligence, performs particularly well. As a data-driven machine learning method, DL is inspired by the connection between neurons in the human brain, and completes the learning of complex features and patterns in the data through multi-level nonlinear changes (Liu et al., 2021). A deep neural network contains multiple hidden layers, each of which processes the input data using a nonlinear activation function to gradually extract more advanced features. Compared with traditional machine learning algorithms, this technology is more efficient in extracting complex feature representations from large-scale data and can adapt to various learning tasks and application fields. It can identify and understand complex data patterns, and perform more accurate tasks such as fruit and vegetable quality assessment, yield prediction, and automatic picking with greater accuracy (Xiao et al., 2023). The development of technology has significantly improved production efficiency and quality control, bringing new opportunities for innovation and sustainable development in the food field. As a structured model for DL, artificial neural networks imitate the operation of biological nervous systems and process information through connections between neurons and weight adjustments. DL expands on traditional artificial neural networks, emphasizing the improvement of learning capabilities by increasing the number of layers and complexity of the network, and can more effectively process complex data features. Therefore, DL can be regarded as an advanced form of artificial neural networks, focusing on automatic feature extraction and learning of large-scale data sets.

DL is composed of many neuron units that transmit and process information by connecting weights. Among them, “depth” refers to the multi-level structure of the neural network model. Each layer maps the input data to a higher-level abstract representation through non-linear transformation, ultimately achieving efficient learning and prediction capabilities for complex problems. In DL, the key components include input layer, multiple hidden layers and output layer. Each level contains multiple neurons, and the connection between the layers is adjusted by weight parameters. These parameters are optimized and adjusted by the back propagation algorithm during the training process to minimize the prediction error or achieve specific task goals. At present, traditional machine learning methods may be limited by the hand-designed feature extraction process, while DL can automatically learn the feature representation suitable for the task from the original data (Abrol et al., 2021). These advantages mean that DL has made significant progress in the field of food fruits and vegetables. For example, DL can identify the quality characteristics of products, detect possible defects, and optimize the production process by analyzing a large number of production data and images (Zhu et al., 2021). This technology improves product quality and consistency while reducing waste and losses during the production process. Simultaneously, food production companies can achieve more precise quality control, automated production adjustments, and personalized product customization. These tasks that used to rely on manual labor can now be efficiently completed by artificial intelligence systems (Wan et al., 2020).

In addition, DL can also enhance the autonomy and adaptability of artificial intelligence systems. Through technologies such as reinforcement learning, artificial intelligence can optimize product formulations, predict market trends, and adjust production strategies in real-time to adapt to changing consumer preferences and market demands (Ding et al., 2023). This capability empowers artificial intelligence in the field of food, fruits, and vegetables industry to respond to complex market competition and supply chain management challenges.

3.2 DL algorithm

DL algorithms play a vital role in the quality inspection of fruits and vegetables, especially in the processing of hyperspectral data. Initial hyperspectral research focused mainly on the analysis of spectral characteristics, but later studies found that the spatial distribution and attributes of hyperspectral data are also crucial to data analysis. By combining spectral features with spatial features, the classification and inspection accuracy of the model has been significantly improved. DL can extract deep feature representations through multi-layer neural networks, so that complex relationships in data can be automatically learned and modeled (Sarker et al., 2021). This data-driven strategy enables DL to discover hidden features in raw data and reduce dependence on human cognition and judgment (Taye et al., 2023).

At present, Convolutional neural network (CNN) and Recurrent neural network (RNN) are widely used in one-dimensional and three-dimensional spectral analysis, performing the automatic extraction of data features. CNN is a powerful DL architecture, mainly composed of a convolution layer, a pooling layer and a fully connected layer. The convolutional layer uses a sliding convolution kernel to perform local feature extraction on the input image to generate a low-dimensional feature map, which can capture important information such as edges and textures in the image. The pooling layer reduces the computational complexity by reducing the size of the feature map, and enhances the robustness of the model to prevent overfitting. Finally, the fully connected layer flattens the feature map after convolution and pooling, and processes it through a series of linear transformations and nonlinear activation functions for image classification or regression tasks, to achieve efficient understanding and prediction of image content (Fig.2A). Further, RNN is a DL architecture that can process sequence data. By receiving the hidden state of the previous time step, RNN can effectively transmit information between time steps, so that the model can capture the dependencies in time series (Fig.2B). The long-term and short-term memory network (LSTM) introduces a gating mechanism based on RNN, which uses input gate, forgetting gate and output gate to control the flow of information, to maintain important information in a long time series and avoid the gradient problem (Fig.2C). This mechanism makes LSTM more efficient and stable in processing complex time series data.

In addition, DL also includes many types of unsupervised learning models (such as deep autoencoders) and supervised learning models (such as residual modules and attention mechanisms) for spectral analysis. These methods provide possibilities for optimization and improvement of model performance (Xue et al., 2020). In the process of training the model, the DL model can accurately extract linear and nonlinear related features without human interference, and has good generalization ability (Zhang et al., 2021). Among them, the deep autoencoder neural network realizes the denoising of data input or original data, extracts the effective features of its data, and applies it to unsupervised task spectrum analysis.

As a subfield of artificial intelligence, DL focuses on simulating human thinking through neural networks to process and analyze complex data. With the continuous advancement of DL technology, artificial intelligence has made significant breakthroughs in research and business. These technologies have been widely used in many aspects such as evaluating the quality of vegetables, fruits and mushrooms (Wieme et al., 2022). Therefore, (de Moraes I A et al., 2024) combined computer vision systems with DL techniques (DCVS) and proposed an integrated explainable artificial intelligence (XAI) method. This study compares two DL architectures—Residual Neural Network (ResNet) and Visual Transformer (ViT). The results indicate that ViT achieved an accuracy of 95% in identifying image regions enhanced by the Random Forest model, while ResNet achieved an accuracy of 91%. This indicates the potential for application in other fruit detection tasks. Meanwhile, (da Silva Ferreira et al., 2024) compared two DL computer vision system architectures, ResNet and ViT transformer, and applied explainable artificial intelligence methods to reveal the decision-making processes of black box models, such as Grad-CAM and attention maps. Their study found that machine learning methods can effectively classify the state of pitaya across four shelf-life stages, while DCVS maps demonstrate the potential of using pitaya morphological features and hyperspectral information to predict its shelf life.

HSI technology can provide abundant information for the extraction of object features. Compared to traditional machine vision systems, HSI captures the reflective properties of objects across different wavelengths, revealing subtle differences that are often imperceptible to the naked eye. This feature provides a distinct advantage in food quality assessment, allowing for a more in-depth analysis of the internal composition and condition of objects. (Ahmed et al., 2024) proposed an innovative method that integrates explainable artificial intelligence with HSI technology, and utilized Shapley additive explanations values to evaluate the model's effectiveness. This method successfully assessed three key quality attributes of sweet potatoes: dry matter content, soluble solids content, and hardness.

HSI holds significant application value in food quality testing, providing detailed and comprehensive analyses.

4. Hyperspectral imaging and Deep learning applications in fruit and vegetable quality

In recent years, HSI technology and DL algorithms are becoming important participants in the field of food composition, quality and food safety assessment. This section focuses on the relevant literature from 2020 to 2024, and elaborate the application of HSI combined with DL technology from three aspects: safety, external quality, and internal quality of fruits and vegetables.

4.1 Inspection of external quality in fruits and vegetables

The external quality of fruits and vegetables refers to their visual characteristics, mainly including detection of external dimensions, appearance defects, and mechanical damage. External quality, as the most intuitive quality characteristic, plays an important role in improving quality evaluation and grading, stimulating consumer desire, increasing product market recognition, and achieving high-quality and cost-effective processes.

4.1.1 External dimensions inspection

The shape inspection of fruits and vegetables directly affects their quality and market value. It can help to distinguish and classify products of different quality, to carry out accurate quality control of fruits and vegetables and ensure that they meet market demand and standards. The shape and size inspection of fruits and vegetables is also one of the key technologies of automatic picking and sorting system, which can effectively reduce labor costs, and improve production efficiency.

(Mesa et al., 2021) developed a HSI and DL technology based non-invasive automation system for the export of quality banana layers, capable of pre-classifying banana grades according to their quality and size. On the other hand, a combination of RGB and HSI models, along with CNN and MLP models was used to analyze RGB and HSI data, successfully predicting the size and performance of bananas from different perspectives (Raghavendra et al., 2022). Their research shows that banana size can be predicted with 99% accuracy using artificial intelligence technology.

Although hyperspectral data provides more spectral information, its ability to process abnormal data still depends on the design of feature extraction and classification algorithms. Hence, a hyperspectral data anomaly inspection method called SSC-AE was proposed based on the joint learning of an autoencoder and a self-supervised classifier (Fig.3A) (Liu et al., 2022). This method can visualize various types of strawberry defects pixel by pixel and accurately predict the location and shape of defects. Compared to simple classification or size prediction, SSC-AE can perform anomaly inspection on hyperspectral data and combine the advanced idea of self-supervised learning, which effectively detect and analyze various defect shapes of fruits and vegetables.

4.1.2 Defect inspection

Fruits and vegetables suffer from cosmetic defects such as rot and scarring due to factors such as inappropriate growing conditions, improper storage or physical damage (Zhang et al., 2021). These defects affect the appearance and quality of fruits and vegetables, thereby reducing their market competitiveness and sales value. Therefore, timely and accurate classification according to the appearance defects of fruits and vegetables plays a vital role in achieving high quality and high prices and improving the income of fruit farmers. Appearance defect classification of fruits and vegetables refers to the classification and evaluation of various defects and damages on the surface of fruits and vegetables.

The appearance characteristics of fruits and vegetables are highly complex, involving various changes in shape, color, and texture. Tiny defects are often misidentified as natural textures or variations in lighting on the surfaces of fruits and vegetables, making accurate differentiation challenging. In recent years, significant advances have been made in the inspection of fruit and vegetable defects using visible and near-infrared HSI technology. For instance, by applying CNN, researchers have successfully captured local features and global contextual information, facilitating the inspection of multiple types of citrus defects (Frederick et al., 2023). However, although this approach performs well in specific application domains, it typically relies on multiple processing stages, including feature extraction and classification.

End-to-end CNN models provide a more comprehensive solution to address this limitation. Zhang et al. proposed an end-to-end CNN qualitative analysis model for Nanfeng tangerine, and compared its performance with traditional classification models (Zhang et al., 2024). They used three preprocessing methods and three feature selection techniques. The results showed that the CNN model based on competitive adaptive weighted sampling showed the highest overall accuracy (97.27%) in defect recognition. Although CNN performs well in defect inspection, its shallow network may not be able to fully extract the deep features of the image, and traditional CNN has a large number of parameters in feature extraction, resulting in high computational complexity and large memory consumption. Hence, (Yadav et al., 2022) developed a new CNN based on VGG-

16 architecture. Compared with the general shallow CNN, VGG-16 can better capture the complex features and structures of the input image, thereby improving the accuracy and sensitivity of citrus defect inspection.

In addition, the application of an automatic fruit and vegetable surface defect inspection system has also significantly improved the inspection efficiency. Zhou et al. proposed a lightweight network with improved knowledge distillation (mobile-slimv5s), which was successfully applied to the surface defect inspection of carrots (Zhou et al., 2023). It significantly reduced the computational complexity of the model while ensuring the inspection accuracy.

4.1.3 Mechanical damage inspection

During fruit harvesting and processing, mechanical damage is regarded as an important stress factor, which is closely related to the physiological and morphological changes of fruit. When the mechanical force applied to the fruit exceeds its elastic threshold, cell walls are destroyed, resulting in a decrease in the cohesion of the fruit tissue. This destruction causes the material inside the cell to leak into the intercellular space. At this time, enzymes, as one of the internal secretions of fruit cells, such as POD and PPO, will accelerate the decomposition process of tissues, resulting in bruising or browning of fruits (Zhang et al., 2023).

HSI technology can capture a large number of spectral data, allowing in-depth analysis of the chemical composition and structural characteristics of fruit epidermis and its underlying tissues. DL models, especially CNN, have been widely used in model based on a one-dimensional CNN (SpectralCNN) shows higher accuracy than traditional chemometric models in detecting apple damage (Gai et al., 2022). Liu et al. proposed a spectral-spatial feature extraction enhanced fully connected neural network (SSFE-FCNN) (Fig.3B), which is specifically used for pixel-by-pixel damage inspection (Liu et al., 2023). This method performs advanced feature extraction and classification of tensor features through fully connected neural networks, which significantly improves the discrimination between damaged areas and non-damaged areas. This method achieves 98.09% accuracy in pixel classification of waxy corn. However, SSFE-FCNN inspection relies on the fully connected layer for feature extraction, and lacks spatial and spectral information analysis in hyperspectral images. Therefore, local spatial spectral near-infrared HSI technology has been introduced, offering a new perspective for early damage inspection of fruits and vegetables (Pourdarbani et al., 2023). They studied 3D-CNN models in 3D tensor hyperspectral image processing, including ResNet, DenseNet, ShuffleNet and MobileNet. The results showed that the ResNet model is significantly better than DenseNet, ShuffleNet and MobileNet in processing images, and its training speed and classification accuracy are outstanding. Although the ResNet model is characterized by a substantial number of parameters, its advantages in accuracy and training efficiency make up for this shortcoming. In contrast, although ShuffleNet and MobileNet are lighter, the classification error is slightly higher, and the performance is not as good as ResNet.

In addition, (Pourdarbani et al., 2023) also compared the application of ResNetV2, PreActResNet and MobileNetV2 in the inspection of lemon bruises by integral gradient. The results showed that ResNetV2 had the highest classification accuracy (92.85%), which further confirmed its application in spatial spectral data. At the same time, Castillo-Girones et al. took photos of plum bruises at different stages and used CNN, HSCNN, and ResNet to construct a bruise inspection model (Castillo-Girones et al., 2024). The research shows that the HSCNN model is superior to the ResNet and 3D-CNN models in inspection performance. It achieved a 90% F1 score when entering the complete image. Further analysis also showed that compared with the 3D-CNN model trained from scratch, the migrated pre-trained HSCNN and ResNet networks perform better in inspection accuracy and efficiency.

Due to the huge differences in shape, color and damage types of different fruits and vegetables, untrained models may not perform well on new fruit and vegetable varieties. To solve this problem, transfer learning has become an effective solution. Transfer learning uses existing data and knowledge to transfer patterns and features learned from a related field or task to a new task to significantly improve the learning effect. For example, transfer learning methods, including transfer component analysis and manifold embedding distribution alignment, have effectively demonstrated their efficacy in examining various types of pear-shaped bruises (Liu et al., 2024). These techniques significantly improved the classification accuracy of the model on the new data set by knowledge transfer between different damage types. Typical application examples of hyperspectral combined with DL in the external quality inspection of fruits and vegetables are shown in Fig.3.

4.2 Inspection of internal quality in fruits and vegetables

The internal quality of fruits and vegetables includes nutritional composition, maturity, and hardness. Nutritional composition comprises soluble solids, sugar content, acidity, and moisture. The internal quality of fruits and vegetables generally cannot be observed by the naked eye and requires traditional physical and chemical testing. However, physical and chemical testing is complicated, time-consuming and laborious, and is detrimental to the inspection, which cannot meet the market demand. At present, the wide application of HSI combined with DL has greatly facilitated the accurate inspection of the internal quality of fruits and vegetables, met the high demand of consumers for food health and quality, and promoted the sustainable development and market competitiveness of food.

4.2.1 Maturity inspection

The growth and maturity of fruits and vegetables is subjected to environmental and physiological factors, which will affect the taste, nutritional value and market value of fruits and vegetables. Therefore, in the food industry, accurate and rapid determination of product maturity plays a key role in determining the optimal harvest time and storage conditions. Maturity inspection involves systematic observation and measurement of the appearance characteristics, hardness, color and other indicators of fruits and vegetables.

Traditional fruit and vegetable maturity assessment methods usually rely on dividing fruit maturity into several categories, or estimating maturity by measuring indirect indicators such as hardness. However, in recent years, new methods of HSI combined with DL regression models have shown significant potential to directly predict fruit ripening time. For example, Davur et al. used CNN and spectral space residual networks to systematically train and test a large number of Hass avocado fruit images (Davur et al., 2023). The results showed that the average error of this method is only 1.17 days when predicting the number of days, it takes for the fruit to reach the mature state, which was significantly better than the traditional classification method based on dimension reduction technology.

Due to the diverse nature of fruits and vegetables, certain varieties are difficult to differentiate based solely on color. For example, in blackberries, some varieties exhibit localized color variation on the surface, including spots or uneven pigmentation. Therefore, a new multi-input CNN ensemble classifier was developed (Olisah et al., 2024) (Fig.4A). Their method combines the image data from visible and near-infrared spectral filters, evaluating maturity by relying on the color of visible light as well as the information provided by near-infrared spectroscopy. A pre-trained VGG16 model and a stacked generalization integration framework were established to effectively identify the ripening characteristics of blackberry fruits. The experimental results show that the accuracy of the model reaches 95.1% and 90.2% respectively under unseen scenes and field conditions.

In addition, Garillos-Manliguez et al. proposed a non-destructive multimodal classification method based on a deep CNN for the maturity evaluation of papaya fruit (Garillos-Manliguez et al., 2021). They used the data features of visible and HSI systems to successfully divide the papaya fruit into six mature stages by adjusting and analyzing a variety of classic DL models (such as AlexNet, VGG16, VGG19, ResNet50, ResNeXt50, MobileNet and MobileNetV2). This method achieved an F1 score of 0.90 in six stages of classification tasks, fully demonstrating the superior performance of multimodal data in maturity assessment.

In the process of hyperspectral data acquisition, the raw data may have an insufficient sample size or insufficient to cover all possible maturity states and environmental conditions. Therefore, (Sanchez et al., 2023) synthesized the data of avocados through a generative adversarial network (GAN), and then used it to train the neural network of avocado maturity classification. The results showed that the synthetic data generated by the GAN network is efficient in cost and time, while also maintaining the training effect comparable to the real data. The introduction of synthetic hyperspectral data addresses the limitations of real data acquisition and opens new possibilities and avenues for development in fruit and vegetable maturity assessment research.

4.2.2 Nutrient inspection

Nutrients in fruits and vegetables are essential for maintaining human life activities. They play a central role in ensuring basic physiological functions and are instrumental in the prevention and treatment of various diseases.

Recent studies have shown the application of different DL models in fruit and vegetable quality inspection. For example, a recent study proposed a regression model based on one-dimensional convolutional ResNet (Con1dResNet), which improved the inspection accuracy of cherry SSC and hardness by 26.4% and 33.7%, respectively (Xiang et al., 2022). In addition, (Li et al., 2023) used a custom CNN network based on VGG16 architecture to successfully predict the SSC value of loquat, and the correlation coefficient was as high as 0.904. The model consisted of an input layer, four convolutional layers, two max-pooling layers, a fully connected layer and an output layer, which reduced the complexity of the model while maintaining the inspection accuracy.

However, traditional CNN may be limited by the ability of feature extraction when processing hyperspectral data, especially for the complex characteristics of fruit and vegetable surfaces, such as unevenness and color uniformity. Therefore, an innovative apple quality detection model based on HSI combined with a 3D-CNN was developed (Wang et al., 2020). Compared with the traditional 1D CNN model, this method can retain and utilize the three-dimensional shape and spatial features more effectively, which is more prominent in complex fruit and vegetable quality tasks.

Considering analysis of time series changes in different growth stages of fruits and vegetables, the information processing of time series is particularly important. Therefore, (Qi et al., 2023) introduced the method of temporal CNN (TCN), and constructed the MLP-CNN-TCN model by stacking one-dimensional convolutional layers and causal convolutional layers to predict the SSC value of pears. This model can effectively capture the temporal characteristics of pears at different time points, and significantly improve the performance and effectiveness of the prediction model. At the same time, through the dimension reduction processing of multi-layer perceptron, combined with CNN and TCN technology, the method performs well in spectral data analysis.

In hyperspectral data analysis, the traditional manual feature extraction process significantly increases the complexity of fruit and vegetable quality analysis. Hence, (Yu et al., 2022) proposed an innovative method based on 2DCNN and fully connected neural network (FCNN) for extracting phenotypic features of lettuce quality (Fig.4B). Unlike traditional methods, this model does not require complex preprocessing or dimensionality reduction steps, and can automatically extract features closely related to quality phenotypic traits. The model does not require any preprocessing or dimensionality reduction, and can automatically extract features related to quality phenotypic traits. The soluble solids content was determined by Deep2 D, and the pH was determined by DeepFC. The determination coefficients were 0.9030 and 0.8490, respectively.

(Gomes et al., 2021) recently proposed a new model based on one-dimensional CNN architecture, which is specifically used to detect the soluble solids content and pH value of grapes. By combining DL and transfer learning mechanism the model achieves improved performance and robustness when evaluation on independent test. Specifically, the integration of DL and transfer learning improves the generalization capability of the model and significantly reduces the training cost and time consumption on the new dataset.

4.2.3 Firmness inspection

The hardness of fruits and vegetables is an important texture attribute of fruit freshness and maturity, and it is also a general quality parameter reflecting mechanical properties, especially for those juicy fruits such as berries, plums and tomatoes. Hardness inspection plays an important guiding role in measuring the maturity of fruits and vegetables, determining the picking time, and improving transportation and storage (Wang et al, 2023).

To deal with the problems of cost, efficiency and accuracy in non-destructive testing of yellow peach quality, Xu et al. proposed a new method for hyperspectral multi-quality parameter inspection based on 3D CNN (Xu et al., 2020) (Fig.4C). This method replaces the traditional feature wavelength selection method by the method of full-band equal interval extraction and recombination wavelength, and adopts the method of shared network convolution layer to realize multi-task learning of sugar content and hardness of yellow peach, to improve the efficiency and accuracy of inspection. The model can deal with multiple quality parameters at the same time, making the comprehensive quality inspection of yellow peach more comprehensive. In addition, depth features can be extracted from the pixel-level spectral data of each sample using a stacked autoencoder (SAE), which facilitates the construction of a DL model for evaluating grape hardness (Xu et al.,2022). Their results showed that the SAE-lssvm model exhibits optimal performance (R=0.9232, RMSEP=0.4422N, RPD=3.26), and the SAE-pls model also showed satisfactory accuracy. It was observed that SAE can be used as an alternative method for processing high-dimensional hyperspectral image data. The research showed that hyperspectral combined with DL model has brought significant progress to fruit and vegetable hardness inspection. Compared with other internal inspection, more extensive exploration is needed. Integrating HSI technology with various DL models presents exciting possibilities for future research.

Typical application examples of hyperspectral combined with DL in the internal quality inspection of fruits and vegetables are shown in Fig.4.

4.3 Inspection of safety quality in fruits and vegetables

The safety quality of fruits and vegetables is mainly aimed at diseases and pests. Failing to remove fruits and vegetables infected with pests and diseases can facilitate their dissemination, leading to substantial economic losses and jeopardizing the health of consumers upon market circulation. Therefore, safety quality is the primary goal of fruit and vegetable quality inspection. According to pathogen category and infectiousness, the safety and quality inspection of fruits and vegetables can be subdivided into fungal disease inspection, bacterial disease inspection and pest inspection.

4.3.1 Fungal disease inspection

Mycotoxins are secondary metabolites produced by filamentous fungi, naturally generated in all stages of growth cycle including harvest, storage, transportation and processing. Fungal diseases of fruits and vegetables are caused by a variety of fungi, which have the characteristics of latent infection. Once the fungus invades the fruit, it can lurk in the dead cell layer in the fruit pores for a long time, then develop and cause disease under suitable conditions. This is the most prevalent form of fruit and vegetable diseases.

Apple, as a nutrient-rich fruit, may be infected by *Rhizopus nigricans*, causing decay and producing harmful metabolites. For the inspection of *Rhizopus nigricans*, the RGB and hyperspectral images of apples can be analyzed by fusing color moments and CNN extracted features (Sha et al., 2023). The results showed that the accuracy of the classifier after feature fusion is 98.6%. In contrast, the accuracy of the classifier using only CNN feature extraction and color moment feature extraction was 95.1% and 93.4%, respectively. This showed that feature fusion improved classification accuracy, and CNN improved the model performance due to its powerful feature extraction ability.

(Fazari et al.,2021) used hyperspectral images and DL techniques to detect the infection of olives at an early stage. They chose the ResNet-101 architecture and adjusted it to process the 61-band hyperspectral image. The results showed that the model had a significant effect on the inspection of infected olives, especially in the early stage, showing high sensitivity (85% on the third day, followed by 100%). Considering the advantages of LSTM in sequence data modeling, Li et al. used LSTM to detect the normal state, canker disease and blue mold (fungal disease) of Gannan navel orange (Li et al., 2022). They modeled the six band features selected by independent component analysis and genetic algorithm. The accuracy of the model was 93.41%, and the inspection time of a single orange was 1.26 seconds. Compared with the full-band feature modeling, the inspection time was reduced by 44.95 seconds.

The attention mechanism can focus on key information for the fine-grained inspection of disease. Therefore, Guo et al. proposed a dual-branch selective attention capsule network (DBSACaps) (Guo et al., 2024) (Fig.5A). The network uses two branches to extract spectral features and spatial features respectively to reduce the mutual interference between the two, and then fuses the two through the attention mechanism. The capsule network is used to replace the CNN to extract features and complete the classification. Compared with the existing methods, this method has the best classification effect for kiwifruit soft rot data, with an overall accuracy rate of 97.08% and a soft rot classification accuracy rate of

97.83%.

4.3.2 Bacterial disease inspection

Bacterial diseases of fruits and vegetables are caused by various bacteria that infect cells and tissues, leading to lesions. These diseases usually show sudden, transmissible and destructive characteristics. Compared with fungal diseases, bacterial diseases of fruits and vegetables are relatively few, so research often focuses on the simultaneous inspection of bacterial and fungal diseases.

Bacterial infection can lead to the decomposition of carbohydrates in fruit and vegetable tissues, which in turn leads to the decay and corruption of fruits and vegetables. An improved deep residual 3D CNN framework was proposed for treating surface rot of fruit peels (Qiao et al., 2020). The framework can quickly extract rich spectral and spatial features, thereby providing more detailed information on blueberry peel decay. In addition, the model combines the tree structure Parzen estimator (TPE), which can adjust the parameters according to the personalized characteristics of the data, thereby improving the performance of the network. Compared with traditional AlexNet and GoogleNet, this method significantly improves classification accuracy, reduces the number of network parameters by half, and shortens the training time by about 10%.

Early inspection of bacterial infection in fruits and vegetables can help to prevent the spread of infection and reduce economic losses. Therefore, (Kuswidiyanto et al., 2023) proposed a non-destructive, in-situ disease inspection system by combining HSI and drone technology. They adopted a method based on a three-dimensional residual network (3D-ResNet). The 3d-ResNet CNN of four residual blocks was followed by a corrected linear unit activation function and a maximum pooling layer behind each residual block.

Combined with the density-based application spatial clustering method, achieved an overall accuracy of 0.876 for cabbage, with a pathological class accuracy of 0.873.

However, using three-dimensional CNN to process hyperspectral data usually requires high hardware consumption. Hence, (Gao et al.,2023) proposed a multi-dimensional Atrous-CNN network structure (Fig.5B), which can combine 1D-CNN to extract spectral information, 2D-CNN to extract spatial information and 3D-CNN to extract spectral information. At the same time, to increase the perception field of the convolution kernel of the model structure and reduce the loss of hyperspectral data, zero convolution was used to extract data features in 1D-CNN and 2D-CNN. The model showed an accuracy of 99.87% for potato disease recognition.

4.3.3 Pest inspection

Pests infects fruits, damaging fruits and leading to crop yield reduction or complete loss. To effectively detect the early pests of fruits and vegetables, (Nguyen et al., 2024) proposed a inspection model based on deep neural network (DNN). The model performed non-destructive inspection of Chinese cabbage, showing excellent classification performance in a laboratory environment. Specifically, the classification accuracy of the model for the sample control plants was 96.4%, and the classification accuracy for aphids, spider mites, and thrips-infected plants were 96.9%, 93.9%, and 100%, respectively. This study verifies the potential of the HSI system combined with DNN classification technology as an autonomous monitoring tool for plant health in indoor crop production.

For outdoor crop pest inspection, (Tan et al., 2024) proposed a two-branch self-correlation network (TBSCN), which combines spectral correlation and random patch correlation branches to make full use of spectral and spatial information. When detecting

2115 hyperspectral images of 30 insect categories, the pest inspection accuracy of this method reached 93.96%. This study significantly promoted the development of insect classification and inspection, and demonstrated the great potential of HSI technology in improving inspection accuracy and reliability.

Although some progress has been made in the inspection of fruit and vegetable pests, methods for detecting pests inside fruits and vegetables are still relatively rare. Typical application examples of DL in the safety and quality inspection of fruits and vegetables are shown in Fig.5. The application of DL in fruit and vegetable quality inspection is summarized in Table 1.

5. Current limitations and challenges

In recent years, HSI technology combined with DL has been widely applied to the non-destructive testing of fruit and vegetable quality, which has promoted the intelligence and automation of the food industry. However, there are still some problems to be solved in the current research field.

(1) High cost of the HSI instrument: Although HSI technology can provide rich spectral information, its hardware equipment is still expensive, and data processing is complex. In addition, there are some limitations on the stability and accuracy of the inspection, which need to be further optimized.

(2) High data dimension and redundant information: Although DL algorithms perform well in feature extraction and pattern recognition, it is still a challenge to effectively process and reduce redundant information in the face of hyperspectral data with high data dimension and redundant information. At present, although some scholars have made some achievements in the feature extraction of fruit and vegetable quality inspection, there is still

a lack of personalized extraction methods for different types of samples.

(3) The poor generalization ability and insufficient robustness of models. Most current DL models constructed are only for single varieties, producing areas or fruit batches, making them less effective in detecting the quality of diverse fruits. Although some scholars use transfer learning and other technologies to improve the generalization ability of the model, DL models still face challenges in accurately detecting the quality of diverse varieties, producing areas or batches. The current DL model lacks sufficient robustness in dealing with these differences and cannot effectively adapt to the complex and changeable actual production environment. Therefore, maintaining the model accuracy and universality across different situations remains a critical issue that in current research.

(4) Models have a long running time and low inspection efficiency. HSI combined with DL technology can achieve high-quality inspection of fruit and vegetable quality. However, the existing models generally have the problems of long running time and low inspection efficiency. Although simple models can effectively detect samples of specific varieties or similar batches, its generalization ability is obviously insufficient in the face of diverse samples. Simultaneously, the complex model is difficult to implement in industrial equipment due to its complex structure, numerous parameters and high computational requirements.

(5) Safety and external quality are mostly qualitative inspection and lack quantitative research. Existing research in the inspection of fruit and vegetable diseases, pests, mechanical damage, appearance defects and other quality attributes pays more attention to inspection, but with limited exploration of infection severity, occurrence time of mechanical damage, and severity of appearance defects. This information has important

guiding effects on exploring the mechanism of fruit quality changes, optimizing transportation schemes, and improving storage conditions.

(6) Limitations of interpretability and efficiency. Explainable artificial intelligence has important value in revealing the decision-making process of DL models, but it also faces many challenges in the application of HSI of fruits and vegetables. HSI can extract rich spectral information and is widely used in the classification, quality assessment and disease detection of fruits and vegetables. However, DL models are often regarded as "black boxes" and their internal decision-making processes are difficult to understand. In addition, different interpretability techniques may provide inconsistent explanations, thereby reducing users' trust in the model. Therefore, how to ensure high performance of the model while considering interpretability remains a major challenge in the research of HSI of fruits and vegetables.

6. Conclusion and future perspectives

In view of the current problems of DL in the non-destructive testing of fruit and vegetable quality, to further promote the intelligence and automation of the food industry, future research should focus on the following aspects.

(1) Cost optimization and equipment development. Advanced modular design and cost-effective hardware equipment can reduce manufacturing costs. Then, the data processing algorithm is optimized and parallel computing technology is introduced to improve processing efficiency and reduce complexity. At the same time, strengthening the calibration and calibration of the instrument and establishing a real-time feedback mechanism will help to improve the stability and accuracy of the inspection. Finally, promoting cooperation and innovation in the industry and exploring the application of new

technologies will help promote the further development and application of HSI technology.

(2) Personalized feature extraction of different types of samples. Adaptive CNN and attention mechanism can be used. By designing multi-layer CNN and dynamic convolution kernels, the convolution parameters are adjusted according to the sample characteristics, and the skip connection is used to capture multi-scale features. In the process of feature extraction, the global and channel attention mechanism and multi-head attention are introduced to improve the extraction effect of key features. Generative adversarial networks may be used to enhance the data and generate diverse samples to improve the generalization ability of the model.

(3) Improve the universality of the model. Data augmentation and diversified data set construction strategies were used to increase the diversity of training samples of the model, covering fruit and vegetable data of different varieties, producing areas and batches. Then, applying transfer learning technology, the pre-training model is preliminarily trained on large-scale and diversified datasets, and then fine-tuned on specific tasks to enhance the adaptability of the model to new data. In addition, by introducing adaptive network structures, such as adaptive CNN and attention mechanism, the model can dynamically adjust its feature extraction process when dealing with different types of samples. In addition, the generative adversarial network can be used to generate more samples of different varieties and origins to improve the robustness and generalization ability of the model. Finally, the combination of meta-learning and online learning strategies enables the model to quickly adapt to new tasks and continuously update, maintaining high accuracy and stability. Through these methods, the model can maintain accuracy in different situations and effectively deal with the complex and variable environments in actual

production, thereby improving the overall performance and practicality of fruit and vegetable quality inspection.

(4) Balance accuracy and efficiency to build a lightweight DL model. Pruning and quantization techniques can be used to reduce model parameters and calculations, thereby improving operating efficiency. In the use of lightweight DL models, such as MobileNet and EfficientNet, these models have lower computational requirements while ensuring accuracy, and are more suitable for real-time deployment in industrial equipment. In addition, the mixed precision training technology is introduced to improve the computational efficiency by using low precision calculation in the process of model training and reasoning. At the hardware level, GPU and FPGA can be used to accelerate hardware-accelerated model inference and improve real-time inspection capabilities. At the same time, the hyperspectral data processing flow is optimized, and the fast-preprocessing algorithm is used to reduce the data processing time. Through the above methods, the inspection efficiency can be greatly improved while ensuring the inspection quality, so that the model can achieve efficient and real-time fruit and vegetable quality inspection in the actual production environment to meet the needs of industrial applications.

(5) Increase quantitative research and improve the corresponding database. To realize the quantitative inspection of appearance defects, image segmentation and feature extraction methods can be used to accurately locate and measure the defect area. In addition, a large-scale and diversified training data set was established to cover fruit and vegetable samples of different varieties, different growth stages and different storage conditions, to improve the generalization ability and adaptability of the model. By regularly updating and expanding the data set, the validity and accuracy of the model in the new environment are

maintained.

(6) Enhance interpretability and establish unified evaluation standards. With the improvement of algorithms and computing power, the development of intuitive and easy-to-understand interpretability tools will help non-professional users effectively use DL models for fruit and vegetable data analysis. For example, future research can explore visualization techniques to intuitively present complex spectral data and model decisions, thereby enhancing users' understanding of the model reasoning process. In addition, as the demand for interpretability of hyperspectral data of fruits and vegetables increases, the establishment of unified evaluation standards and best practices will promote the standardization of this field. Therefore, future research should focus on both interpretability itself and its effectiveness in the practical application of HSI of fruits and vegetables to promote the widespread application of DL in this field.

When discussing the wide application of HSI combined with DL in fruit and vegetable quality inspection, its advantages are obvious compared with traditional inspection methods. HSI technology inherits the advantages of high-resolution and multi-dimensional data acquisition, and significantly improves the inspection accuracy and efficiency through the introduction of DL, which gives it a clear competitive advantage in specific application scenarios. However, the development of hyperspectral combined with DL technology still faces some challenges. The first is how to improve the generalization ability and real-time inspection performance of the model while maintaining the integrity of hyperspectral data. This requires in-depth research and optimization algorithms to cope with data changes and processing complexity under different environmental conditions. Secondly, the high cost of equipment and the complexity of data processing also limit its wide application in industrial production.

Declaration of competing interest

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

Data availability

Data will be made available on request.

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Figures Captions

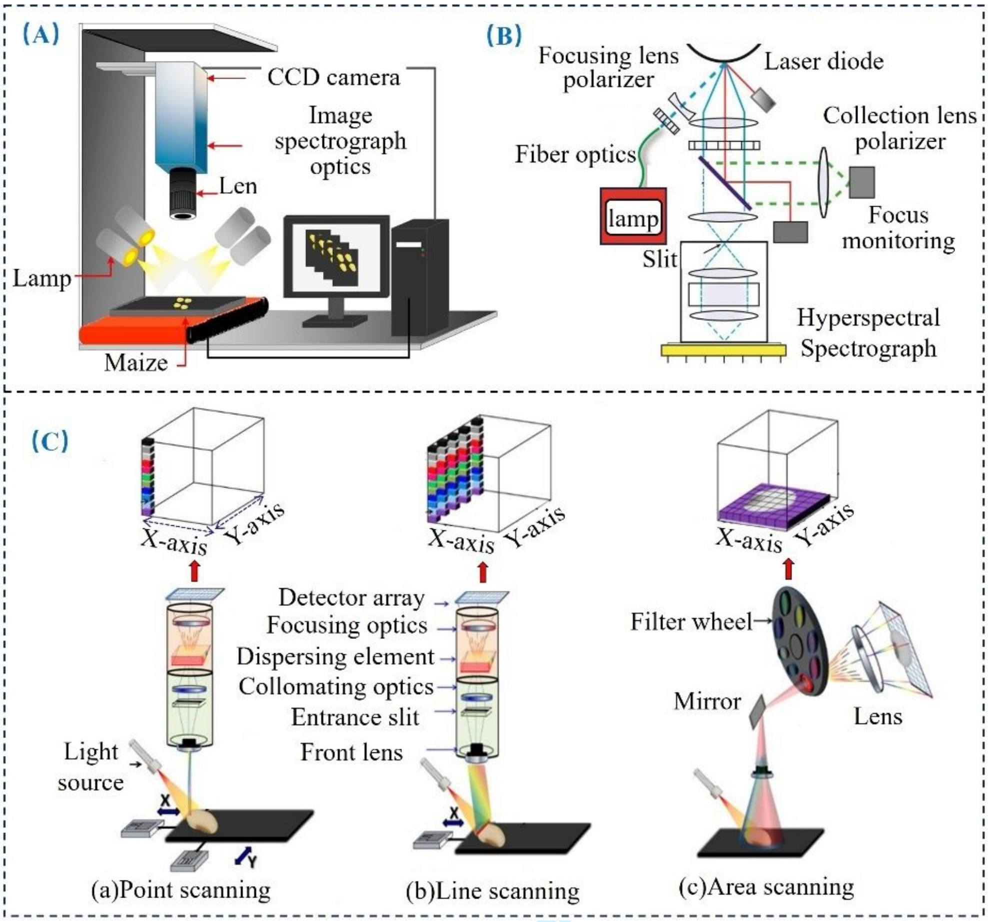
Fig.1. The principles and process of HSI technology. (A): Diagram of the HSI system (Wang et al.2018). (B): Diagram of the HSI principle (Chen et al., 2023). (C): Diagram of the acquisition method for HSI system. (a): Point scanning: Scan the spectral image of one point at a time. (b): Line scan: Scan the spectral image of the entire line at once. (c): Area scanning: Scan spectral images of one region at a time. The blue dashed arrows indicate scanning directions in each approach for sequential acquisitions to complete the volume of spatial and spectral 3D data cube (Halicek et al., 2019).

Fig.2. (A): CNN model with input layer, convolution layer, pooling layer and output layer. (B): RNN (left) and its non-rolling version (right). The state starting from time t-1 is remembered and used as the input of time. (C): LSTM model structure

Fig.3. Application of hyperspectral combined with deep learning in external quality inspection of fruits and vegetables (A): SSC-AE network structure diagram. (B): SSFE-FCNN network structure diagram.

Fig.4. Application of hyperspectral combined with deep learning in internal quality inspection of fruits and vegetables (A): Multi-input CNN structure diagram (B): Customize VGG16-CNN network structure diagram (C): 2DCNN-FCNN network structure diagram

Fig.5. Application of hyperspectral combined with deep learning in fruit and vegetable safety quality inspection (A): DBSACaps network structure diagram (B): Atrous-CNN network structure diagram.



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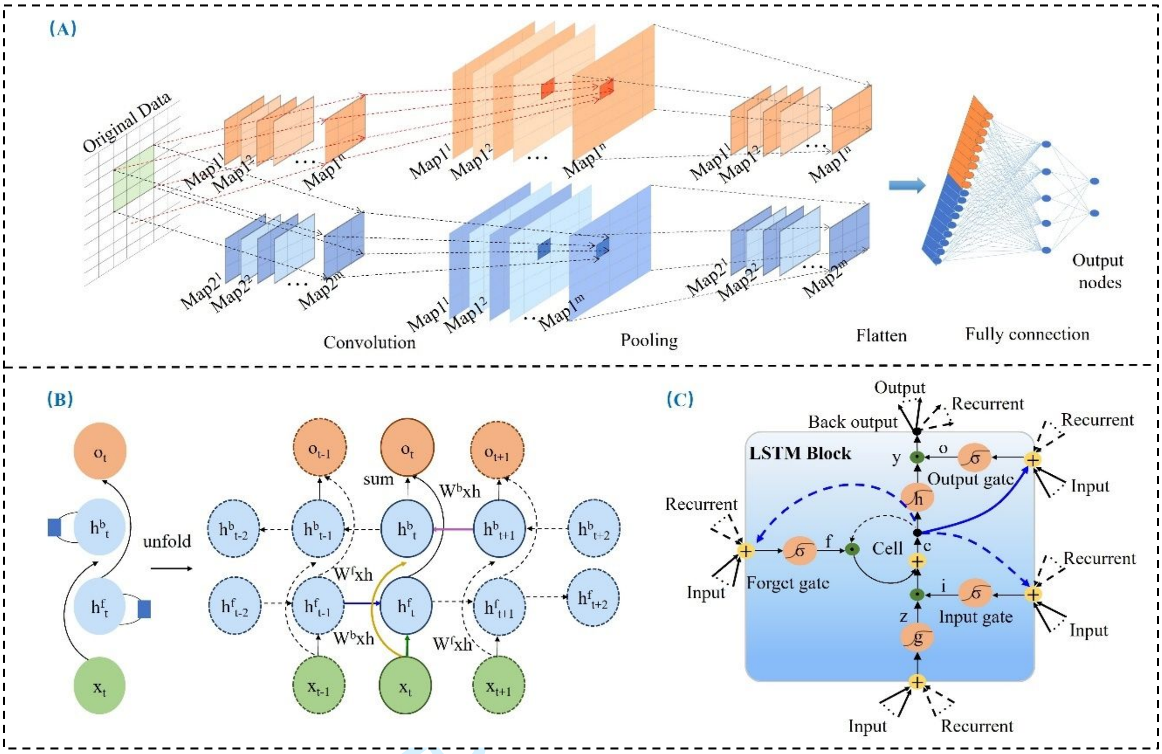

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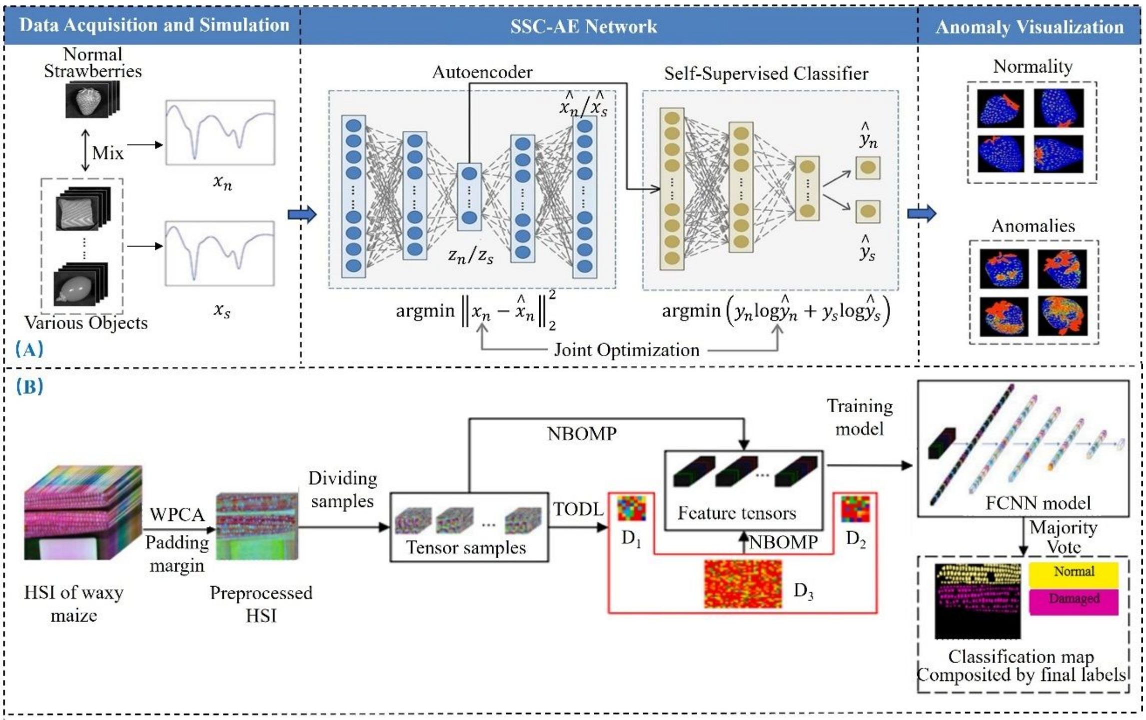

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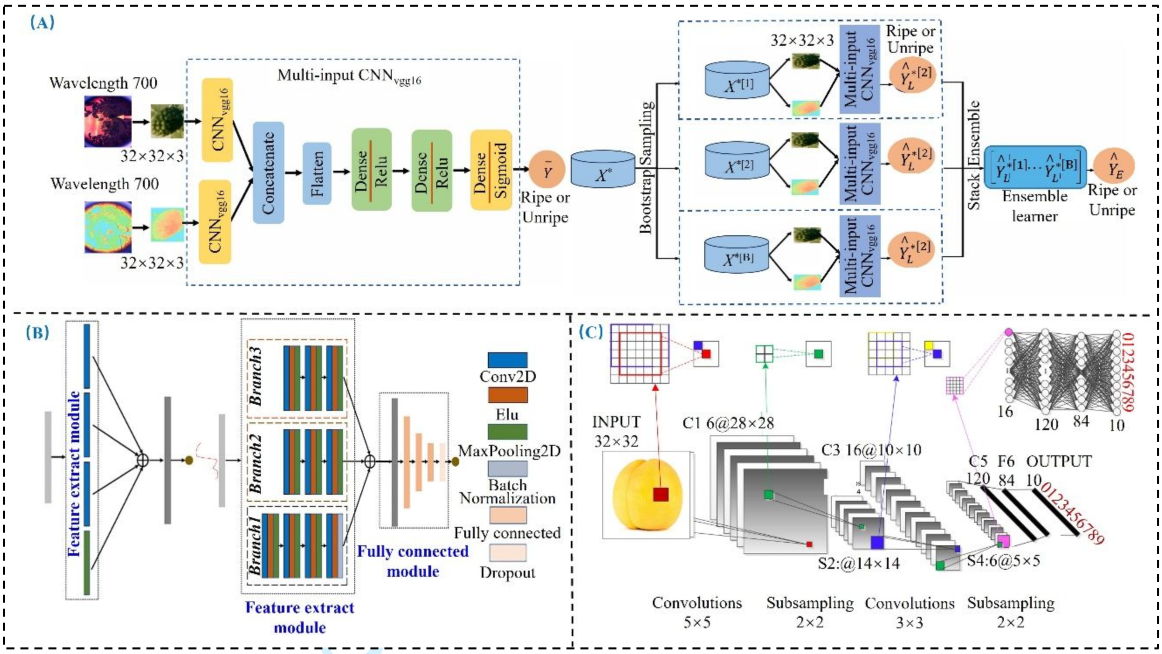


Fig.4. Application of hyperspectral combined with deep learning in internal quality inspection of fruits and vegetables (A): Multi-input CNN structure diagram (B): Customize VGG16-CNN network structure diagram (C): 2DCNN-FCNN network structure diagram

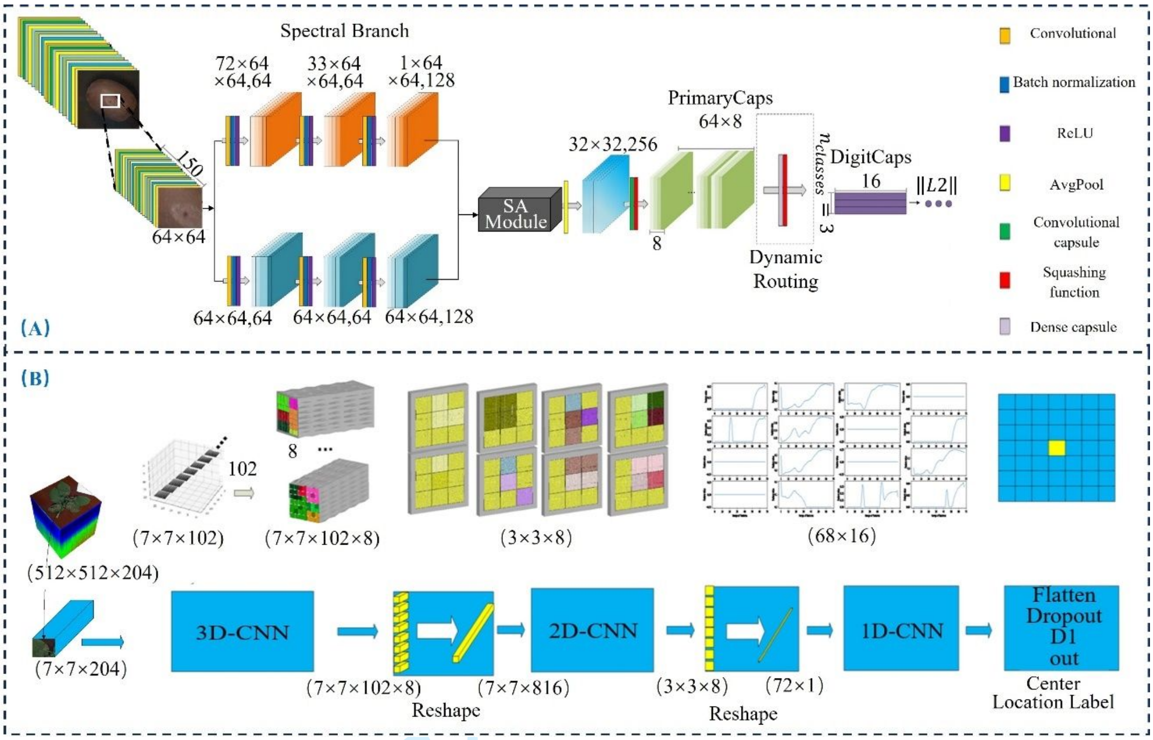


Fig.5. Application of hyperspectral combined with deep learning in fruit and vegetable safety quality inspection (A): DBSACaps network structure diagram (B): Atrous-CNN network structure diagram.

Table Captions

Table 1

Summary of the application of hyperspectral combined with deep learning in fruit and vegetable quality inspection

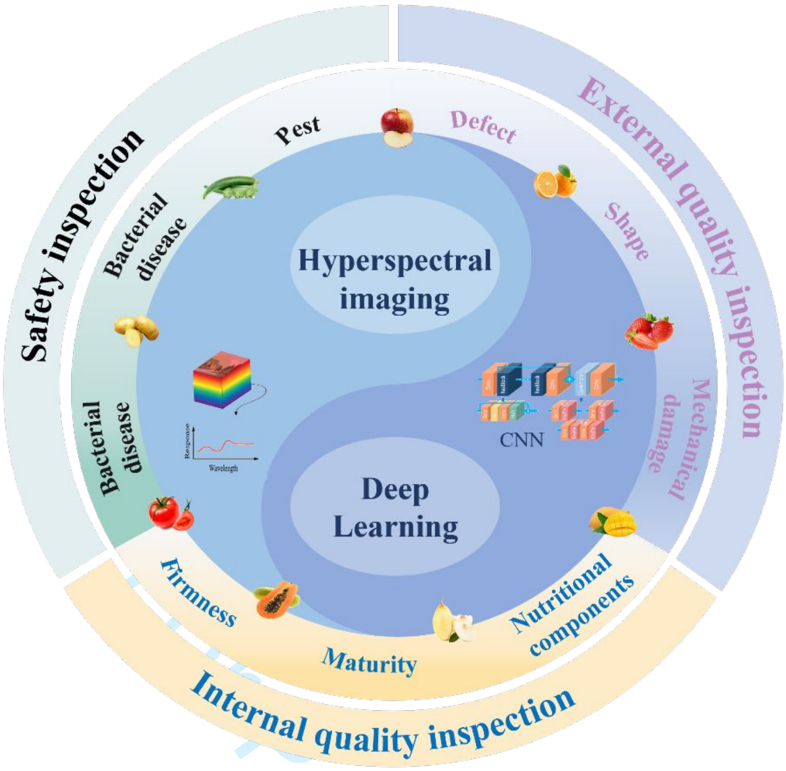
Table 1

Summary of the application of hyperspectral combined with deep learning in fruit and vegetable quality inspection

Application	Research object	Models	Inspection contents	Reference
External dimensions	Banana	CNN MLP	Shape	(Raghavendra et al., 2022)
	Strawberry	SSC-AE	Shape	(Liu et al., 2022)
Defect inspection	Citrus	CNN	Defect	(Frederick et al., 2023)
	Mandarin	CNN	Defect	(Zhang et al., 2024)
	Citrus	VGG-16-CNN	Defect	(Yadav et al., 2022)
	Carrot	mobile-slimv5s	Defect	(Zhou et al., 2023)
	Apple	SpectralCNN	Damage	(Gai et al., 2022)
	Corn	SSFE-FCNN	Damage	(Liu et al., 2023)
Mechanical damage inspection	Lemon	Resnet	Damage	(Pourdarbani et al., 2023)
	Lemon	ResNetV2	Bruising	(Pourdarbani et al., 2023)
	Plum	HSCNN	Bruising	(Castillo-Girones et al., 2024)
Maturity	Hass avocado	CNN	Maturity	(Davur et al., 2023)

inspection	Boxberry	VGG16-CNN	Maturity	(Olisah et al., 2024)
	Papaya	MD-VGG16	Maturity	(Garillos-Manliguez et al., 2021)
	Avocado	GAN	Maturity	(Sanchez et al., 2023)
Nutrient inspection	Cherry	Con1dResNet	SSC/Firmness	(Xiang et al., 2022)
	Loquat	VGG16-CNN	SSC	(Li et al., 2023)
	Apple	3D-CNN	Apple	(Wang et al., 2020)
	Pear	MLP-CNN-TCN	SSC	(Qi et al., 2023)
	Romaine lettuce	2DCNN	SSC/pH	(Yu et al., 2022)
	Grape	1DCNN	SSC/pH	(Gomes et al., 2021)
Firmness inspection	Yellow peach	3DCNN	Firmness	(Xu et al., 2020)
	Grape	SAE	Firmness	(Xu et al., 2022)
Fungal disease inspection	Apple	CNN	Fungal disease	(Sha et al., 2023)
	Olive	Resnet	Fungal disease	(Fazari et al., 2021)
	Orange	LSTM	Fungal disease	(Li et al., 2022)
	Kiwifruit	DBSACaps	Fungal disease	(Guo et al., 2024)
Bacterial disease	Blueberries	3D-CNN	Bacterial disease	(Qiao et al., 2020)
	Cabbage	3D-CNN	Bacterial disease	(Kuswidiyanto et

inspection				al., 2023)
	Potato	Atrous-CNN	Bacterial disease	(Gao et al., 2023)
Pest inspection	Cabbage	DNN	Pest	(Nguyen D et al., 2024)



Graphical Abstract

Supplementary material

1.1. Applications of HSI in assessing fruit and vegetable quality

As an efficient, rapid and non-destructive detection technology, HSI technology is widely utilized for quality assessment and detection in food, fruits and vegetables （Vignati et al.， 2023） . Traditional methods for detecting the quality of fruits and vegetables primarily rely on visual assessment and basic sensor technologies. While effective in certain instances, these approaches often fall short of providing a comprehensive analysis of the complex chemical composition and structural organization of the samples. By capturing data images and spectral information of samples, hyperspectral imaging technology comprehensively encompasses the internal chemical information and physical structural characteristics of fruits and vegetables, offering new opportunities for precise management and control of fruit and vegetable quality.

HSI technology can analyze external spectral data and image information of fruits and vegetables, enabling the extraction of parameters such as color, texture, and surface defects. This information is essential for the quality assessment and screening of fruits and vegetables. For example, (Shang et al., 2023) proposed a hyperspectral online sorting device specifically designed to detect full-surface defects in navel oranges. Utilizing images from the selected 1655.72 nm spectral band, they employed a non-uniformity correction method based on quadratic curve fitting to enhance the light intensity at the edges of the navel orange surfaces. By integrating this approach with threshold segmentation technology, they successfully detected surface defects in navel oranges, achieving a detection accuracy of 100%. This result demonstrates the effectiveness of hyperspectral technology in practical applications. (Huang et al., 2020) utilized hyperspectral technology to investigate early-stage diseases in blueberries. They identified effective spectral bands through correlation analysis and developed partial least squares discriminant analysis models, achieving recognition rates of 100% and 99%, respectively. The findings indicate that hyperspectral imaging holds significant promise for detecting early signs of disease, including opaque appearances and spots on fruits and vegetables. Furthermore, hyperspectral technology effectively captures changes in the spectral characteristics of fruits at various developmental stages and under different storage conditions, thereby directly reflecting their chemical composition and quality status. This capability is particularly crucial for accurately assessing growth stages during post-harvest quality evaluation. For example, (Shao et al., 2024) employed a colorimetric instrument to acquire hyperspectral images of tomatoes at various growth stages, including green maturity, discoloration, half maturity, and full maturity. They analyzed color coordinates (L*, a*, b*, C, h) and utilized support vector machines, k-nearest neighbors, and linear discriminant analysis to identify these growth stages. The results demonstrated that the linear discriminant analysis model yielded the highest performance, with a prediction accuracy of 93.1%. This indicates that hyperspectral imaging technology can non-destructively detect the growth stages of tomatoes.

In the internal quality assessment of fruits and vegetables, spectral data across different wavelengths reflect changes in the physical and chemical properties of the samples, capturing the reflection or absorption characteristics of their internal tissues, which are directly related to quality. Therefore, (Gao et al., 2024) proposed an adaptive window length Savitzky-Golay smoothing algorithm that adjusts the window length based on the rate of change in spectral data at various wavelengths, thereby enhancing the smoothing effect. They established a ridge regression prediction model by integrating continuous projection and principal component analysis, achieving an R^2 value of 0.9146 for apple hardness detection. Hyperspectral technology proves effective in evaluating the taste, composition, and shelf life of fruits and vegetables, offering significant insights for quality assessment.

Although HSI technology has made significant strides in assessing the quality of fruits and vegetables, it continues to face challenges in terms of big data processing, classification accuracy, and feature extraction (Guerri et al., 2024). Consequently, the integration of deep learning algorithms has become crucial for addressing these issues. With its superior capabilities in pattern recognition and feature extraction, deep learning technology can enhance the analysis and interpretation of hyperspectral data, thereby improving the accuracy and efficiency of fruit and vegetable quality assessments. Future research should concentrate on optimizing the integration of HSI technology and deep learning algorithms to effectively handle data variability, increase classification accuracy, and refine feature extraction processes.

1.2. Applications of DL in assessing fruit and vegetable quality

Deep learning, as a machine learning method with excellent performance, can handle complex data by constructing and training multi-layer neural networks. This approach has been widely explored, particularly in the field of fruits and vegetables. Convolutional Neural Networks (CNN) and Recurrent Neural Networks (RNN) have become the focus of research due to their superior performance in high-dimensional spectral data and complex feature extraction. Compared to traditional methods, the deep learning architecture can effectively manage large-scale and high-dimensional datasets, providing more accurate and robust prediction results. For example, (Wang et al., 2024) combined CNN and LSTM to successfully predict the occurrence of cucumber downy mildew, showcasing the potential of deep learning in crop disease detection.

Fruits and vegetables exhibit a wide range of external defects, with considerable variation in shape, size, and color. Traditional methods often struggle to account for all possible types and variations of these defects. In contrast, deep learning models can automatically learn defect features across diverse types, shapes, sizes, and colors, demonstrating superior adaptability to the inherent diversity and variability of fruits and vegetables. (Dhiman et al., 2023) proposed a combination of CNN and LSTM models integrated with edge computing to utilize local edge information in citrus fruit disease detection effectively. Their model successfully distinguished between two characteristics of citrus disease—pruning and non-pruning—with detection accuracies of 97.18% and 98.25%, respectively. Deep learning not only significantly enhances accuracy in fruit and vegetable detection tasks but also simplifies the data processing workflow. For instance, through the application of deep learning models, various types of fruit and vegetable data, including those with irregular shapes, diverse colors, and different sizes, can be effectively processed (Ukwuoma et al., 2022).

The application of deep learning technology extends beyond a single type of fruit and vegetable, encompassing quality analysis across a diverse range of products, from root vegetables to fruits. Given the similarities among various fruits and challenges posed by factors such as illumination and background changes, (Hussain et al., 2022) introduced a deep dilated Convolutional Neural Network within a deep learning framework to automatically detect and identify fruits and vegetables in challenging practical scenarios, achieving a detection accuracy of 96%. Therefore, (Xu et al., 2023) developed a hybrid fruit image classification framework called the Attention-based Densely Connected Convolutional Network with Convolutional Autoencoder (CAE-AND). This framework employs a convolutional autoencoder for pre-training images and combines attention-based DenseNet for feature extraction. Compared to the DCNN model, CAE-AND integrates an attention mechanism with a dense connection structure, enabling it to intensively learn and utilize key features in images, thereby enhancing classification accuracy while maintaining computational efficiency. Additionally, CAE-AND demonstrates improved performance in handling complex scenes and varied fruit images under conditions of significant noise or uneven illumination. Current research progress indicates that deep learning has broad applicability in multiple fields, including quality detection, disease prediction, and nutrient composition analysis. The adoption of these technologies not only facilitates real-time detection and analysis but also significantly enhances production line efficiency and product quality stability.

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Dear Editors,

We submit a revised manuscript entitled, ***Hyperspectral imaging and deep learning for quality and safety inspection of fruits and vegetables: A systematic review***, to ***Comprehensive Reviews in Food Science and Food Safety***. All the authors agree for submitting this manuscript, and this manuscript is our original work. The manuscript has not been published elsewhere.

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

Thank you and best regards.

Yours sincerely,

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