THE JOURNAL OF HORTICULTURAL SCIENCE AND BIOTECHNOLOGY
https://doi.org/10.1080/14620316.2025.2489974

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REVIEW

An overview of non-destructive technologies for postharvest quality assessment in horticultural crops

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ABSTRACT
Artificial intelligence and machine vision are increasingly popular within food supply chains for automated decision making in quality grading and disease identification. There are many types of data that these models can be trained on, and choosing which information is needed is a critical factor in minimising both food loss and cost, while maximising the impact on food quality. Non-destructive technologies give information about crop phenotypes (e.g. external colour, oil content, sweetness) without damaging the crop, allowing a greater and more representative proportion the stored food to be analysed. These non-destructive technologies use different methods to analyse the product, each with different intrinsic capabilities and limitations. Therefore, choosing which technology is most appropriate for each application is a complex and costly decision. This mini-review summarises the physical and chemical basis of how some popular non-destructive technologies function, and how these different methods give unique advantages and limitations. The most popular technologies summarised include Red-Green-Blue (RGB) imaging, visible and near-infrared spectroscopy, and vibrometry. We also review technologies that are growing in popularity, including X-ray imaging, ultraviolet spectroscopy, and magnetic resonance imaging.

ARTICLE HISTORY
Received 31 January 2025
Accepted 2 April 2025

KEYWORDS
Spectroscopy; vibrometry; imaging; food loss; crop quality

Introduction

An estimated one third of all food grown globally is lost during postharvest storage (FAO, 2011, 2019). Facing pressure to feed an increasing global population, volatile yields from climate change, and disease risks, the need to minimise these postharvest losses has never been greater. Not only do we have physical losses of crops, but also quality and nutritional losses occur during postharvest storage (Yang et al., 2025), making it a critical stage for intervention, as highlighted by the United Nations Sustainable Development Goal 12.3. To achieve this, the physiological state of the produce needs to be regularly assessed to monitor senescence and quality changes, including early detection of disease, in order to deliver food to the consumer at their optimal physiological and organoleptic state.

Artificial intelligence (AI) and machine learning are huge topics currently both within scientific research and wider society. They are also commonly applied to monitor the quality of fresh fruit and vegetables during storage. In many cases, these computational decision-making tools use information collected from non-destructive technologies to assess produce physiology (reviewed by Tempelaere et al., 2023). These non-destructive technologies have been used across the food system for decades and continue to be developed and improved due to their advantages over the traditional destructive technologies. One advantage is not creating losses at each sampling stage, i.e. the tested produce is not wasted and can still be sold to the retail market. Also, because individual produce can be retested through storage, a larger and more representative portion, or all of the stock can be evaluated when compared to the destructive phenotyping methods. By ensuring that produce is at the highest possible quality when sold, consumers receive the most nutritious food and have higher satisfaction rates, while the reduced economic losses benefit farmers and other supply chain stakeholders (Gamble et al., 2010; Jaeger et al., 2016, 2018; Tempelaere et al., 2023).

However, the decisions on which non-destructive technology should be used in each stage of the supply chain must be carefully considered. This is because 1) the purchase and integration of the equipment into supply chains is time consuming and expensive; 2) models will need to be trained and validated; and 3) technologies have intrinsic limitations in what they can detect, and therefore using an inappropriate technology may lead to poor model outputs (Table 1).

RGB imaging

Image analysis has been long and widely used to assess and sort crops, with one of the earliest examples

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Table 1. An overview of the current most popular non-destructive technologies being used for postharvest crop physiology assessments. Price estimates are relative to one another, and will vary with suppliers and product specifications.

Technology	Price estimate	Major limitations
RGB imaging	$	Can detect surface-level attributes only. Only detects qualities visible to the human eye.
Point near infrared (NIR) spectroscopy	$$–$$$	Sensitive to temperature changes. Limited penetration depth. Quality measurements are often over-simplified e.g. TSS representing sweetness. Cannot provide spatially-resolved information.
Hyperspectral imaging	$$$$	Sensitive to temperature changes. Limited penetration depth.
Acoustics and vibrometry	$$	Cannot provide spatial information, only the average of the entire object. Interference from environmental noise (e.g. on packing lines).
X-ray and Computed Tomography (CT) imaging	$$–$$$	Acquisition time and resolution trade off.
Ultraviolet (UV) spectroscopy	$$$	Adds additional cost with each additional wavelength included.
Magnetic resonance imaging (MRI)	$$$$$	Hazardous magnetic fields produced during imaging. High cost.

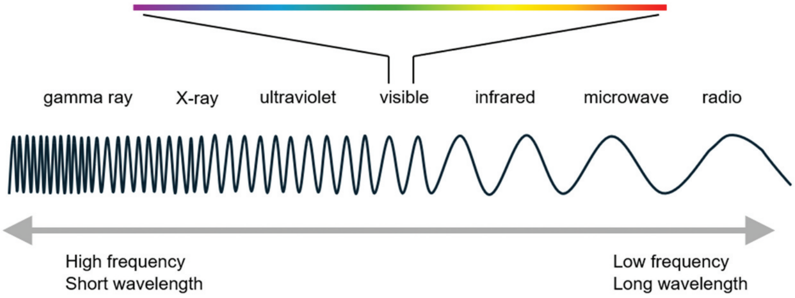

Figure 1. The electromagnetic spectrum.

coming from 1985 where Sarkar and Wolfe (1985) developed tomato classification models for size, shape, colour, and surface defects. It was later that RGB images were used, where one red, two green, and one blue sensors are used to mimic what is seen by the human eye, broadly dividing the visible spectrum (400 to 780 nm) into three parts (Nisha et al., 2021). RGB imaging coupled with machine vision still has several advantages over manual inspection, including consistent objectivity, the ability to analyse images more quickly, and the equipment is affordable. However, it can only assess surface-level features, such as damage, disease, size and shape.

While RGB imaging remains in use in many sorting/grading lines, there are lots of important physicochemical properties of plant material that do not appear within the visible spectrum or are not visible on the surface of the crop. The visible spectrum only accounts for a small portion of the total electromagnetic spectrum (Figure 1), and other postharvest technologies can make use of other wavelengths/frequencies either alone or in combination with the visible spectrum to evaluate quality traits not visible to the human eye.

Visible and near-infrared spectroscopy

While RGB cameras split the visible spectrum of light (400 to 780 nm) into three broad wavebands, many important biochemical compounds can be detected in the near infrared (NIR, 780 to 2500 nm) region. Measuring the scattering of light by plants within the vis-NIR region has allowed highly accurate estimation of water content (Anderson et al., 2020, 2021; Dirks & Poole, 2022; Mishra & Woltering, 2023), sugar content (Delwiche et al., 2008), and other biochemical compounds than can affect the spectrum in the NIR region (primarily through the stretching of O-H bonds (Rungpichayapichet et al., 2015; Hayati et al., 2020; Kusumiyati et al., 2021a, 2021b). It has also allowed for predictions of more complex traits based on their correlation to the chemical composition (and hence spectral information) such as firmness (Marques et al., 2016; Kasim et al., 2021; Mishra et al., 2020; Rungpichayapichet et al., 2016) and ripeness (Delwiche et al., 2008; Izneid & Al-Kharazi, 2013; Izneid et al., 2014) in mango. Because of this, vis-NIR spectroscopy has become one of the most widely used non-destructive technologies across postharvest supply chains (Anderson et al., 2020; Anderson et al., 2021; Kasim et al., 2021; Kusumiyati et al., 2021b; Delwiche et al., 2008; Dirks & Poole, 2022; Kusumiyati et al., 2021b; Mishra & Woltering, 2023; Tempelaere et al., 2023).

Vis-NIR spectroscopy can be generally broken down into different acquisition modes: reflectance, interactance, and transmission(Figure 2; Pasquini, 2003). The reflection and absorption spectra are often highly impacted by surface texture, which is common in fruit and vegetable skins. Transmission

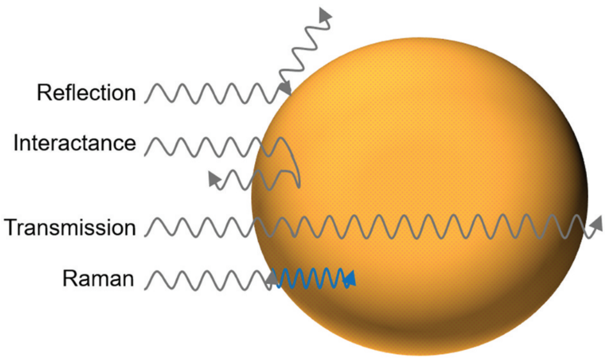

Figure 2. Different responses of light to the surface of an orange, which can be detected by different acquisition modes for spectroscopy. Electromagnetic radiation is introduced (grey arrows) and comes into contact with the object (orange). It can then reflect off the objects surface, be absorbed, interact with, or pass through the object without changing wavelength (elastic scattering). In Raman spectroscopy, a change in the wavelength is detected (blue arrow) as the light is inelastically scattered.

spectroscopy has a deeper penetration depth, and may be better at predicting internal properties than reflectance, but very little light tends to penetrate such large objects. Interactance provides some of the benefits of both transmission and reflectance modes, but requires a light seal between the detector and the surface (Schaare & Fraser, 2000). Raman spectroscopy, is another spectroscopic acquisition method that has been used for postharvest quality assessment, with growing interest in recent years that may translate to increased industrial applications in the near future (Andersen et al., 2023; Monago-Maraña et al., 2021; Wattanasan et al., 2024). However, like transmission, the Raman scattering is a weak phenomenon and therefore less utilised compared to vis-NIR spectroscopy for postharvest applications (Lan et al., 2022; Vaskó et al., 2024).

The use of spectroscopy has not been without fault. Some major considerations are that this technique is temperature sensitive (Walsh et al., 2020) and the penetration depth is relatively limited, which can especially affect fruits with thick peels (Rodríguez-Ortega et al., 2023). However, one of the most prevalent issues within these models is not due to the nature of the technology, but the assumptions made within the phenotyping methods chosen. For example, total soluble solids (TSS) are frequently used as a proxy for sugar content, and therefore is used as a sweetness and ripening indicator in many fruits throughout storage (Beckles, 2012; K. Kusumiyati et al., 2020). This gives several advantages over quantifying the sugars individually, as it is fast, cheap, and does not require specialist training to carry out the analyses. It is particularly favoured for use in spectroscopy, as it is an optical density measurement, and therefore intrinsically linked to the absorption/reflection of light. However, when investigating the relationship between TSS and the individual sugar concentrations, many papers have reported that a large proportion of these soluble solids are not sugars: 35% of TSS in tomato (Balibrea et al., 2006; Beckles, 2012) and 20% in orange (Kelebek et al., 2009). Additionally, no correlation was found between sugar content and TSS in mango fruit (O'Brien et al., 2024). Furthermore, TSS does not take into account the differences in sweetness between glucose, sucrose, and fructose, or the acid content, which both impact the perceived sweetness by consumers (Mao et al., 2019; Obenland et al., 2009).

Despite the challenges, the applications of vis-NIR spectroscopy have reached nearly every corner of the food system, from selecting seeds with the best germination potential (Xia et al., 2019; T. Zhang et al., 2020), to deciding when fruit have reached the optimal harvesting maturity (Bertone et al., 2012; François et al., 2009), to identifying which fruit are ripe for consumers (François et al., 2009; Bertone et al., 2012; Cortés et al., 2016; Blasco et al., 2016; Kasim et al., 2021; Mishra et al., 2020; O'Brien et al., 2024). A recent development has been 'ripeness checkers' for avocadoes appearing in supermarkets, which are believed to be based on NIR spectroscopy (Fruitnet, 2024; One Third, 2023). These devices have been appearing across several European countries in 2024, helping consumers select the fruit that are ready to eat, and avoiding shoppers squeezing the fruit, which may cause bruising. While there is limited information on the exact technology used, expanding the availability of these scanners to different countries, and applying them to different crops, may be the next step in reducing food waste in the household.

While the power of vis-NIR spectroscopy has long been clear, point spectroscopy does not provide information about the spatial distribution of chemical components within a sample. Most, if not all, crops have significant spatial variability in both chemical composition and physical properties, including in important quality indicators such as oil content and firmness in avocado (Landahl et al., 2009). There are also many postharvest disorders that appear in a spatially-distinct manner, such as bruising and chilling injury (Castillo-Girones et al., 2024; Guo et al., 2023) that may be missed if only a single point on the produce is assessed. In this context, and following the fundamentals previously described for vis-NIR spectroscopy, hyperspectral imaging (HSI) collects a complete spectrum from every pixel within an image of a sample (recently reviewed by Wieme et al., 2022 and summarised in Alamar et al., 2023).

As it requires the collection of many more spectra than point spectroscopy, HSI has also been slower, and therefore one of the major limitations in recent years has been acquisition time. However, with the development of snapshot (or single-shot) imaging methods acquisition speeds of hyperspectral images are considerably faster than previous modes (Kester et al., 2011). The acceleration of information acquisition is essential, as many companies integrate their non-destructive quality testing into grading lines, so that every individual piece of fruit or vegetable can be assessed and treated appropriately. While more slowly assessing a few selected crops from each batch is possible, assessing too few can mean the heterogeneity of the batch is not captured, then leading to the disposal of acceptable quality produce, or the sale of produce that should have been discarded (Tempelaere et al., 2023).

Acoustics and vibrometry

Another class of non-destructive technologies utilises the relationship between the resonant frequency (*f*), the natural frequency where the object will vibrate at the highest amplitude and the texture (Landahl & Terry, 2020; Padda et al., 2011; Sneddon et al., 2024; Zakaria et al., 2012). In most cases, these vibrations are measured through acoustic sensors, and therefore commonly called acoustics. However, other sensors (for example lasers, in laser Doppler vibrometry [LDV] [Landahl & Terry, 2020; O'Brien et al., 2024]) can also record the *f*, and therefore a more appropriate name for the category is vibrometry. The texture of a food product is one of the most important aspects to a consumer, but is often one of the most challenging to predict non-destructively (Landahl & Terry, 2020; O'Brien et al., 2024). This is partially because of its complexity, as texture consists of several interrelated factors such as juiciness, firmness, and stiffness. These factors are genetically controlled through cell wall architecture and cell-to-cell adhesion (Marín-Rodríguez, 2002), which change through fruit ripening and senescence, and are impacted by environmental factors including relative humidity (Hertog et al., 2004). Texture can also vary spatially within a crop (Okaniwa et al., 2022; One Third, 2023), and vibrometry can only give a single measure for the entire object. Despite this, LDV has been successfully applied to assess the texture of two stone fruits, avocado and mango (Landahl & Terry, 2020; O'Brien et al., 2024).

Currently, the most common industry practice to quantify texture is using the Magness-Taylor firmness, measured using penetrometers, which quantify the firmness by measuring the force needed to insert a probe to a specific depth into the flesh (Cooke, 1972). However, more detailed information can be obtained from force deformation curves, which highlight the complexity within texture phenotypes (Figure 3). While the Magness-Taylor firmness is most commonly recorded at a specific penetration depth, the maximum load can also be used. In

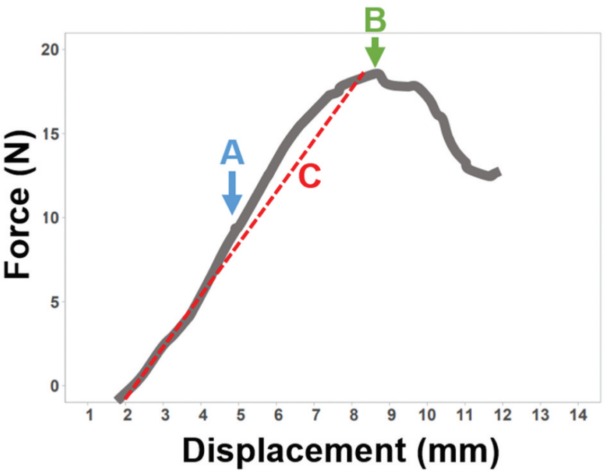

Figure 3. Force deformation curve of a slice of mango pulp. (A) the Magness-Taylor firmness based on a 3 mm penetration depth. (B) The maximum load, also an indicator of Magness-Taylor firmness. (C) The stiffness (S) is based on the slipe of the line (red, dashed) between the initial point of penetration and the maximum load. Based on data published in O'Brien et al. (2024).

vibrometry, the stiffness (S) is commonly used, and is a separate measure from the Magness-Taylor firmness that cannot be quantified using penetrometers. The use of S rather than Magness-Taylor firmness in vibrometry is based on the intrinsic relationship between the S and *f* of a material, outlined in Equation 1 (Cooke, 1972; Landahl & Terry, 2020).

$$S = f^2 m^{2/3} \tag{1}$$

Equation 1: The relationship between stiffness (S), resonant frequency (*f*), and the mass (m) in a spherical object of uniform material.

Like the previously discussed non-destructive technologies, vibrometry has several limitations, principally, the assumptions made in Equation (1). First, the equation assumes a spherical shape, which is not true of most fruits and vegetables. Secondly, many crops have significant textural variation within different tissues (e.g. stone, mesocarp, skin) which may contribute unequally to the *f*, where the equation assumes a homogenous internal structure. An example of how the complexity of texture phenotypes can impact supply chains is in mango, where both visible and vibrational predictions of texture have been investigated. O'Brien et al. (2024) found that while the *f* of mango could be quantified using LDV, it poorly predicted the Magness-Taylor firmness. The authors found that while *f* decreased linearly through time, the maximum load decreased exponentially. Instead of predicting maximum load, using vibration-based methods to predict the stiffness/elasticity of a crop may yield higher R^2 values (as *f* and S are related through Equation (1). However, the continued reliance of retailers on penetrometers (Magness and Taylor, 1925; Padda et al., 2011) means that this approach could lead to crops being rejected at one point of the supply chain that would be accepted at other points. Crucially, the predictions of texture using vis-NIR spectroscopy can be improved by using vibration-based methods, rather than destructive methods (Valente et al., 2011). Using acoustic-texture measurements as a reference variable has led to some of the highest reported R^2 values for mango firmness prediction using vis-NIR spectroscopy (Kasim et al., 2021; Mishra et al., 2020), which may not reflect their accuracy in predicting penetrometer firmness, and thus cause additional food waste if implemented in the wrong supply chains.

Other technologies

While the technologies discussed above are the majority of those currently used in postharvest management of fresh produce, there are many other approaches to assessing the physiology and quality of crops, including X-rays, ultraviolet (UV) spectroscopy, and magnetic resonance imaging (MRI). There are also many examples of new technologies being developed specifically for or adapted to postharvest applications, such as a soft gripper that measures fruit firmness (Valente et al., 2009) and electronic nose sensors, which can detect volatile substances to identify decay in peaches (Lin et al., 2023).

X-rays can be used to visualise internal density changes, either giving two-dimensional information, or sequential images being compiled for three-dimensional computed tomography (CT) information (Nisha et al., 2021). Many different diseases and disorders can lead to changes in density, including internal rot (Wei et al., 2018), flesh browning (Matsui et al., 2023), and shrivelling (Matsui et al., 2025). Like spectroscopy, X-ray imaging has different modes suited to different applications, where dark-field radiography is better when detecting low-porosity areas, and absorption radiography is better for high-porosity areas. A high resolution is necessary for the detection of most physiological disorders, but a quick assessment is necessary for a technology to be integrated into high-throughput sorting lines. This trade-off is the major limitation to CT being used in more postharvest supply chains (Janssen et al., 2020; Zhang et al., 2024).

The UV portion of the electromagnetic spectrum is broadly broken down into the UV-A (320–400 nm), UV-B (280–320 nm, which can alleviate oxidative stress during storage (Li et al., 2019), and UV-C (200–280 nm, which has been used to extend postharvest storage potential with its antimicrobial properties [Shang et al., 2025]) wavebands. A number of recent vis-NIR spectroscopy studies have also included wavelengths across the UV spectrum (Bertone et al., 2012; Joshi et al., 2022; Melado-Herreros et al., 2021; Xin et al., 2024). While some of these studies produce high-quality models, the inclusion of additional wavelengths incurs additional cost, and can lead to longer analysis times.

MRI has been shown to produce highly detailed information about crop physiology in the past few decades (Musse et al., 2009; Taglienti et al., 2009; Ullah et al., 2019; L. Zhang & McCarthy, 2013). This technology utilises strong magnetic forces to align the protons in a sample, which are then offset by a radiofrequency pulse, which, when removed, allow the protons to realign with the magnetic field, releasing energy. The energy released and time taken for the change are used to form an image (Vlaardingerbroek & Boer, 2013; Fyfe et al., 2023). This can provide information about the structure of the produce, such as water accumulation, air pockets, and surface topography (Musse et al., 2009; Ullah et al., 2019). Vis-NIR spectroscopy has limited penetration depth, typically giving information only for the few millimetres of tissue nearest the surface (Rodríguez-Ortega et al., 2023), but MRI can image all areas within the object (Fyfe et al., 2023). Unlike X-rays, they do not use ionising radiation, but the magnetic fields are so strong they pose a significant safety risk if any magnetisable objects are present, such as iron and steel, found in essentially every step of the food supply chain. MRI is also one of the most expensive of the possible technologies for postharvest quality assessment. Because of these limitations, MRI is currently only used to gain a better understanding of the changes in tissue micro- and macrostructure during processes such as ripening, rather than being implemented within real supply chains (Nisha et al., 2021; Tempelaere et al., 2023; L. Zhang & McCarthy, 2013).

Conclusions and future prospects

Food loss and waste affects our social, economic, and environmental systems negatively (Gage et al., 2024). Given that postharvest losses can account for a third of the world's crops (Food and Agriculture Organization of the United Nations FAO, 2011, 2019), this is a critical point for intervention and innovation. An effective way of reducing these losses is using non-destructive technologies to assess crop quality, ensuring diseased produce is removed immediately and crops are delivered to the consumer at their optimal ripening or maturity stage, minimising quality losses during storage. Significant developments have been made in data processing and computational modelling techniques over recent years, including chemometrics and machine learning algorithms (Dirks & Poole, 2022; Mishra & Woltering, 2023; Mishra et al., 2020; Nisha et al., 2021; Tempelaere et al., 2023). These have enabled faster assessment times, allowing higher crop volumes to be assessed, and for these technologies to be seamlessly integrated into fast-moving production lines. However, selection of the appropriate technology on which these models can be built remains a challenge. When comparing technologies based on different physical principles, although they may share a similar goal of reducing food losses, each will be uniquely suited to specific applications within that food chain. Therefore, understanding the strengths and limitations of the technologies currently available is an integral step in creating a net-zero food system towards a greener future.

The number of studies published mentioning non-destructive technologies for postharvest applications grew from only ~ 300 in 2004, to ~ 1,000 in 2014, to nearly 4,000 in 2024 (based on Google Scholar results). This highlights the fact that, while our understanding of postharvest physiology is growing, and our applications of new technologies expanding, so are the challenges caused by climate change, geopolitical affairs, and diseases. Therefore, we need to commit to implementing these technologies in industrial settings, innovating new technologies for crop quality assessment, and continually increasing model performance through improved data analysis including machine learning and AI.

Acknowledgements

This work was funded by Orchard House Foods Ltd. and Cranfield University through the Cranfield Industrial Partnership PhD Scheme.

Data sharing is not applicable to this article as no new data were created or analysed in this study.

Disclosure statement

No potential conflict of interest was reported by the author(s).

Funding

This work was funded by Orchard House Foods Ltd. and Cranfield University through the Cranfield Industrial Partnership PhD Scheme.

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2025-10

O'Brien C, Alamar MC. (2025) An overview of non-destructive technologies for postharvest quality assessment in horticultural crops. The Journal of Horticultural Science and Biotechnology, Volume 100, Issue 5, October 2025, pp. 628-636

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