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NON-DESTRUCTIVE EARLY DETECTION OF BRUISING IN FRUITS USING HYPERSPECTRAL IMAGING: PRINCIPLES, RECENT ADVANCES AND FUTURE PERSPECTIVES

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ABSTRACT

Bruising is the most prevalent form of mechanical damage in horticultural produce, occurring throughout the postharvest chain and causing significant quality deterioration, economic losses and increased vulnerability to microbial infection. Conventional inspection methods rely on manual visual assessment, which is often subjective, time consuming, and unable to detect early or subsurface bruises before visible symptoms appear. Hyperspectral imaging (HSI) has emerged as a promising non-destructive technique that combines imaging and spectroscopy to capture detailed spatial and spectral information, enabling the early detection of subtle biochemical and structural changes associated with bruising. This review outlines the fundamental principles of HSI, key spectral regions, and data processing approaches, while highlighting recent advances in its integration with machine learning and deep learning for improved quality assessment and varietal discrimination in fruits. It also discusses the challenges of real-time industrial implementation and explores future prospects for integrating HSI into commercial postharvest sorting systems.

Key words : Hyperspectral imaging, Non-destructive evaluation, Postharvest quality, Machine learning, Deep learning.

Introduction

India is one of the world's leading producers of fruits and vegetables, however 30-40% of this produce is lost between harvest and consumption, mainly due to inadequate infrastructure, improper handling, transportation damage, market inefficiencies, and technological limitations (Ranjan and Sahni, 2023). A major contributor to this loss is bruising, the most common type of mechanical damage, which occurs when the mechanical load placed on fruits and vegetables exceeds what the plant tissue can withstand (Hussein *et al*., 2019). At the cellular level, this impact ruptures cell membranes, allowing enzymes from the cytoplasm to come into contact with compounds normally stored separately in the vacuole. This reaction causes enzymatic browning and sets off a chain of changes that eventually appear as visible discoloration and quality loss (Liu *et al*., 2025).

The consequences of bruising extend well beyond this visible damage. Bruised produce breathes faster, produces more ethylene and loses moisture and mass more quickly, along with changes in colour and a loss of firmness all of which shorten shelf life and lower overall quality. Bruising also affects taste, reducing sugar and organic acid content and making the produce less appealing to consumers. Worse, damaged tissue becomes an easy target for microbial infection, fermentation, and mould, and this decay can spread to healthy produce nearby during storage and transport (Du *et al*., 2020). Taken together, these effects mean bruising substantially lowers the commercial value of horticultural produce while driving up postharvest losses and food safety risks.

Early bruise detection is essential for effective postharvest quality management, accurate grading, and minimizing economic losses. Identifying bruises at an early stage enables timely sorting and handling of damaged produce before quality deterioration becomes severe. However, this remains challenging because bruises often do not become visible immediately after impact. Depending on the intensity of the mechanical force and

the type of produce, visible symptoms may take 12 hours or longer to appear, allowing damaged fruits and vegetables to pass through the supply chain undetected. During this latent period, bruised tissues undergo cell membrane disruption, enzymatic browning, altered water distribution, and accelerated deterioration despite the absence of visible external symptoms (Lu, 2003; Tian *et al.*, 2023). Conventional detection methods including manual inspection, firmness testing, and destructive slicing are subjective, labour-intensive, invasive, or impractical at industrial scale, while RGB machine vision, though automated, detects only surface defects and misses early or subsurface bruising (Wang and Liang, 2026). These shortcomings highlight the need for rapid, non-destructive, objective detection technologies capable of identifying bruises before visible symptoms emerge, improving postharvest management, reducing food waste and preserving the commercial value of horticultural produce.

In recent years, Optical non-destructive techniques have emerged as promising tools for early bruise detection in horticultural produce, capable of detecting internal damage before it becomes visible, without harming the sample, while enabling rapid, repeatable, online inspection during postharvest handling (Wan *et al*., 2025a). Several such techniques have been explored, including hyperspectral imaging (HSI), magnetic resonance imaging (MRI), fluorescence imaging (FI), X-ray imaging, thermal imaging, multispectral imaging and near-infrared (NIR) spectroscopy, with applicability varying by commodity and use case depending on the physical or chemical attributes each method measures (Mei and Li, 2023; Dankowska and Kowalewski, 2019).

Among these, HSI offers the best balance of sensitivity, practicality, and information richness. By capturing a continuous spectrum at every pixel, it combines spatial and spectral data to reveal subtle biochemical and structural changes before symptoms become visible, and when paired with machine learning and deep learning algorithms, it delivers accurate, comprehensive, and efficient detection making it the most widely researched non-destructive imaging technique for this purpose. Over the past two decades, numerous studies have confirmed its effectiveness across the visible (VIS), near-infrared (NIR), and short-wave infrared (SWIR) regions for bruise detection in apples, pears, berries, kiwifruit, and citrus fruits (Fan *et al*., 2017a; Okere *et al*., 2023).

This review presents the principles and methodologies of hyperspectral imaging for rapid and non-destructive bruise detection in horticultural produce. Recent advances in HSI-based bruise assessment are critically examined, along with current limitations and future research opportunities. The review aims to provide valuable insights into modern quality assessment technologies and support the development of efficient postharvest management systems in the fruit and vegetable industry.

Hyperspectral imaging technology

Hyperspectral imaging (HSI) originated during the 1970s and 1980s through advances in remote sensing, particularly for mineral mapping. Its development was driven by the introduction of the Airborne Imaging Spectrometer (AIS), pioneered by Alexander Goetz and his research team at the California Institute of Technology, who demonstrated its ability to identify surface materials using detailed spectral information(Siche *et al.*, 2016). Over the years, HSI has expanded well beyond its original remote sensing applications and has found widespread use in diverse fields, including environmental monitoring, geology, pharmaceutical manufacturing (Al Ktash *et al.*, 2021) medical diagnostics (Harvey *et al*., 2002) and the food industry (Gowen *et al*., 2007; Kamruzzaman *et al*., 2015). Its ability to provide rapid, non-destructive analysis has made it an increasingly valuable tool for quality evaluation and safety assessment across these sectors.

Principles of Hyperspectral imaging

Hyperspectral imaging is a technique that collects detailed spectral information across hundreds or thousands of narrow electromagnetic bands for each pixel in an image, creating a three-dimensional "hypercube" (Okere *et al*., 2021zh). HIS operates on the principle that every material, owing to its distinct chemical composition and physical structure, interacts with electromagnetic radiation in a characteristic way reflecting, absorbing, scattering, and emitting energy at specific wavelengths to produce what is known as a spectral signature or spectral fingerprint (Elmasry *et al*., 2012). Unlike conventional RGB imaging, which records only three broad spectral bands, an HSI system captures data across hundreds of narrow, contiguous bands spanning the ultraviolet, visible, near-infrared, and shortwave infrared regions (roughly 300-2600 nm), with a typical spectral resolution of 2-10 nm(Ma *et al*., 2019). This is achieved by integrating conventional imaging with spectroscopy and chemometrics into a single sensing platform, allowing spatial and spectral information to be acquired simultaneously (Mishra *et al*., 2020a; Fu and Chen 2019).

Depending on how light interacts with the sample, data can be collected in reflectance, transmittance, or interactance modes (Wu and Sun, 2013). The resulting output is a three-dimensional hypercube, in which two axes (x, y) represent spatial coordinates and the third

represents the wavelength dimension, so that every pixel in the image carries a complete spectrum (Kamruzzaman *et al.*, 2013). This dual spatial spectral nature means the technique can simultaneously reveal a sample's external attributes shape, size, texture, and surface distribution and its internal chemical and physical composition, since spectral absorptions in the near-infrared region often correspond to molecular overtones and combination vibrations of O–H, N–H, and C–H bonds (Zareef *et al.*, 2020). It is this combination of spatially resolved chemical information that distinguishes HSI from conventional imaging or point spectroscopy alone.

Hyperspectral imaging system

A typical HSI system (Fig. 1) is built around five core components: a lighting source, a camera, a spectrograph, a moving stage, and a computer running image acquisition software (Wan *et al.*, 2023). Depending on the illumination, spectrograph, and camera used, these systems can capture spectral data across different ranges with camera choice typically matched to the target range: CCD/CMOS sensors for 400–1000 nm, In GaAs for 900–1700 nm, and PbS for 1100–2500 nm (Saha and Manickavasagan, 2021). Tungsten halogen lamps are the standard lighting choice for their stability, durability, and low cost, though their limited light penetration makes it harder to detect deeper or earlier stage defects structured illumination (SI) addresses this by using patterned rather than uniform light to better reveal subsurface defects, giving rise to structural hyperspectral imaging (S-HSI) systems. Image acquisition itself can follow four modes (Fig. 2) point scanning, line scanning, area scanning, and single shot (Su, 2020), of which line scanning is most widely used in food inspection due to its compatibility with conveyor-belt systems, scanning line by line as samples pass beneath it (Qin *et al.*, 2013). Snapshot imaging, though faster and suited to real-time use, is limited by a narrower spectral range

Hyperspectral data processing and analysis

Raw hyperspectral data are high-dimensional and often contain problems such as overlapping spectral bands, light scattering, stripe noise, baseline shift, random noise, and variation in path length, caused by both the equipment and the physical properties of the sample (Cozzolino *et al.*, 2023). Before this data can be used for detection and classification, it must go through several processing steps. Preprocessing plays a key role here, as it reduces the amount of data, removes redundant information, and makes the analysis more reliable. This usually starts with radiometric correction, where white and dark reference calibration is used to convert raw

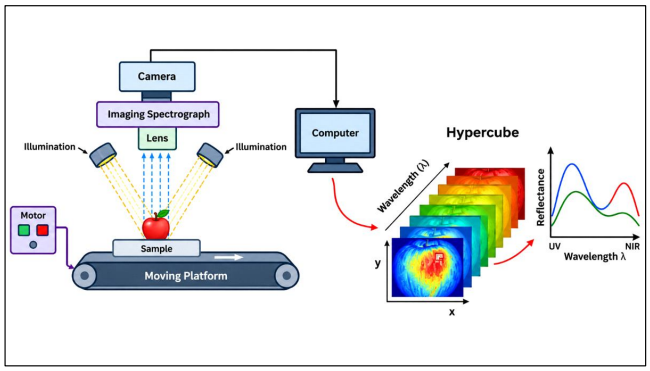


Fig. 1 : Schematic workflow of hyperspectral imaging for non-destructive quality assessment, illustrating image acquisition, spectral-spatial data collection, hyperspectral cube formation and extraction of spectral reflectance information.

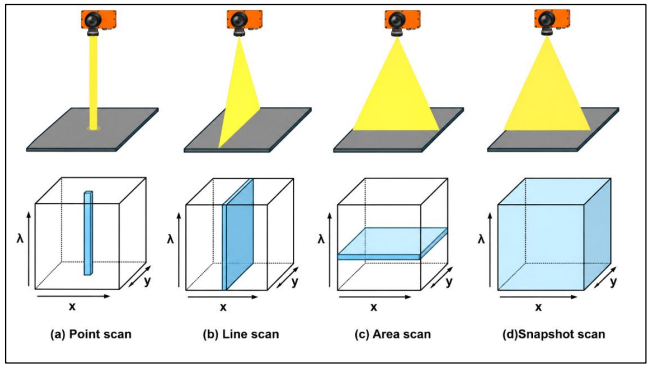


Fig. 2 : Different hyperspectral imaging acquisition configurations used for non-destructive inspection of horticultural produce: (a) point scanning, (b) line scanning, (c) area scanning and (d) snapshot imaging.

data into reflectance values, along with corrections for sensor nonlinearity and, when needed, atmospheric effects (Pan *et al.*, 2022). Noise is typically reduced using principal component analysis (PCA), Savitzky-Golay (SG) filtering, and minimum noise fraction (MNF) transformation, while the background is removed through automated segmentation and binary masking to isolate the region of interest (ROI), which is then refined using morphological operations. Spectral preprocessing itself falls into two broad categories: smoothing and derivative methods such as SG filtering, moving smoothing, wavelet transform (WT), first- and second-derivative transforms, and the Karl Norris derivative filter which remove noise and separate overlapping peaks; and scatter/baseline correction methods such as multiplicative scatter correction (MSC), standard normal variate (SNV), de-trending (DT) and orthogonal signal correction (OSC/DOSC), which correct for light scattering, particle size effects, and variation in signal intensity (Nikzadfar *et al.*, 2024; Shi *et al.*, 2024; Ozdogan and Gowen, 2025; Wan *et al.*, 2025b). Since no single method works for every

situation, the choice of preprocessing technique depends on the equipment being used and the specific goal of the inspection.

Because hyperspectral data tends to be highly correlated across bands, it must go through dimensionality reduction and statistical modelling before meaningful analysis is possible (Mishra *et al*., 2020b). PCA is the most widely used technique for this, as it captures the key patterns of variation in the data and is often used to visualise bruise contrast (Che *et al*., 2018a). Partial least squares discriminant analysis (PLS-DA) is another common choice, especially when a supervised approach is required, while independent component analysis (ICA) and linear discriminant analysis (LDA) are used less frequently (Baranowski *et al*., 2013). Since processing the full spectrum is too slow for real-time use, researchers use wavelength selection methods such as competitive adaptive reweighted sampling (CARS), the successive projections algorithm (SPA) and uninformative variable elimination (UVE) to identify only the most useful spectral bands. This not only speeds up analysis but also helps in designing affordable multispectral systems for practical use (Fan *et al*., 2017b; Tan *et al*., 2018). For classification, support vector machine (SVM) is the most commonly used method, largely because it performs well even with high-dimensional data and small sample sizes, and it has been applied successfully to fruits such as apples and blueberries (Nturambirwe *et al*., 2021a; Jiang *et al*., 2016a). Random forest (RF) has also proven highly effective, achieving over 99% accuracy in detecting bruises in blueberries (Liu *et al*., 2025a). More recently, deep learning methods have become increasingly important: convolutional neural networks (CNNs) and hybrid CNN long short-term memory (CNN-LSTM) models, which combine spatial and spectral information, have made it easier to detect subtle, early-stage bruises that are otherwise hard to identify (Li *et al*., 2024; Yang *et al*., 2024; C. Liu *et al*., 2025). In addition, lightweight transformer-based models and transfer learning techniques are being explored to address the limited availability of labelled postharvest datasets (Liu *et al*., 2024b).

HSI-based approaches for Bruise Detection across Fruit Commodities

Hyperspectral imaging is used more widely in fruit crops than in vegetables for several reasons. Fruits are high-value, perishable products where even minor bruising can significantly reduce marketability, creating strong incentive for early, non-destructive detection, whereas many vegetables are lower-value or less bruise-sensitive, offering less economic motivation for such monitoring. Fruits' simple, rounded shape also makes them easier to image consistently than the more irregular or leafy structures typical of vegetables. Additionally, fruit tissue undergoes distinct, well-characterized biochemical changes such as enzymatic browning and pigment degradation after mechanical damage, producing measurable spectral shifts that HSI detects well, whereas vegetables often show more variable or less pronounced responses. Fruits are also commonly sorted on high-throughput packing lines, making them a natural fit for conveyor-integrated HSI systems. These factors have made fruit crops the primary focus of HSI-based bruise detection research, with vegetable applications comparatively limited.

Apple

Being a widely consumed fruit produced exclusively in temperate climate, apple (*Malus* sp.) is regarded as one of the choicest fruits in the world owing to its rich nutrient profile including phenolic compounds, minerals and dietary fibre. Apple has drawn the most research attention in this domain, given its 93 million metric tonne global production and its vulnerability to mechanical damage during harvest, sorting, and transport. Lu (2003b) first showed that near-infrared (NIR) and short-wave infrared (SWIR) reflectance could reveal subsurface cell wall rupture, moisture loss, and polyphenol oxidase driven browning before any visible symptoms emerged, and ElMasry *et al*. (2008) linked such spectral differences to changes in water content and light scattering using NIR hyperspectral imaging (HSI, 900–1700 nm). Keresztes *et al*. (2016) pushed sensitivity further, detecting bruises as young as 2 hours old in Golden Delicious apples via applying an iterative algorithm on bruise probability maps on SWIR HSI (950–1700 nm), while Nturambirwe *et al*. (2021b) paired SWIR HSI with ensemble subspace discriminant and support vector machine (SVM) classifiers to catch latent bruises at their earliest, least visible stage.

To reducing the large amount of spectral data and improving computational efficiency various dimensionality-reduction and wavelength-selection methods, including Partial Least Squares (PLS), Principal Component Analysis (PCA), Successive Projections Algorithm (SPA) and Competitive Adaptive Reweighted Sampling (CARS), have been used to identify important wavelengths associated with water and phenolic compounds (Zhang *et al*., 2023; Zhu and Li, 2019). Tan *et al*. (2018b) used SPA to identify suitable wavelengths for the development of multispectral systems and early

bruise grading. Che *et al*. (2018b) applied PCA and ratio-based imaging to Vis-NIR data for pixel-level identification of bruise regions. Their study also considered interference from the stem and calyx and evaluated changes in bruise development over time, achieving recognition rates above 92%.

Selected wavelengths have been combined with machine-learning methods such as Partial Least Squares Discriminant Analysis, Support Vector Machine, K-Nearest Neighbors and Random Forest to improve discrimination between bruised and healthy apple tissues (Nturambirwe *et al*., 2021c). Recent studies have increasingly adopted deep-learning approaches, including Convolutional Neural Networks, object-detection models, and three-dimensional spatial-spectral networks, for rapid and automated bruise detection (Hou *et al*., 2024; Okere *et al*., 2023a). Yuan *et al*. (2022) detected bruises as early as 0.5 h after impact using a Near-Infrared camera combined with deep learning, while Yang *et al*. (2024b) developed advanced spatial-spectral models for detecting weak bruise signals at early stages.

Pear

Pear is another pome fruit that is extensively cultivated in the temperate and subtropical climates which comprises of two distinct classes *viz*.; the Asiatic (*Pyrus communis*) and European (*Pyrus pyrifolia*) types. Hyperspectral imaging (HSI) has demonstrated considerable potential for detecting both visible and early-stage bruising in pears. Li *et al*. (2024b) used visible and short-wave near-infrared (Vis-SWNIR) HSI (400–1000 nm) and identified important spectral regions related to bruising; combining selected spectral variables with gray-level co-occurrence matrix (GLCM) features and partial least squares discriminant analysis (PLS-DA) achieved 98.8% accuracy. Jiang *et al.* (2016) reduced the spectral data to two wavelengths (472 and 967 nm) using principal component analysis (PCA) and receiver operating characteristic (ROC) analysis, achieving 98.9–100% accuracy with PLS-DA. In the short-wave infrared (SWIR) region, Lee *et al*. (2014) obtained 92% accuracy for subsurface bruise detection using a two-band ratio, while Akter *et al*. (2024) achieved up to 100% classification accuracy for bruises, scars, and disease using visible-near-infrared (VNIR) and SWIR HSI with PLS-DA and successive projections algorithm (SPA). Overall, combining wavelength or variable-selection techniques with classifiers such as PLS-DA, support vector machine (SVM), extreme learning machine (ELM), random forest (RF), and linear discriminant analysis (LDA) generally provided better performance than using the full spectrum.

Recent studies have further improved pear bruise detection through optimized machine learning, transfer learning, deep learning, and fluorescence-based HSI. Wang *et al*. (2024) developed an optimized SVM model that classified bruise type and age with more than 92% accuracy, while Liu *et al*. (2024c) used transfer-learning approaches to improve recognition across different bruise types, achieving 88–93% accuracy. Fully convolutional networks (FCNs) have also been applied for automatic segmentation of bruised regions without extensive manual feature selection. In addition, Fu and Wang (2022) demonstrated that fluorescence HSI could detect bruises within 15 min of impact with 93.33% accuracy and achieve 99.33% accuracy in distinguishing bruised from sound pears.

Peaches

Peaches (*Prunus persica*) grown mostly in the temperate and sub-tropical climatic conditions, are widely acclaimed for their antioxidant properties due to their high contents of ascorbic acid, carotenoids and B group vitamins. Hyperspectral imaging (HSI) has shown strong potential for detecting early bruising in peaches, where visible browning and softening may not appear for up to two days after mechanical impact. Li *et al*. (2021) and Li *et al*. (2022) demonstrated that changes in moisture, firmness, soluble sugars, and chlorophyll can be detected before visible symptoms develop, with important wavelengths around 680–740 nm associated with chlorophyll degradation and 900–1020 nm related to water and soluble sugars. Principal component analysis (PCA) and competitive adaptive reweighted sampling (CARS) have been used to reduce spectral dimensionality, while machine-learning methods such as partial least squares discriminant analysis (PLS-DA), least squares support vector machine (LS-SVM), random forest (RF), and extreme gradient boosting (XGBoost) achieved 90–95% accuracy in estimating bruise age from 2 to 48 h. Li *et al*. (2018) further reported that short-wave near-infrared (SW-NIR) systems were more effective than long-wave near-infrared (LW-NIR) systems for early bruise detection, achieving over 96.5% accuracy using five selected wavelengths and an improved watershed segmentation method (I-WSM). More recently, Sun *et al*. (2024) combined structured hyperspectral imaging (S-HSI) with artificial neural network discriminant analysis (ANN-DA) to classify impact, falling, and compression damage.

Strawberry

An enlarged flower receptacle and not a true berry,

comprising of many true fruits or *achenes*, strawberry (*Fragaria* sp) is valued for its health protective properties imparted by the high levels of antioxidants including anthocyanins. Hyperspectral imaging (HSI) has been widely used for non-destructive detection of bruising and fungal contamination in strawberries. Liu *et al*. (2018) combined HSI with minimum noise fraction (MNF) transformation, morphological processing, and support vector machine (SVM) classification, achieving 92.59% accuracy in distinguishing healthy, bruised, and fungal-infected strawberries. Shanthini *et al*. (2025) used visible-near-infrared (Vis-NIR) HSI with multiplicative scatter correction (MSC) and recursive feature elimination (RFE), with SVM and linear discriminant analysis (LDA) achieving 99.99% classification accuracy, while random forest (RF) provided accurate bruise-age prediction (R^2 = 0.989). Sun *et al*. (2026) achieved 99.21% accuracy using partial least squares–linear discriminant analysis (PLS-LDA) and further applied the You Only Look Once version 5 (YOLOv5) model for automatic bruise localization, obtaining an F1-score above 93%. Recent studies have increasingly incorporated deep-learning approaches; Feng *et al*. (2025) combined a convolutional neural network and bidirectional long short-term memory (CNN-BiLSTM) with competitive adaptive reweighted sampling (CARS) and uninformative variable elimination (UVE), achieving 97.8% accuracy for detecting subtle bruises 12 h after impact. Du *et al*. (2026) developed a lightweight Efficient1DNet model for dual-band Vis-NIR/short-wave infrared (SWIR) HSI, achieving 97.68–98.41% classification accuracy and enabling bruise-area quantification with a mean absolute error (MAE) as low as 0.70%.

Blue berry

One of the most acclaimed fruits for its immunity boosting properties owing to the high contents of antioxidants including phenolic compounds such as anthocyanins, blue berry (*Vaccinium corymbosum*) a member of the Ericaceae family, is commonly cultivated in cooler regions, especially in temperate climate. Jiang *et al*. (2016b) demonstrated that near-infrared (NIR) hyperspectral imaging (HSI; 950 -1650 nm) could detect and quantify blueberry bruising, with a support vector machine (SVM) achieving over 96% accuracy across different cultivars. Fan *et al*. (2017b) detected bruise development from 30 min to 12 h after impact, with accuracy increasing from 77.5% to 95.0%, while a two-band ratio (1235/1035 nm) provided comparable performance with lower computational requirements. Water-related wavelengths around 970, 1200, and 1450 nm were identified as important indicators of tissue damage and water redistribution, although the calyx remained a major source of misclassification. Subsequent transmittance HSI enabled bruise detection as early as 30 min after impact with 94.5% accuracy using SVM, while Zhang *et al*. (2017) improved segmentation using fully convolutional networks (FCNs), achieving an intersection-over-union (IoU) of 84.5%. Recent studies have further integrated spatial-spectral features and advanced models, including the Beluga Whale Optimization algorithm and Tab Transformer, improving early bruise detection and severity classification (Liu *et al*., 2025; Huang *et al*., 2026).

Pomegranate

Highly regarded as a component of healthy diets, pomegranate (*Punica granatum*) is a rich source of antioxidant compounds as the arils of the fruit contain very high levels of anthocyanins and dietary fibre. The concentration of anthocyanins is responsible for the degree of redness in the arils, which is directly related to consumer acceptability and market potential of this fruit. The fruit is cultivated successfully with expected quality characteristics in the arid zones with sub-tropical climate and low atmospheric humidity. It is one of the rare examples wherein the thick rind conceals the internal fruit quality. The thick rind of pomegranate delays visible bruise development, making early non-destructive detection important for quality assessment. Okere *et al*. (2023b) used visible-near-infrared (VNIR; 400-1000 nm) and short-wave infrared (SWIR; 950-2500 nm) hyperspectral imaging (HSI) to detect bruising in 'Wonderful' pomegranates, with a feedforward artificial neural network (FF-ANN) achieving 88.3% accuracy immediately after bruising and 100% after 14 days. In a related study, Okere *et al*. (2023c) reported higher bruise-severity classification accuracy using SWIR (88.9%) than VNIR (74.4%), indicating greater sensitivity of SWIR to subsurface moisture changes. The noise-whitened Harsanyi Farrand Chang (NWHFC) method was used to reduce hundreds of spectral bands to a small number of informative wavelengths, enabling more efficient models for real-time sorting.

Kiwi

A hardy vine grown in cooler regions, kiwi fruit (*Actinidia chinensis*) is one of the widely marketed fruits due to its unique appearance and distinct flavour. Lu *et al*. (2012) demonstrated the potential of visible/near-infrared (Vis/NIR) hyperspectral imaging (HSI; 408- 1117 nm) for kiwifruit bruise detection, using principal component analysis (PCA) and a radial basis function support vector machine (RBF-SVM) to identify bruised

regions with a detection error of 12.5%. Bu *et al*. (2024) improved wavelength selection using segmented principal component analysis and combined three optimal wavelengths (928.19, 1051.03 and 1190.47 nm) with a You Only Look Once version 5 small (YOLOv5s) model, achieving an F1-score of 97.87% and mean average precision (mAP) of 99.12%. Ebrahimi *et al*. (2023) applied two- and three-dimensional convolutional neural networks (2D-CNN and 3D-CNN) for bruise detection in unripe and ripe kiwifruit, with classification accuracy reaching 98%. More recently, Liang *et al*. (2025) introduced structured hyperspectral imaging (S-HSI) with an artificial neural network discriminant model, achieving 100% classification accuracy and improving damage-degree classification and early-stage detection compared with conventional HSI.

Citrus

One of the most widely cultivated and consumed fruit crops comprising of a large group of fruits, citrus fruits vary widely in their size, shape, colour and flavour properties. Pourdarbani *et al.* (2023) used HSI (400-1100 nm) with three-dimensional convolutional neural networks (3D-CNNs), including ResNetV2, PreActResNet, and MobileNetV2, to classify sound and bruised lemons at 8 and 16 h after impact, with ResNetV2 achieving 92.85% accuracy. Integrated Gradients further confirmed that the model focused on regions associated with bruising. Lee *et al*. (2025) employed fluorescence HSI with ultraviolet (UV) illumination at 365 nm to detect bruising in mandarins, where conventional colour differences between healthy and bruised peel were limited. Deep-learning models, including ResNet50, EfficientNetB0, and MobileNet, achieved 100% test accuracy using principal component analysis (PCA)-compressed images, while Grad-CAM showed that model attention was concentrated on actual bruised regions. The models also maintained accuracy above 97% on an independent batch collected one year later, indicating good generalization.

Mango

Mango, the national fruit of India is a good source of ascorbic acid, carotenoids, phenolic com pounds and dietary fibre. It is widely grown in the tropics but is of great demand all over the world. India being the Centre of Origin of the fruit, has rich diversity in mango germplasm. Quality of the fruit is severely hampered by the incidence of fruit fly and anthracnose disease (Gomez *et al.*, 2021). Velez-Rivera *et al*. (2014) used NIR HSI (650-1080 nm) with a k-nearest neighbour classifier to detect mechanical bruising, achieving 95-98% accuracy depending on time since injury, with reduced-wavelength models (as few as ten bands) still reaching ~91%. Yao *et al*. (2024) extended this to estimating how long a mango had been bruised, combining spectral features with texture descriptors from principal-component images; their best CNN model, using feature fusion after variable selection, reached ~93.5% accuracy in classifying storage time post-bruising. Velasquez *et al*. (2024) instead targeted anthracnose, a fungal disease that develops before visible symptoms appear, using HSI in the 450–970 nm range; a multilayer perceptron classifier achieved 96.1% and 97.5% accuracy for the 'Keitt' and 'Osteen' cultivars, respectively, within 48 hours of infection. Together, these studies show HSI's expanding role in mango postharvest inspection.

Other Produce: Jujubes, Persimmons and Plum

Jujubes present a particularly challenging case for bruise detection because the browning of bruised tissue closely resembles natural skin coloration in healthy fruit. Yuan *et al*. (2021) used Vis-NIR HSI combined with PLS-DA for temporal classification of internal jujube bruises, achieving near-100% accuracy for healthy sample identification. Feng *et al*. (2019) applied pixel-wise deep learning to detect subtle bruises on winter jujubes using HSI, achieving almost 100% accuracy for healthy samples and lower but still high accuracy for bruised ones. Munera *et al*. (2021) used HSI and chemometrics for detection of invisible bruising at different stages in persimmon, demonstrating that spectral differences were detectable long before visible symptoms appeared. Castillo-Girones *et al*. (2024) proposed a deep learning approach with optimal wavelength selection for subsurface bruise detection in plums, achieving high classification performance using a compact set of informative bands

Challenges

Despite its strong potential, several challenges still limit the widespread adoption of hyperspectral imaging for early bruise detection in commercial postharvest applications. Natural variability in fruit size, shape, colour, surface texture, ripeness, and cultivar introduces spectral differences that reduce model robustness across different produce, seasons and growing conditions. Curved fruit surfaces also cause uneven illumination, leading to spectral distortions that can mask bruises, while geometric correction methods improve accuracy at the cost of greater computational complexity. In addition, HSI generates large volumes of data and operates more slowly than conventional imaging systems, requiring substantial computational resources and further validation before laboratory models can be reliably deployed in real-time

industrial settings. The limited availability of large, diverse, and well-annotated datasets further restricts the generalisability of machine learning models. High equipment costs, specialised hardware, calibration requirements, and the need for expertise in optics, image processing, and data analysis also hinder practical implementation, particularly for small-scale operators. Together, these technical, economic, and operational challenges continue to constrain the large-scale commercial adoption of HSI.

Future prospects

The future of hyperspectral imaging (HSI) for bruise detection is highly promising, with ongoing advances making the technology more practical and accessible. Improvements in artificial intelligence (AI) and machine learning (ML) are expected to reduce costs, speed up data processing, and enhance detection accuracy. At the same time, the development of compact and portable HSI systems will enable bruise detection directly in the field or at packhouses, allowing damage to be identified earlier in the supply chain. Combining HSI with complementary technologies such as 3D imaging, thermal imaging, RGB cameras and X-ray is also expected to improve detection accuracy and provide more detailed information about bruise location and severity. Emerging approaches, including self-supervised learning and foundation models, can make better use of unlabelled data and reduce the dependence on large labelled datasets. In addition, creating standardised hyperspectral datasets and adopting explainable AI techniques, such as Grad-CAM, will improve model reliability, transparency, and comparison across studies. Together, these developments are expected to make HSI a more affordable, reliable, and widely adopted tool for commercial postharvest quality assessment.

Conclusion

Hyperspectral imaging (HSI) has emerged as a powerful non-destructive technique for early bruise detection in fruits and vegetables by combining imaging and spectroscopy to identify latent bruises that are invisible to conventional inspection. When integrated with advanced machine learning and deep learning algorithms, HSI has achieved bruise detection accuracies exceeding 90% across a wide range of horticultural produce. However, its widespread industrial adoption is still constrained by high equipment costs, technical complexity, specialised expertise, and the challenges of processing large volumes of hyperspectral data. Detecting early bruises in produce with thick or tough skins also remains difficult. Despite these limitations, continued advances in sensor technology, artificial intelligence, and data reduction methods are expected to make HSI more practical for commercial quality assessment, grading and sorting, ultimately reducing postharvest losses and improving supply chain efficiency.

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Conflict of interest

There is no conflict of interest among the authors

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