

HYPERSPECTRAL IMAGING IN FRUIT QUALITY ASSESSMENT: SPECTRAL ANALYSIS, MACHINE LEARNING AND APPLICATIONS

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ABSTRACT

Fruit quality assessment is important for maintaining postharvest quality, reducing losses and improving the efficiency of sorting and grading operations. Conventional destructive methods provide reliable measurements of physicochemical, chemical, mechanical and microbiological attributes, but generally require sample preparation, laboratory analysis and destruction of the fruit. Non-destructive techniques such as visual inspection, machine vision, near-infrared spectroscopy, multispectral imaging, thermal imaging and electronic nose systems have been increasingly used for fruit quality evaluation, although their ability to provide detailed spatial and spectral information simultaneously is limited. Hyperspectral imaging (HSI) combines imaging and spectroscopy to acquire spatially resolved spectral information from intact fruits, allowing both internal quality attributes and external defects to be assessed. This review discusses the development and working principles of HSI, scanning and illumination modes, and the major steps involved in spectral data processing, including preprocessing, feature extraction, wavelength selection and dimensionality reduction. Applications of HSI for internal quality attributes such as soluble solids content, pH, firmness and total soluble solids, as well as external defects and fungal diseases, are reviewed with emphasis on spectral range, data analysis methods and machine-learning models. The major challenges include limited and cultivar-specific datasets, environmental variability, laboratory-to-field transferability, insufficient external validation, high-dimensional data and the lack of standardized protocols. Future research should focus on compact and portable HSI systems, real-time inspection, artificial intelligence, multimodal sensing, transfer learning, standardized datasets and commercial-scale validation to support reliable and practical fruit quality assessment.

KEYWORDS: Hyperspectral imaging; Fruit quality; Non-destructive testing; Spectral processing; Machine learning

1. INTRODUCTION

Fruits are an important part of the global food system, supporting human nutrition, agricultural income, food security, and the livelihoods of producers and other supply-chain stakeholders. They provide dietary fibre, vitamins, minerals, and a wide range of bioactive compounds, making them an important part of a healthy diet (Komati et al., 2025). Global fruit production has increased considerably over the past several decades, driven by population growth, changing dietary preferences and increasing demand for fresh and processed fruit products. Global fruit production has shown a steady upward trend over the past decade. In 2023, worldwide fruit production reached approximately 951.51 million tonnes, cultivated across nearly 68.10 million hectares, highlighting the continued importance of fruit production worldwide (Gonzatto & Santos, 2025). Despite this large production volume, a considerable proportion of fruits fails to reach consumers in an acceptable condition. Fruits are highly perishable due to their high moisture content, active metabolism and susceptibility to mechanical damage, physiological disorders and microbial deterioration. Quality deterioration may occur at several stages of the supply chain, from harvesting and handling to packaging, transportation, storage, marketing and retail (El-Ramady et al., 2015).

Postharvest losses therefore represent not only a reduction in the amount of food available for consumption but also a loss of the water, energy, labour, land and other resources invested in fruit production (Yahia et al., 2019). Despite the increasing production of fruits and vegetables, a considerable proportion is lost before reaching consumers. Globally, approximately 25–50% of fruits and vegetables may be lost between harvest and consumption. These losses occurring throughout the supply chain are collectively referred to as post-harvest losses (Bancal & Ray, 2022). In developing regions, inadequate cold-chain facilities, inappropriate packaging and handling, poor transportation conditions and limited access to postharvest technologies can further increase these

losses. Therefore, maintaining fruit quality requires not only appropriate production, handling and storage practices but also rapid and reliable methods for detecting quality deterioration and defects at different stages of the supply chain (Edo et al., 2026). Fruit quality is a multidimensional characteristic that influences consumer acceptance, market value, storage life and overall postharvest performance. It includes both external attributes, such as colour, size, shape and visible defects, and internal attributes, including soluble solids content (SSC), titratable acidity, firmness, moisture and other physicochemical and biochemical properties. In addition, mechanical damage, physiological disorders and microbial or fungal infections can substantially reduce fruit quality during handling, storage and marketing (Harker et al., 2003; Hu et al., 2026). Accurate and timely assessment of these attributes is therefore important for fruit grading, storage management and quality control throughout the postharvest chain.

Traditionally, fruit quality has been assessed using sensory evaluation, physical measurements, and destructive physicochemical, chemical, biochemical and microbiological analyses. Parameters such as soluble solids content (SSC), acidity, moisture, sugars and bioactive compounds are generally determined through laboratory-based procedures, while firmness and other textural properties are measured using mechanical or texture-analysis instruments. Microbiological and pathological analyses may also be required to confirm fungal or microbial deterioration (Fu & Sun, 2026). Although these methods provide reliable measurements and are widely used as reference techniques, they usually require sample preparation, fruit destruction, considerable time and labour, as well as laboratory facilities and trained personnel. Their destructive nature also limits repeated monitoring of individual fruits and their application in rapid, high-throughput inspection. Sensory evaluation may additionally be influenced by operator experience and subjectivity (Rizzo et al., 2023). The limitations of conventional methods have encouraged the development of non-destructive techniques for rapid fruit quality assessment. Machine vision, visible–near-infrared (Vis–NIR) spectroscopy, multispectral imaging, thermal imaging, fluorescence imaging and electronic nose systems have been investigated for this purpose. These techniques allow quality information to be obtained with minimal or no damage to the fruit and can support rapid inspection and repeated monitoring (Liu et al., 2025). However, individual techniques have specific limitations. Machine vision primarily provides information on external appearance and visible defects, while point spectroscopy provides spectral information from a limited measurement area without spatial information. Assessment of internal properties may also be affected by limited light penetration, particularly in fruits with thick skins or rinds (Akte et al., 2024).

Hyperspectral imaging (HSI) combines the spatial capability of imaging with the continuous spectral information of spectroscopy. It records a spectrum at each image pixel, producing a three-dimensional data cube containing spatial and spectral information (Bhargava et al., 2024). This enables both the characterization of fruit composition and the detection and localization of quality changes, defects and disease symptoms. Spectral responses are influenced by factors such as water, pigments, chemical constituents and tissue structure. Therefore, changes associated with maturation, physical damage, physiological disorders and disease can be identified through their spectral characteristics (Liu et al., 2025).

The integration of HSI with chemometric and machine-learning methods has further improved its application in fruit quality assessment. Spectral preprocessing, feature extraction and wavelength selection are commonly used to reduce unwanted variation and the high dimensionality of hyperspectral data (Rogers et al., 2023). Regression models can predict quantitative attributes such as SSC and firmness, whereas classification and segmentation models can identify defects and disease conditions. However, model performance can be influenced by cultivar, maturity, illumination, imaging conditions, spectral range, sample size, preprocessing and modelling approach (J. Lu et al., 2026). Limited datasets, laboratory-based experiments, instrument cost and computational requirements also remain important challenges for large-scale implementation. Accordingly, this review examines the application of HSI in fruit quality assessment under three major areas: internal quality attributes; external quality and physical defects; and fungal diseases and other biological defects. It also discusses spectral data processing, feature extraction and selection, machine-learning approaches, factors affecting model performance, current challenges and research gaps, and prospects for practical application of HSI in the fruit industry.

2. Destructive Methods for Fruit Quality Assessment

Conventionally, fruit quality has been evaluated using physicochemical, chemical, biochemical, mechanical and microbiological methods. These methods are well established and provide direct measurements of important quality attributes related to fruit maturity, freshness, nutritional composition and deterioration (Fu & Sun, 2026). They are also commonly used as reference methods for validating newer instrumental and non-destructive techniques. Conventional physicochemical methods are widely used to determine parameters such as soluble solids content (SSC), titratable acidity, pH, moisture content and colour. SSC is generally measured using a refractometer after extracting juice from the fruit, while titratable acidity is determined through chemical titration. Moisture content is commonly estimated by oven drying or other gravimetric procedures (Magwaza & Opara, 2015). Although these methods are relatively simple, they require preparation of fruit tissue and usually provide measurements from only a small portion of the fruit.

Chemical and biochemical analyses provide more detailed information about the composition of fruits. Sugars, organic acids, pigments, phenolic compounds, antioxidants and other bioactive constituents can be quantified using methods such as spectrophotometry, titration, chromatography and other laboratory-based techniques. Depending on the parameter, the fruit tissue may need to be homogenized, extracted, filtered and subjected to

several analytical steps (Al Kafi et al., 2025; Salim et al., 2026). These procedures are useful for understanding changes in fruit composition during maturation, storage and deterioration, but they are not convenient for examining large numbers of fruits. Texture and firmness measurements are important indicators of fruit maturity, ripening and mechanical damage. Penetrometers and texture analysers are commonly used to determine the force required to penetrate, compress or deform fruit tissue. More detailed texture analysis can provide information on hardness, cohesiveness, elasticity and other mechanical properties (Burdon & McGlone, 2026). However, penetration tests generally damage the fruit surface, while compression or deformation tests may alter the physical condition of the sample.

For the assessment of fungal and microbial deterioration, microbiological and pathological methods are used to confirm the presence and identity of the causal organism. These procedures may involve collecting tissue from the suspected infected region, culturing the organism on suitable growth media and identifying it based on morphological characteristics. Further biochemical, molecular or microscopic analyses may be required when accurate identification of the pathogen is necessary (Ohanu et al., 2015; Nguyen et al., 2026). Such methods are particularly useful for disease confirmation, although they may not provide immediate information about the extent or spatial distribution of infection within an intact fruit. Overall, these established methods provide accurate and quantitative measurements and remain important for research, quality standards and validation studies. However, their dependence on destructive sampling, sample preparation, laboratory facilities, skilled personnel and individual measurements limits their use for rapid, repeated and high-throughput assessment of intact fruits (Hasanzadeh et al., 2022). These limitations have increased the need for non-destructive techniques that can evaluate quality while retaining the fruit for further handling, storage or sale.

3. Non-destructive Techniques for Fruit Quality Assessment

The limitations associated with destructive analysis have increased the interest in non-destructive techniques that enable fruit quality to be evaluated without damaging the sample. These approaches rely on different physical principles, including visible-light imaging, molecular absorption, thermal radiation and volatile-compound sensing. Their applications range from external grading and defect detection to the estimation of internal physicochemical attributes such as soluble solids content (SSC), moisture, firmness and maturity.

Machine vision and RGB imaging provide a more objective approach by combining digital cameras, controlled illumination and image-processing algorithms to quantify fruit colour, size, shape, surface texture and visible defects (Irerri et al., 2019). Compared with manual inspection, these systems offer more consistent measurements and can be integrated with automated sorting and grading operations. Image-processing and machine-learning techniques are also used to identify bruises, scars, colour abnormalities, decay and other external defects (Eissa & Khalik, 2012). However, conventional RGB imaging records only three broad spectral channels, limiting its ability to distinguish materials with similar colour or detect subtle spectral changes (Karukayil et al., 2026). It mainly provides surface information and therefore has limited capability for assessing internal attributes such as SSC, moisture, internal browning and early-stage fungal infection in the absence of visible symptoms. Near-infrared (NIR) spectroscopy measures the interaction of near-infrared radiation with fruit tissue, with absorption and scattering influenced by molecular bonds such as C–H, O–H and N–H. The technique has been widely investigated for non-destructive estimation of SSC, dry matter, moisture, acidity, firmness and other internal quality attributes, using reflectance, interreflectance or transmittance configurations (Liu et al., 2025). Chemometric methods, particularly partial least squares (PLS) regression, are commonly used to relate spectral responses to reference measurements. A major limitation is that conventional NIR spectroscopy generally provides spectral information from a measurement point or relatively small area rather than a spatially resolved map (Cuzzolino, 2025). Consequently, localized defects may be missed, while factors such as fruit size, tissue structure, temperature, cultivar and growing conditions can influence light penetration and calibration performance.

Multispectral imaging combines spatial imaging with measurements at a limited number of selected wavelengths, allowing selected spectral features to be related to fruit colour, maturity, bruising, physiological disorders and other quality characteristics. Since fewer wavelength bands are acquired than in hyperspectral imaging, multispectral systems generate smaller datasets and can offer faster processing, making them attractive for real-time industrial applications (Liu et al., 2014). However, the use of predefined and relatively few wavelength bands limits the ability to capture subtle spectral differences associated with specific chemical constituents or early-stage defects (ElMasry et al., 2019). The appropriate wavelengths may also vary with fruit type and quality attribute, reducing the flexibility of the system compared with HSI. Thermal imaging records infrared radiation emitted from the fruit surface and converts it into a spatial temperature distribution. Changes in temperature patterns can be associated with water loss, respiration, tissue damage, physiological disorders and microbial activity, making the technique useful for investigating quality deterioration and certain forms of biological damage (Pathmanaban et al., 2023). Its rapid and non-contact nature is advantageous for fruit inspection. However, thermal imaging primarily measures surface temperature rather than chemical composition, and the observed thermal response can be strongly affected by ambient temperature, humidity, airflow, emissivity and fruit orientation (Ishimwe et al., 2014). These influences can make small temperature differences associated with internal deterioration difficult to distinguish from environmental variation.

Electronic nose (E-nose) provides another non-destructive approach by detecting volatile compounds released from fruits. E-nose systems generally employ an array of partially selective gas sensors that generate characteristic response patterns associated with ripening, freshness, aroma development, fermentation and microbial

deterioration (Bonah et al., 2020). Chemometric and machine-learning methods such as PCA, LDA and SVM are commonly used to interpret these sensor-response patterns. However, E-nose systems measure the headspace volatile profile rather than the spatial distribution or direct chemical composition of fruit tissue. Sensor responses can also be influenced by temperature, humidity, background volatiles, sensor drift, cultivar and storage conditions, which can affect calibration and model transferability (J. Tan & Xu, 2020). The above non-destructive techniques provide useful information on different aspects of fruit quality, but each has limitations in terms of the type, spatial coverage or spectral detail of information obtained. These limitations highlight the need for an approach that combines spatially resolved imaging with detailed spectral information. Hyperspectral imaging (HSI) addresses this requirement by acquiring a continuous spectrum at each pixel, thereby generating a three-dimensional data cube containing both spatial and spectral information. This enables the location of a quality change and its associated spectral characteristics to be examined simultaneously within the same fruit (Wang et al., 2023). Consequently, HSI has gained increasing attention as a non-destructive technique for assessing internal quality attributes, external defects, physiological disorders and fungal or microbial deterioration in fruits and vegetables.

4. Hyperspectral Imaging (HSI)

4.1 Principles and Components of HSI

Hyperspectral imaging (HSI) emerged from the integration of spectroscopy and digital imaging, combining the spectral information obtained from spectroscopy with the spatial information provided by imaging (Bhargava et al., 2024). Conventional spectroscopy generally provides an average spectral response from a selected measurement area, whereas conventional imaging systems, such as RGB cameras, capture information through only a few broad wavelength channels. HSI addresses these limitations by acquiring numerous narrow and contiguous spectral bands for each spatial position within a sample. As a result, every pixel contains a spectral signature that reflects the physical and chemical characteristics of the corresponding region (Tran et al., 2026). The technology was initially developed for remote sensing and was subsequently adopted in agriculture, food processing, medicine and other fields where spatially resolved chemical information is required (Ahmed et al., 2025a). In food and agricultural applications, HSI has become increasingly useful for non-destructive assessment because it enables spatial and spectral information to be obtained simultaneously. The acquired information is commonly represented as a three-dimensional hyperspectral data cube, $I(x, y, \lambda)$, where x and y represent the spatial coordinates and λ represents wavelength. Each wavelength band forms a two-dimensional image of the sample, while the spectral values recorded across wavelengths at an individual pixel form its spectral signature (Raj et al., 2021). This arrangement allows a quality-related change to be examined not only in terms of where it occurs on the fruit but also how its spectral response varies with wavelength.

The working principle of HSI is based on the interaction of electromagnetic radiation with matter. When radiation falls on a fruit surface, a portion is reflected, another portion is absorbed, and some may penetrate and undergo scattering within the tissue. The extent of these interactions varies with wavelength and is influenced by the chemical composition, physical structure and optical properties of the fruit. Constituents such as water, sugars, organic compounds and pigments contribute to wavelength-dependent absorption, while tissue structure and cellular organization influence scattering (Liu et al., 2025). Consequently, changes associated with ripening, moisture loss, mechanical damage, physiological disorders or microbial infection can alter the spectral response of the fruit and produce measurable differences in its hyperspectral signature. A typical HSI system comprises an illumination source, imaging optics, spectrograph or spectral dispersion unit, detector, sample positioning or movement system, and computer with image-acquisition and analysis software. The illumination source provides stable and sufficiently uniform radiation over the selected spectral range (Min et al., 2023). Halogen lamps are commonly used in visible and near-infrared applications because of their broad spectral output, although the choice of light source depends on the wavelength region and application. The imaging optics collect radiation from the fruit and direct it towards the spectrograph, where the incoming radiation is separated into individual wavelength components. The detector then records the spatially resolved spectral information (Medina-García et al., 2025).

The detector plays an important role in determining the quality of the acquired hyperspectral data, particularly in terms of spectral sensitivity and signal-to-noise ratio. Silicon-based detectors are commonly used in the visible and shorter near-infrared regions, whereas indium gallium arsenide (InGaAs) detectors are widely employed for longer near-infrared wavelengths, typically covering approximately 900–1700 nm (Kheiralipour et al., 2025). Detector selection therefore depends on the spectral range required for the intended application. The sample holder, translation stage or conveyor system maintains the position and movement of the fruit during image acquisition, while the computer and associated software control acquisition, calibration, visualization and subsequent spectral analysis (Morales et al., 2022). Prior to analysis, raw detector measurements are generally converted into calibrated reflectance or transmittance values using dark and white reference images. The dark reference accounts for the detector signal obtained in the absence of illumination, whereas the white reference represents the system response obtained from a material with known high reflectance. These references are used to minimize the effects of detector characteristics and non-uniform illumination and to obtain more consistent spectral measurements (Wu et al., 2026). In fruit applications, controlling illumination intensity, camera-to-sample distance, exposure time, fruit orientation and imaging geometry is particularly important because fruits have curved surfaces and naturally occurring spatial variations in colour, texture and composition.

4.2 HSI Scanning and Illumination Modes

Hyperspectral image acquisition involves two main considerations: how the spatial-spectral data are collected and how light interacts with the sample before reaching the detector. Based on the scanning mechanism, HSI systems are commonly classified as point-scanning (whiskbroom), line-scanning (pushbroom), area-scanning (staring or wavelength scanning) and snapshot systems (Bhargava et al., 2024). These configurations differ in acquisition speed, spatial coverage, mechanical requirements and suitability for different applications. The choice of scanning and illumination mode depends on the fruit characteristics, target quality attribute, spectral range, required spatial resolution and intended application.

In point-scanning or whiskbroom systems, one spatial point is measured at a time across the required wavelengths, and the complete image is constructed by scanning the point across the sample. Although this configuration can provide high spectral resolution, sequential data acquisition makes it relatively slow and less suitable for high-speed fruit inspection (Wang et al., 2023). Line-scanning or pushbroom systems acquire one spatial line along with its spectral information at each acquisition step. Relative movement between the sample and camera allows successive lines to be collected and assembled into a complete hyperspectral cube (Morales et al., 2022). Pushbroom systems are widely used in food and agricultural applications because they provide a practical balance between spectral resolution, spatial resolution and acquisition speed and can be integrated with conveyor-based inspection systems. In area-scanning or staring systems, a two-dimensional image is recorded at one wavelength, and the wavelength is sequentially changed to obtain a series of images. The resulting image stack forms the hyperspectral cube. This configuration is suitable for stationary samples, although sequential wavelength acquisition can increase imaging time (Ahmed et al., 2025b). Snapshot systems, in contrast, capture spatial and spectral information simultaneously in a single exposure, enabling rapid acquisition without mechanical scanning. However, depending on the detector and optical design, this may involve trade-offs in spectral resolution, spatial resolution or spectral range (Salas et al., 2025).

HSI systems can also be classified according to illumination and detection geometry, with reflectance, transmittance and interactance being the principal modes used in fruit-quality assessment (Ahmed et al., 2025b). In reflectance mode, the illumination source and detector are positioned on the same side of the fruit, and the detector records radiation reflected from the surface and subsurface tissue. Its relatively simple configuration makes it the most widely used mode for evaluating surface colour, texture, bruising, visible defects and selected internal quality attributes (Gowen et al., 2009). However, light penetration is limited in thick or highly scattering tissues. In transmittance mode, the fruit is placed between the illumination source and detector, and the transmitted radiation is measured after passing through the sample. Since the signal is influenced by light absorption and scattering across the fruit, this mode can provide useful information about certain internal defects and compositional characteristics (Lu & Peng, 2006). However, the transmitted signal decreases with increasing fruit thickness and optical density, requiring adequate illumination and detector sensitivity. Interactance mode provides an intermediate configuration in which the illumination source and detector are positioned on the same side of the fruit but separated by a defined distance. This arrangement reduces the contribution of directly reflected surface light and allows the detected radiation to interact with subsurface tissue before reaching the detector (Min et al., 2023). It can therefore provide information from greater tissue depth than conventional reflectance while avoiding some of the weak-signal limitations of full transmittance.

5. HSI Data Processing and Analysis Workflow

5.1 Spectral Data Processing

Hyperspectral images contain a large number of spectral variables for each pixel, along with information from the fruit, background, illumination conditions, surface characteristics and instrumental noise. Directly using these raw data for statistical or machine-learning analysis may therefore introduce unwanted variability and increase computational complexity (Moharram & Sundaram, 2023). Spectral data processing is carried out to reduce such interference while retaining the spectral information relevant to the quality attribute being investigated. A typical workflow includes region-of-interest (ROI) extraction, spectral preprocessing, feature extraction, wavelength selection and dimensionality reduction. ROI extraction is generally the first step in isolating the fruit region from the background and obtaining representative spectral information. Background pixels, shadows, saturated areas and specular reflections can introduce variations that are unrelated to fruit quality (Li et al., 2026). Different segmentation approaches, including thresholding, binary masking, edge detection, clustering and spectral-based methods such as the Spectral Angle Mapper, have been used to identify fruit regions or specific defective areas (Fauvel et al., 2013). Following segmentation, spectra may be obtained from individual pixels, selected ROIs or averaged across an ROI, depending on whether the analysis aims to retain pixel-level or sample-level information (Li et al., 2026). This step is particularly important for heterogeneous fruits, where a poorly selected or unrepresentative ROI may not adequately describe the quality variation within the sample.

Once the ROI has been defined, spectral preprocessing is applied to minimize noise and unwanted physical variations while retaining useful spectral features. Raw spectra may contain baseline shifts, scattering effects, random noise and variations caused by sample geometry or illumination. Common preprocessing techniques include normalization, Standard Normal Variate (SNV), Multiplicative Scatter Correction (MSC), Savitzky–Golay (SG) smoothing and first- or second-order derivatives (Min et al., 2023). Normalization brings spectral values to a common scale, while SNV and MSC help correct scattering-related variations. SG smoothing reduces high-frequency noise while maintaining the overall spectral shape, whereas derivative transformations can

enhance subtle spectral features and reduce baseline effects. Mean centering or autoscaling may also be applied before multivariate analysis to ensure that variables with different numerical scales do not disproportionately influence the model (Wei et al., 2026). The effectiveness of preprocessing depends on the fruit, spectral range, measurement conditions and target quality attribute, and no single method is suitable for all HSI datasets. Therefore, different preprocessing treatments or combinations are often evaluated to determine which one provides the most consistent and informative spectral representation.

The preprocessed spectra can then be subjected to feature extraction, in which the original spectral variables are transformed into a smaller set of variables that retain important information from the dataset. Principal component analysis (PCA) is one of the most widely used methods for this purpose. It transforms correlated wavelength variables into a smaller number of orthogonal principal components that account for successive proportions of the variance. PCA is therefore useful for data visualization, exploring sample separation and generating compact feature sets for subsequent modelling (Souza et al., 2024). Other approaches include spectral indices, band ratios, statistical descriptors and spatial or spectral-spatial features (Min et al., 2023). In addition, deep-learning approaches can learn spectral and spatial representations directly from hyperspectral data.

In contrast, wavelength selection retains a subset of the original spectral bands rather than transforming them into new variables. This is useful because adjacent HSI bands are often highly correlated, while some wavelengths may contribute little useful information or may contain considerable noise. Common wavelength-selection techniques include Successive Projections Algorithm (SPA), Competitive Adaptive Reweighted Sampling (CARS), Uninformative Variable Elimination (UVE), regression coefficients, variable-importance measures and genetic algorithms (Kamruzzaman et al., 2022). Wavelength selection retains specific informative bands from the original spectrum, helping to reduce redundancy, noise and model complexity. Dimensionality reduction encompasses both approaches by reducing the number of variables through feature transformation or wavelength selection, depending on the study objective. The selected features or wavelengths can improve model efficiency, retain relevant spectral information and support the development of simplified multispectral imaging systems (Islam et al., 2024). Overall, these processing steps convert raw HSI data into a cleaner and more informative representation for subsequent regression, classification or deep-learning analysis. The overall workflow of HSI for non-destructive fruit quality assessment is illustrated in Figure 1.

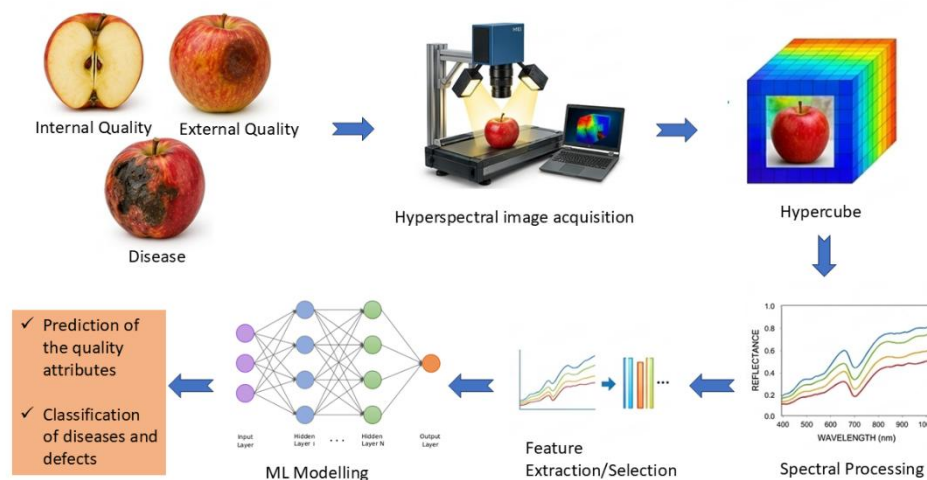


Figure 1. Overall workflow of hyperspectral imaging for non-destructive fruit quality assessment

5.2 Machine Learning Models and Performance Evaluation

Following spectral preprocessing and reduction to informative variables, machine-learning (ML) models are used to establish relationships between hyperspectral measurements and fruit-quality attributes. Depending on the nature of the target variable, HSI-based analysis can be broadly divided into regression for quantitative prediction and classification for qualitative discrimination (Min et al., 2023). The choice of model is influenced by the dimensionality and structure of the spectral data, sample size, distribution of the target classes and whether the relationship between spectral variables and quality attributes is linear or nonlinear. For quantitative quality prediction, regression techniques such as partial least squares regression (PLSR), multiple linear regression (MLR), least-squares support vector machine (LS-SVM), support vector regression (SVR) and artificial neural networks (ANN) are commonly used (Balabin & Lomakina, 2011). PLSR is particularly suitable for hyperspectral data because it can handle highly correlated spectral variables by projecting them into a smaller number of latent variables. In contrast, SVR and LS-SVM can model nonlinear relationships through appropriate kernel functions and are therefore useful when the relationship between spectral response and quality attributes is complex. ANN-based models can also capture nonlinear patterns, although their performance is generally more dependent on the

amount and representativeness of the training data (Sharma et al., 2026). These approaches have been applied to predict attributes such as SSC, dry matter, firmness, acidity, moisture and maturity-related parameters. For qualitative assessment, classification models assign fruits, pixels or image regions to predefined categories such as maturity stages, quality grades, healthy and defective samples or different types of physiological and microbial disorders. Commonly used algorithms include support vector machine (SVM), partial least squares discriminant analysis (PLS-DA), random forest (RF), k-nearest neighbours (k-NN) and linear discriminant analysis (LDA) (M. Liu et al., 2013). SVM is well suited to high-dimensional datasets and can effectively separate classes with complex decision boundaries, while RF can capture nonlinear relationships and interactions among variables and is relatively robust to noisy features. PLS-DA is particularly useful when the number of spectral variables is large and strong collinearity exists (Y. Zhang & Wang, 2023). The relative performance of these models can vary considerably with the fruit type, spectral range, preprocessing method, feature-selection strategy and number of samples. Deep-learning approaches have further expanded the analysis of hyperspectral data by enabling the direct learning of complex spectral and spatial patterns. Convolutional neural networks (CNNs), autoencoders and other deep neural architectures can extract hierarchical features from spectral, spatial or combined spectral-spatial information, reducing the need for manually engineered features (Guerri et al., 2024). Three-dimensional CNNs and related architectures can simultaneously exploit spatial and spectral dimensions and have therefore been investigated for defect detection, maturity classification and quality prediction. However, deep-learning models generally require larger and more diverse datasets than conventional ML methods and involve greater computational requirements. Their performance can also depend strongly on network architecture, hyperparameter selection, training strategy and the representativeness of the available samples (Raiaan et al., 2024).

The performance of regression models is generally assessed using the coefficient of determination (R^2), root mean square error (RMSE) and residual predictive deviation (RPD). In HSI studies, calibration and prediction statistics such as R^2_c/R^2_p , RMSEC and RMSEP are commonly reported to distinguish model fitting from performance on unseen samples. R^2 indicates the proportion of variation in the reference measurements explained by the model, whereas RMSE represents the magnitude of prediction error in the original units of the quality attribute. Lower RMSE values indicate smaller prediction errors, while higher R^2 values indicate closer agreement between predicted and reference values (Su et al., 2026). RPD relates the standard deviation of the reference data to the prediction error and provides an additional indication of model usefulness; however, its interpretation should be considered alongside the distribution and variability of the reference dataset rather than used as a standalone measure (Tian et al., 2026). For classification, commonly reported measures include overall accuracy, precision, recall or sensitivity, specificity and F1-score (Aqeel et al., 2024). Accuracy represents the proportion of correctly classified observations, while precision indicates how many samples predicted as a particular class actually belong to that class. Recall measures the ability to correctly identify samples of the target class, whereas specificity reflects the ability to correctly reject samples belonging to other classes. The F1-score combines precision and recall and can be particularly informative when class sizes are unequal. Confusion matrices provide a more detailed view of class-specific errors and can reveal whether a model performs consistently across all quality or defect categories rather than relying only on overall accuracy (Kramarczyk & Hejmanowska, 2025).

Reliable model validation and independent testing are essential for assessing the generalization of HSI-based models beyond the training data. A high training accuracy or low calibration error alone does not ensure reliable performance on unseen fruit samples. Training, validation and test datasets, together with k-fold cross-validation, are commonly used for model development and parameter optimization (Verma et al., 2024). In fruit HSI studies, particular attention is required when multiple pixels, ROIs or image patches originate from the same fruit. Randomly distributing such observations across training and test sets can cause data leakage and lead to overly optimistic performance estimates. Therefore, data splitting should preferably be performed at the fruit or sample level to ensure that test samples are truly independent. External samples from different fruits, batches or acquisition conditions can provide a more realistic assessment of model robustness (Joeres et al., 2025). Model performance should also be examined across variations in cultivar, maturity, storage conditions and instrumental settings. Thus, model evaluation should consider not only predictive accuracy but also consistency, robustness and transferability to new samples.

6. Applications of HSI for Fruit Quality Assessment

6.1 Internal Quality Assessment

HSI has been increasingly studied for the non-destructive assessment of internal fruit quality attributes such as soluble solids content (SSC), pH, firmness and total soluble solids (TSS). Ma et al. (2021) used object-rotation near-infrared hyperspectral imaging (NIR-HSI) in the 1002–2300 nm range to determine the spatial distribution of SSC and pH in intact kiwifruit. Using selected wavelengths, partial least squares regression (PLSR) models were developed and achieved cross-validation R^2 values of 0.74 for SSC and 0.64 for pH, with RMSECV values of 0.70% and 0.14, respectively. The rotation-based imaging approach also allowed the quality attributes to be visualized over the entire 360° surface of the fruit. Zhang et al. (2020) used full-transmittance HSI in the 325–1100 nm range to predict SSC in oranges. Competitive adaptive reweighted sampling combined with the successive projections algorithm (CARS-SPA) was used for wavelength selection, and the CARS-SPA-LS-SVM model with fruit-size compensation achieved an R^2 of 0.90, RMSEP of 0.40% and RPD of 3.18. Zhao et al. (2020) compared Vis-NIR and NIR-HSI for SSC prediction in winter jujubes and applied area normalization to minimize

the influence of uneven illumination caused by the curved fruit surface. The SPA-LS-SVM model gave R^2p values of 0.894 and 0.873 for the Vis-NIR and NIR regions, respectively. Yu et al. (2018) developed a stacked autoencoder–fully connected neural network (SAE-FNN) using HSI data from 380–1030 nm to predict firmness and SSC in Korla fragrant pears. The model achieved R^2p values of 0.890 for firmness and 0.921 for SSC. Rungpichayapichet et al. (2017) used NIR-HSI in the 935–1720 nm range to predict TSS and SO_2 content in treated and dehydrated mangoes using PLSR, obtaining prediction correlation coefficients of 0.82 for TSS and 0.83 for SO_2 . Guo et al. (2016) investigated SSC prediction in two kiwifruit varieties using NIR-HSI in the 865–1711 nm range. Mean ROI spectra and SPA-selected wavelengths were used with PLS and least-squares support vector machine (LSSVM) models, with the best models giving R^2p values of 0.766, 0.971 and 0.911 for the Xixuan variety, Huayou variety and combined dataset, respectively. These studies used different HSI acquisition modes, wavelength regions and modelling approaches to predict internal quality attributes, with both reflectance- and transmittance-based systems being applied depending on the fruit and target attribute. The various applications of hyperspectral imaging for fruit quality assessment are summarized in Table 1.

6.2 External Quality Assessment

HSI has also been used to detect external quality problems and physical damage in fruits, including bruising, impact injury and chilling injury. Liu et al. (2019) developed a two-branch convolutional neural network (2B-CNN) for spectral-spatial classification of bruises in strawberries using HSI data in the 900–1700 nm range. The network separately extracted spectral and spatial features and achieved an average classification accuracy of 96.72%. The learned network weights were also used for wavelength selection, while maintaining high classification performance. Tan et al. (2018) classified different levels of bruising in apples using HSI in the 400–1000 nm range. Among the preprocessing methods evaluated, standard normal variate (SNV) gave the best results, after which the successive projections algorithm (SPA) was used to reduce the number of spectral variables. The resulting SNV-SPA-GS-SVM model classified four bruising levels with a prediction accuracy of 95%. Che et al. (2018) developed a pixel-based approach for identifying complete bruise regions in apples using Vis-NIR HSI. Principal component analysis (PCA) was first applied to reduce redundant spectral information, followed by Random Forest (RF) classification of bruised and sound pixels. The method achieved an average bruise-region extraction accuracy of 99.9%. Xu et al. (2019) used HSI in the 900–1700 nm range to quantitatively assess impact damage in apples by relating spectral features to mechanical properties. The PLSR models achieved prediction R^2p values of 0.80 for damaged area, 0.89 for absorbed energy, 0.53 for contact load and 0.65 for undamaged firmness. Pan et al. (2016) investigated chilling injury in peaches using hyperspectral reflectance imaging in the 400–1000 nm range. Eight representative wavelengths were selected and used as inputs to a back-propagation artificial neural network (ANN), which classified normal and chill-damaged peaches with an overall accuracy of 95.8%. The corresponding prediction models for quality parameters produced correlation coefficients ranging from 0.6979 to 0.9026. Overall, the reported studies cover a range of HSI applications, including pixel-level bruise detection, classification of bruising severity, quantitative assessment of impact damage and identification of chilling injury.

6.3 Disease Detection

HSI has been applied to the detection of fungal diseases and other biological defects in fruits, particularly where early symptoms are difficult to identify by visual inspection. Frederick et al. (2023) investigated citrus black spot caused by *Phyllosticta citricarpa*, along with other peel defects in oranges, using HSI in the 452–928 nm range. Binary masking, PCA- and LDA-based wavelength selection, and CNN-based feature extraction were combined with Softmax, support vector machine (SVM), Random Forest (RF) and k-nearest neighbor (KNN) classifiers. Among the models tested, the PCA-selected five-band SVM achieved a mean overall accuracy of 94.9% for distinguishing different peel conditions. Pérez-Roncal et al. (2020) studied powdery mildew caused by *Erysiphe necator* in Carignan Noir grape bunches using HSI in the 900–1700 nm range. Different spectral preprocessing combinations were evaluated, with smoothing followed by standard normal variate (SNV) and mean centering giving the best PLS-DA model, which achieved a cross-validation accuracy of 85.33%. The model also allowed healthy and infected pixels to be spatially distinguished within the grape bunches. Pan et al. (2019) investigated the development and early detection of black spot disease caused by *Alternaria alternata* in pears using HSI in the 400–1000 nm range. Spectral Angle Mapping was used to identify infected regions, followed by SVM, KNN and PLS-DA classification. SVM gave the highest overall accuracy of 97.5% and was able to detect early disease symptoms. Sun et al. (2018) developed a rotating HSI system for detecting peach decay caused by *Rhizopus stolonifer* using the 400–1000 nm range. Band-ratio analysis and thresholding were used to locate decayed regions, while the successive projections algorithm (SPA) was applied for spectral variable selection. The classification accuracy for sound and rotten peaches reached 100%, although performance differed across the various stages of decay. Overall, these studies used HSI for disease classification as well as for locating infected regions within fruit tissues, with some approaches also addressing changes associated with disease progression. Spectral preprocessing, wavelength selection, image segmentation and machine-learning or chemometric models were commonly combined to distinguish healthy and diseased tissues.

Table 1. Applications of hyperspectral imaging for various quality assessments in fruits

Category	Fruit	Quality attribute/defect	Spectral range (nm)	Spectral Data Processing	ML models	Performance metrics	References
Internal Quality Attributes	Kiwifruit	SSC and pH	1002–2300	SG smoothing, SNV	PLSR	SSC: $R_p^2 = 0.74$, RMSE = 0.70%; pH: $R^2_{cv} = 0.64$, RMSE = 0.14	(Ma et al., 2021)
	Orange	SSC	325–1100	CARS; CARS-SPA	PLS, MLR, LS-SVM	$R_p^2 = 0.90$, RMSE = 0.40%, RPD = 3.18	(Zhang et al., 2020)
	Winter jujube	SSC	380–1030; 874–1734	Wavelet transform; moving-average smoothing; area normalization; SPA	LS-SVM	Vis-NIR: $R_p^2 = 0.894$, RPD = 3.07; NIR: $R_p^2 = 0.873$, RPD = 2.81	(Zhao et al., 2020)
	Pear	Firmness and SSC	380–1030	MSC; SPA; deep spectral feature extraction using SAE	SAE-FNN	Firmness: $R_p^2 = 0.890$, RMSEP = 1.81 N; SSC: $R_p^2 = 0.921$, RMSEP = 0.22%	(Yu et al., 2018)
	Mango	TSS and SO_2 content	935–1720	SG smoothing for TSS; original spectra for SO_2	PLSR	TSS: $R_p = 0.82$, RMSEP = 2.42%; SO_2 : $R_p = 0.83$, RMSEP = 56.40 mg/kg	(Rungpichayapichet et al., 2017)
	Kiwifruit	SSC	865.11–1711.71	mean spectra from ROI; SPA	PLSR, LSSVM	Xixuan: $R_p^2 = 0.766$, RMSEP = 0.968; Huayou: $R_p^2 = 0.971$, RMSEP = 0.589; combined: $R_p^2 = 0.911$, RMSEP = 1.137	(Guo et al., 2016)
External Quality Attributes	Strawberry	Bruise detection	900–1700	SG first-order derivative; SPA	2B-CNN	accuracy = 96.72%;	(Liu et al., 2019)
	Apple	Impact damage	900–1700	SG smoothing, SNV, MSC	PLSR	Damaged area: $R_p^2 = 0.80$; absorbed energy: $R_p^2 = 0.89$; contact load: $R_p^2 = 0.53$; firmness: $R_p^2 = 0.65$	(Xu et al., 2019)
	Apple	Bruising detection	400–1000	SNV; first derivative; SG smoothing; SPA; CARS	GS-SVM	Accuracy: 95%	(Tan et al., 2018)
	Apple	Bruise detection	400–1000	mean spectra from ROI, PCA	RF	accuracy = 99.9%	(Che et al., 2018)
	Peach	Cold injury	400–1000	Global thresholding, mean spectra from ROI	ANN	Accuracy = 95.8%; quality-parameter correlation coefficients = 0.6979–0.9026	(Pan et al., 2016)
Disease Detection	Citrus	Citrus black spot (Phyllosticta citricarpa)	452–928	binary masking; PCA/LDA band selection; CNN	SoftMax, SVM, RF, KNN	Accuracy = 94.9%	(Frederick et al., 2023)

Grape	Powdery mildew (Erysiphe necator)	900–1700	feature extraction SG smoothing; SNV; mean centering; first/second derivatives; PCA	PLS-DA	Accuracy = 85.33%	(Pérez-Roncal et al., 2020)
Pear	Black spot disease (Alternaria alternata)	400–1000	First derivative; MSC; mean centering; infected-area segmentation	SVM, k-NN, PLS-DA	Accuracy = 97.5%	(Pan et al., 2019)
Peach	Decay caused by Rhizopus stolonifer	400–1000	ROI masking; autoscaling; band-ratio analysis; SPA	PLS-DA	Accuracy for binary classification (sound vs rotten): 100%	(Sun et al., 2018)

7. Challenges and Future Perspectives

Despite the growing application of HSI for fruit quality assessment, several challenges still limit its transition from experimental research to routine postharvest inspection. A major limitation is the relatively small and narrowly defined datasets used in many studies. HSI models are often developed using a limited number of fruits, cultivars, maturity stages or controlled production conditions, although spectral characteristics can vary with cultivar, growing region, maturity, moisture content, tissue structure and environmental conditions. In disease-related applications, differences in pathogen development and symptom expression can further increase this variability. Consequently, a model developed under one experimental condition may not provide consistent performance when applied to new cultivars or production environments. Developing larger datasets covering multiple cultivars, seasons, geographical locations, maturity stages and disease severities would provide a stronger basis for model development and validation.

Another important challenge is the transfer of HSI models from laboratory conditions to field and commercial environments. Laboratory measurements are generally obtained under controlled illumination, sample positioning and environmental conditions, whereas practical systems experience variations in illumination, temperature, humidity, fruit orientation, background and conveyor speed. These factors can introduce spectral variability and affect model performance. Robust calibration, illumination correction, standardized acquisition geometry and representative samples collected under practical conditions are therefore important for improving model transferability. Model validation also requires careful consideration because HSI datasets contain a large number of correlated pixels from the same fruit. Randomly assigning pixels or ROIs from a single fruit to both training and testing sets can cause data leakage and produce overly optimistic performance estimates. Fruit-wise, batch-wise or season-wise data partitioning, together with independent external validation, provides a more realistic assessment of model generalization and robustness.

Early detection of fungal diseases presents an additional challenge because infection-related biochemical and structural changes may occur before visible symptoms develop. The resulting spectral differences between healthy and infected tissues can be subtle, while disease progression may also be spatially heterogeneous. The infected region may occupy only a small part of the fruit, making reliable identification more difficult. Future studies should therefore give greater attention to sensitive wavelength identification, spectral-spatial analysis, pixel-level classification and time-series imaging during disease development. Linking spectral responses with physiological, biochemical and pathological measurements could further improve the interpretation of spectral changes associated with early infection. The high dimensionality of HSI data is another practical limitation. Hundreds of contiguous wavelength bands generate large data volumes and often contain redundant or highly correlated information, increasing storage, processing time and model complexity. Deep-learning approaches can further increase computational requirements because they generally require large and representative datasets for effective training. Wavelength selection, dimensionality reduction and feature extraction can reduce the number of variables while retaining relevant information. Selected-band HSI and multispectral imaging may therefore offer a useful balance between spectral information, acquisition speed and computational efficiency for specific quality-assessment applications.

Differences in instrumentation and experimental protocols also affect the comparability and reproducibility of HSI studies. Variations in spectral range, illumination source, calibration procedure, acquisition geometry, preprocessing, ROI selection, model development and validation methods can influence reported performance. More consistent protocols for calibration, spectral processing, data partitioning and performance reporting would facilitate meaningful comparison among studies and improve reproducibility across instruments and laboratories. In quantitative applications, reliable reference measurements obtained using established analytical methods should also be clearly documented. Although high classification and prediction accuracies are frequently reported, relatively few HSI systems have progressed to continuous industrial operation. Equipment cost, computational requirements, acquisition speed, system maintenance and integration with existing grading lines remain important considerations. Future development should therefore focus on compact and application-specific sensors, selected-wavelength or multispectral configurations, automated fruit handling and real-time image processing. Integration of HSI with conveyor-based grading systems and edge-computing platforms could enable rapid assessment of individual fruits during sorting and packing.

Artificial intelligence and deep-learning approaches, including convolutional neural networks and transformer-based models, are likely to support more advanced spectral-spatial analysis as larger datasets become available. Transfer learning and domain adaptation may also help improve model performance when conditions change across cultivars, instruments, seasons or geographical regions. In addition, combining HSI with complementary techniques such as RGB, thermal, fluorescence or 3D imaging could provide additional information for complex quality and disease assessment. The development of standardized and openly accessible datasets, independent external validation, commercial-scale trials and economic evaluation will be important in establishing the reliability and practical feasibility of these systems. Overall, future research should move beyond achieving high laboratory-based accuracy and place greater emphasis on robustness, reproducibility, real-time operation and transferability, which are essential for the practical deployment of HSI in fruit quality inspection.

8. CONCLUSION

HSI has become an important non-destructive approach for fruit quality assessment because it combines spatial information with continuous spectral measurements from intact samples. Conventional destructive methods provide reliable measurements of physicochemical, chemical, mechanical and microbiological attributes, but usually require sample preparation, laboratory analysis and destruction of the fruit. Other non-destructive techniques, including visual inspection, machine vision, NIR spectroscopy, multispectral imaging, thermal imaging and electronic nose systems, provide useful information for specific applications but are often limited by their spectral resolution, spatial coverage, penetration depth or sensitivity to environmental conditions. HSI provides a more comprehensive measurement by recording both spatial and spectral variations across the fruit. The studies reviewed in this paper show that HSI has been applied across three major areas of fruit quality assessment: internal quality attributes, external quality and physical defects, and fungal diseases or other biological defects. Internal quality assessment has mainly focused on attributes such as SSC, pH, TSS and firmness using visible-NIR and NIR spectral regions. Regression techniques, including PLSR, LS-SVM and neural-network models, have been used for quantitative prediction as well as spatial mapping of quality attributes. For external quality assessment, HSI has been applied to bruising, impact damage and chilling injury through spectral analysis, pixel-level segmentation and classification. In fungal disease assessment, studies have addressed defects such as citrus black spot, powdery mildew, pear black spot and Rhizopus-associated peach decay, with some approaches also detecting early disease symptoms and locating infected regions.

The reliability of these applications depends strongly on appropriate spectral data processing and model development. ROI extraction, spectral preprocessing, wavelength selection, feature extraction and dimensionality reduction help minimize noise and redundant information while retaining features relevant to the target quality attribute. Machine-learning methods such as SVM, PLS-DA, RF, LS-SVM and PLSR have been widely employed, while deep-learning approaches offer greater scope for learning complex spectral-spatial patterns directly from HSI data. However, reported model performance is highly dependent on dataset composition, preprocessing, feature selection, validation strategy and acquisition conditions. Despite considerable progress, several gaps remain before HSI can be routinely implemented in commercial fruit inspection. Small and cultivar-specific datasets, environmental variability, limited independent validation, high-dimensional data, differences in acquisition and preprocessing protocols, and the relatively limited number of industrial-scale studies continue to restrict wider adoption. Future research should focus on larger and more diverse datasets, standardized acquisition and validation procedures, fruit-wise external testing, efficient wavelength selection and compact HSI or multispectral systems. Greater attention to real-time inline inspection, multimodal sensing, transfer learning and domain adaptation could further improve robustness across cultivars, instruments and operating conditions. Overall, successful implementation of HSI will depend not only on achieving high model accuracy, but also on ensuring reproducibility, robustness, processing speed and economic feasibility under practical postharvest conditions.

ACKNOWLEDGMENTS

The authors wish to express their sincere gratitude to Tamil Nadu Agricultural University for providing the necessary infrastructure and institutional support. The authors also acknowledge the Indian Council of Agricultural Research – All India Coordinated Research Project on Post-Harvest Engineering and Technology for their valuable guidance and support.

Author contributions

S. Manikandan: Conceptualization, Methodology, Investigation, Writing – original draft, Validation. **S. Parveen:** Conceptualization, Formal analysis, Validation, Writing – review & editing. **P. Rajkumar:** Formal analysis, Investigation. **Balaji Kannan:** Formal analysis, Investigation. **R. Kannan:** Formal analysis, Investigation.

Funding

No financial support was received for this study.

Data availability

No data were used for the research described in the article.

Conflict of interest

The authors declare that they have no conflict of interest.

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