Anjali et al.
Food Production, Processing and Nutrition (2024) 6:56
https://doi.org/10.1186/s43014-023-00205-5

Food Production, Processing and Nutrition

REVIEW

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State-of-the-art non-destructive approaches for maturity index determination in fruits and vegetables: principles, applications, and future directions

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Abstract

Recent advancements in signal processing and computational power have revolutionized computer vision applications in diverse industries such as agriculture, food processing, biomedical, and the military. These developments are propelling efforts to automate processes and enhance efficiency. Notably, computational techniques are replacing labor-intensive manual methods for assessing the maturity indices of fruits and vegetables during critical growth stages.

This review paper focuses on recent advancements in computer vision techniques specifically applied to determine the maturity indices of fruits and vegetables within the food processing sector. It highlights successful applications of Nuclear Magnetic Resonance (NMR), Near-Infrared Spectroscopy (NIR), thermal imaging, and image scanning. By examining these techniques, their underlying principles, and practical feasibility, it offers valuable insights into their effectiveness and potential widespread adoption. Additionally, integrating biosensors and AI techniques further improves accuracy and efficiency in maturity index determination.

In summary, this review underscores the significant role of computational techniques in advancing maturity index assessment and provides insights into their principles and effective utilization. Looking ahead, the future of computer vision techniques holds immense potential. Collaborative efforts among experts from various fields will be crucial to address challenges, ensure standardization, and safeguard data privacy. Embracing these advancements can lead to sustainable practices, optimized resource management, and progress across industries.

Highlights

1. Recent advancements in signal processing and computation drive interest in computer vision across industries.
2. The review focuses on non-destructive methods in fruits and vegetables.
3. Computational techniques replace manual methods for maturity index determination.

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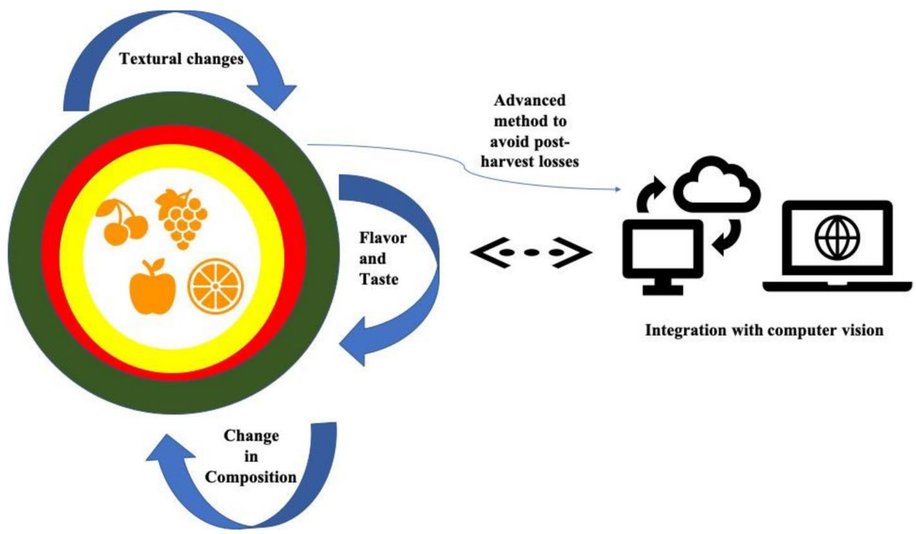
4. The principles of techniques are highlighted, along with their successful applications.
5. The potential of computation techniques in destructive, non-destructive methods, biosensors, and AI summarized.

Keywords Computational techniques, Biosensors, Machine learning, Maturity index, Fruits and vegetables

Graphical Abstract



Introduction

Incorporation of fruits and vegetables into our daily diet is essential for overall health, providing vital nutrients and contributing to disease prevention (Slavin et al. 2012). However, sourcing high-quality produce can be challenging, and ensuring timely delivery to consumers is crucial (Tata et al. 2022). The etymology of "fruit" and "vegetable" adds an interesting twist to our understanding of these dietary components, with Latin roots suggesting concepts of enjoyment, growth, and flourishing (Vidal et al. 2013; Vijayakumar and Vinothkanna 2020). These natural health capsules are rich in carbohydrates, minerals, vitamins, and dietary fibers, playing a role in the prevention of various diseases like cardiovascular conditions and cancer. Scientific studies consistently highlight the connection between their consumption and reduced chronic diseases (Magwaza et al. 2015). Nevertheless, assessing the maturity of fruits and vegetables accurately has been a traditional, manual, and labor-intensive process, often reliant on subjective judgments by experienced personnel (Prasad et al. 2018). Compared to traditional methods of maturity index determination for fruits and vegetables, the integration of state-of-the-art computer vision techniques represents a significant advancement. Traditional approaches often rely on manual and labor-intensive assessments, which are inherently subjective and time-consuming. These methods are prone to errors, lack consistency across different evaluations, and can result in delays in the supply chain. Moreover, destructive techniques used in traditional assessments involve disintegrating the produce, leading to product loss and waste (Vyawahare et al. 2013; Karunathilake et al. 2023).

The recent advancement in the field of computer vision has revolutionized various industries, with agriculture benefiting significantly from computer vision applications. The evaluation of maturity is a crucial step in the supply chain, impacting quality, taste, and marketability (Naik et al. 2017). While traditional methods have been somewhat effective, they are prone to errors, time-consuming, and lack consistency across different evaluations. Moreover, destructive techniques used in traditional assessments, such as disintegrating the produce, lead to product loss and waste (Gupta et al. 2022a). To overcome these challenges, researchers and technologists have turned to state-of-the-art computer vision approaches, leveraging image processing, sensor-based solutions, and artificial intelligence (AI) models to automate and optimize the maturity assessment process (Xiao et al. 2023; Dhanya et al. 2022; Cárdenas-Pérez et al. 2017).

AI models play a pivotal role in grading produce based on factors like size, shape, and color, significantly influencing market acceptability. These models, trained on extensive datasets, excel at accurately categorizing fruits and vegetables, offering scalability and adaptability (Xiao et al. 2023). Pre-processing methods, including data augmentation, normalization, Principal Component Analysis (PCA), and Convolutional Neural Networks (CNN), further enhance accuracy and efficiency. Mobile applications powered by AI and neural networks have made it user-friendly, allowing consumers to snap a picture and receive instant quality feedback (Naranjo-Torres et al. 2020).

Moreover, sensor-based techniques, utilizing emitted gases to determine maturity index, offer non-invasive and real-time insights into physiological changes, aiding timely harvesting and supply chain management. These advancements encompass both destructive techniques, involving high-performance chromatography methods, and non-destructive methods like Near-Infrared (NIR) spectroscopy, Nuclear Magnetic Resonance (NMR), and Raman Spectroscopy-imaging, providing rapid and efficient evaluation while minimizing waste (Gupta et al. 2022a).

As global populations grow and resources dwindle, the integration of computer vision in agriculture becomes imperative for sustainable practices. Combined with precision agriculture, computer vision optimizes the entire supply chain while reducing environmental impact. Compared to traditional methods of maturity index determination, computer vision techniques offer greater accuracy, efficiency, and scalability, making them a transformative solution in the field of maturity assessment for fruits and vegetables. This review aims to provide a comprehensive understanding of the principles, applications, and future directions of computer vision in this field, contributing to the advancement of sustainable and efficient agricultural practices worldwide.

Collection of literature data

To collect data, we conducted a systematic review using the Scopus and Google Scholar databases. Initially, we employed various keywords, resulting in varying paper counts for different search queries. Specifically, we identified 192 papers related to "Fruits and vegetables + Biosensors," 114 papers for "Fruits and vegetables + Maturity Index," 4 papers for "Fruits and vegetables + Biosensors + Machine Learning," 342 papers for "Fruits and vegetables + Machine Learning," 714 papers for "Fruits and vegetables + Maturity," and 59 papers for "Fruits and vegetables + Maturity Detection using Biosensors" from Scopus. In addition, Google Scholar yielded 329 papers for "fruits and vegetable" AND "maturity detection," 9 papers for "Fruits and vegetables" AND "maturity detection" AND "Biosensor," 194 papers for "Fruits and vegetables" AND "maturity detection" AND "Machine learning," and 105 papers for "Fruits and vegetables" AND "maturity detection" AND "Machine learning" AND "Sensor." For a detailed screening process, please see to Fig. 1.

Maturity indices of fruits and vegetables

Maturity refers to the stage of development when produce has completed its natural growth and is ready for harvest, facilitating proper ripening. However, horticultural maturation is determined based on utilization purposes. Specific maturity indices must be developed for each commodity due to significant variations. Harvesting fruits at an immature stage often leads to their inability to ripen, resulting in a firm texture, low flavors, and susceptibility to internal breakdown and wooliness during extended cold storage (Doerflinger et al. 2015). Maturity indices play a crucial role in determining the ideal harvest time, providing marketing flexibility, and ensuring acceptable eating quality for consumers. These indices consider factors such as chronological age, size, shape, surface characteristics, color, firmness, soluble solids, abscission layer development, surface morphology, tenderness, sugar and starch presence, sweetness index (sugar-to-acid ratio), and oil content. Fruits and vegetables are classified into physiological maturity when development reaches a sufficient stage while attached to the plant, and horticultural/commercial maturity when they exhibit desired characteristics for consumers (Arefi et al. 2015; Kang et al. 2008; Khaled et al. 2015). The stages of development, ripening, maturation, and deterioration are predictable for most horticultural food products, varying from early harvest for certain crops like sprouts and salad crops, to late harvest for seeds or nut crops based on consumer preference (Kurita et al. 2006; Kyriacou and Rouphael 2018; Mehinagic et al. 2004). Detailed information on the maturity indices and determination methods for selected fruits and vegetables is provided in Table 1.

Methods of maturity determination

Destructive methods

Measurements of physical, chemical, and sensory properties of texture and their relationships are essential. A sensory test is a method through which the qualities of agricultural yields are evaluated based on the senses of touch, smell, taste, sight, or hearing. Individuals are well-prepared for this task, scoring the instances based on specified properties. Furthermore, sensory tests can be complemented by physical and chemical measurements (Gupta et al. 2022b). Synopses of these techniques

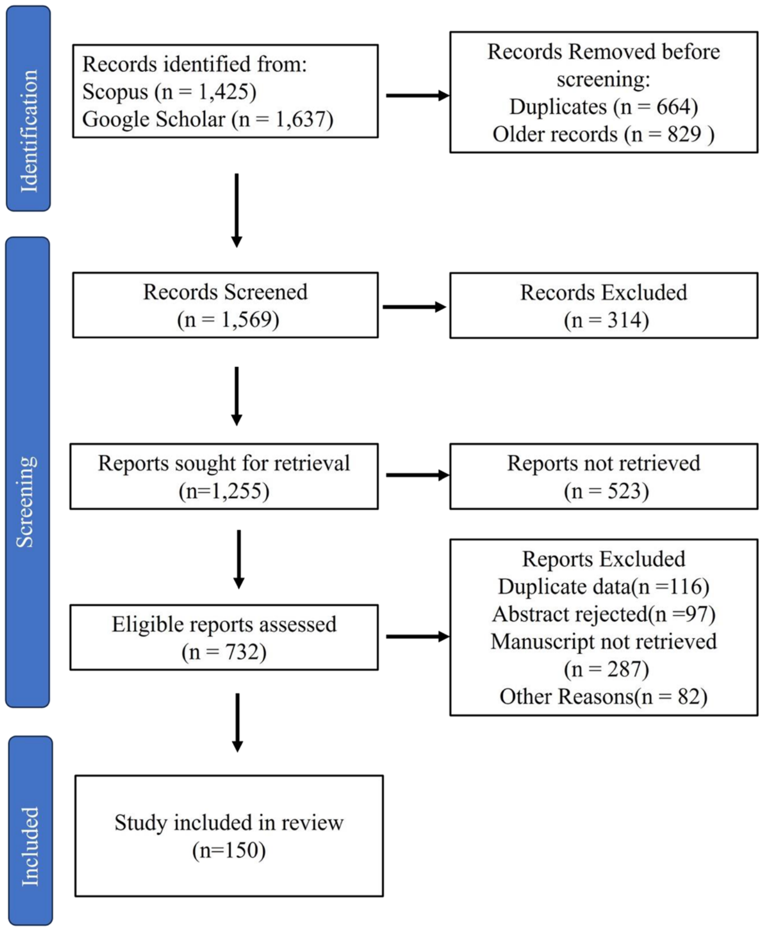


Fig. 1 Study selection for review (PRISMA criteria described in Moher et al. 2014)

applied to mealiness identification in potatoes and apples follow below:

Various tests, including puncture, twist, tensile, and Kramer shear tests, as well as recording of chewing sounds, can be conducted to elucidate the textural attributes of apples, as assessed by a taste panel. The puncture test has been identified as the most effective method for describing crispness, crunchiness, hardness, juiciness, ease of disintegration, and mealiness (Pereira et al.2018; Surya Prabha and Satheesh Kumar 2015). As mentioned earlier, the level of juiciness and softness in apples is also related to mealiness. Crispiness can serve as a good indicator of softness. Several other methods have been employed to assess the crispiness of apples by analyzing chewing sounds. This involves investigating the relationship by recording the chewing sounds with a microphone placed near the mouth and utilizing Fourier transformation to record signals. However, this test may not yield highly significant results, as chewing speed and techniques vary among individuals (Kurita et al. 2006; Kyriacou and Rouphael 2018; Mehinagic et al. 2004).

In recent years, chewing has been replaced by invented devices. In this method, acoustic systems have been integrated into the standard measurement tools for assessing the mechanical characteristics of tissues. Consequently, a microphone can record the sound produced during mechanical tests, such as penetration tests. Hence, it can be concluded that the compression test is preferable for identifying mealy apples because it simultaneously measures free juiciness and flesh stiffness (Vidal et al. 2013; Vijayakumar and Vinothkanna 2020).

Raman spectroscopy can be employed to detect changes in the amount of tannin in pomegranate fruits as they mature. Tannins are a class of polyphenolic biomolecules with astringent properties, capable of binding and precipitating proteins, as well as other organic components like amino acids and alkaloids. They are present in both fruits and vegetables (Vargas-Murga et al. 2016), and their significant health benefits have garnered increased interest. Tannins are chromoplasts, which are fat-soluble

Table 1 Maturity indices of selected fruits and vegetables and their methods to determine (Prasad et al. 2018)

Non-Destructive	Fruits/Vegetables	Methods
Calendar date	All fruits	
Size and Shape	All fruit, beans, carrot, cucumber, cheery asparagus, and cauliflower	Vernier Calliper
Colour	All fruits, tomato, muskmelon, apple, pears, mango, papaya and watermelon	Munsell Colour chart, Colourimetry
Specific Gravity	Cherries, Mango	Displacement Method (Archimedes principle)
Optical Properties	Apple, Tomato	NMR, NIR, Raman Spectroscopy, UV–VIS Spectroscopy and Thermal Imaging
Surface Morphology	Grape (cuticle formation), banana, and litchi	Magnetic Resonance Imaging (MRI) and Surface Electron Microscope (SEM)
Destructive Method		
TSS	All fruits, tomatoes, and melons	Hand held Refractometer, Abbey's Refractometer
Firmness/Texture	Pome and stone fruits, beans, lettuce, and muskmelon	Penetrometer, Universal Texture Analyzer, Pressure Gauge
Juice Content	Citrus fruits	Volume
Titrable Acidity	Pomegranate, citrus fruits, papaya, and kiwifruit	Analytical Chemistry
Oil Content	Avocado	Soxhlet Apparatus
Moisture content	All fruits	Karl fischer method and Conventional Hot Air Oven
Volatile compounds Naringin, Limonene (Bitterness) Tannin (Astringency)	Citrus fruits Persimmon and dates	GCMS, LCMS, HPLC, Spectrophotometer
Sugar	Pome, stone fruits, and grape	Alcohol Test, Phenol -sulphuric acid for reducing sugar
Respiration Rate (Ethylene Content	Apple and pears	Biosenser connected tom respirator chamber

microconstituents with crucial functions, antioxidant properties, and physiological effects (Both et al. 2018). Pomegranate fruit (*Punica granatum* L.) is among the most productive fruits, primarily found in tropical and subtropical regions, including India, Iran, Afghanistan, as well as Mediterranean countries like Morocco, Spain, Italy, Turkey, Egypt, and other Middle Eastern countries (Khodabakhshian and Emadi 2016). It contains high concentrations of tannins, carotenoids, phenolics, flavonoid glycosides, flavones, flavonols, and flavoxanthin (Hmid et al. 2017). Furthermore, the concentration of these phytochemicals changes as the fruit matures. Pomegranate fruit has an astringent flavor in its early stages of development, closely linked to increasing tannin content as the fruit ripens. Therefore, it is crucial to develop effective and efficient methods for determining the optimal harvesting period for pomegranate fruit to ensure the highest quality accepted by consumers. While visible spectrophotometry and high-performance liquid chromatography (HPLC) have been the standard techniques for determining tannin presence in recent years, numerous novel and suitable analytical methods are being introduced. Raman spectroscopy is one such method, providing quick and in-situ analysis, offering information on chemical and structural molecules, and enabling multiple analyses with minimal sample preparation (Boyaci et al. 2015). The International Pharmacopoeia and Association of Official Analytical Chemists (AOAC) methodologies were employed with minor modifications to analyze tannin concentration in pomegranates.

In FT-Raman spectroscopy, cross-sections of cut pomegranates undergo analysis within a specific spectral range spanning from 100 to 3000 cm^{-1}. This analysis involves the use of a Bruker FRA106 Raman module and Opus 5.5 acquisition software, with laser excitation at 1064 nm. The laser spot employed during the examination is approximately 100 µm in size, and the power of the laser applied to the pomegranate samples is set at approximately 100 mW. To ensure accurate and reliable data, the experiment involves obtaining 1000 scans, each with a spectral resolution of 4 cm^{-1}. This is achieved using a Thermo Nicolet NEXUS 870 spectrometer, manufactured by Thermo Electron Corp, based in Madison, Wisconsin, U.S.A. By utilizing this specialized instrumentation and precise parameters, researchers can extract valuable information regarding the molecular composition and characteristics of pomegranates, contributing to a deeper understanding of their properties and potential applications.

Non- destructive methods

The raising awareness of consumers in high quality of foods directs the producers to a reliable, rapid, non-destructive, and noninvasive technique for maturity determination, especially during harvesting and packaging processes. Therefore, in recent years, the application of nondestructive, noninvasive, and noncontact methods and designing new instruments for food quality determination have been the focus of interest by researchers (Yahaya et al.2014; Yang et al. 2021). These techniques are becoming more favored and practical compared to destructive techniques as nondestructive methods allow the measurement and analysis of individual fruit, reduce waste, and permit repeated measurements on the same item (Arendse et al. 2018). Different quality parameters have been determined in several agricultural products by a variety of nondestructive methods. These methods are based on optical, mechanical, electrical, and electromagneticmeasurements (Pourkhak et al. 2017; Mireei et al. 2015). Nuclear magnetic resonance imaging (NMRI) (Suchanek et al. 2017; Zhang et al. 2012), Raman imaging (Munera et al . 2017), ultraviolet (UV), NIR, mid-infrared (MIR), electronic nose (e-nose) (Srivastava and Sadistap 2018), ultrasonic technique (Ikeda et al. 2015), and machine vision (Hitchman et al. 2016) are some widely used nondestructive methods. Non-destructive fruit ripeness assessment offers numerous advantages over conventional destructive procedures, including high throughput evaluation, concurrent multiple measurements, and real-time decision-making capabilities. As fruits ripen, they undergo complex phenotypic changes, transitioning from green, hard, and immature to more colorful, softer, sweeter, and aromatic states (Uluışık et al. 2018).

Destructive measures, due to the large number of samples needed, are time-consuming and cannot simultaneously evaluate all quality parameters in the field. Consequently, the need for simple and representative non-destructive measurements arises to determine fruit ripeness effectively (Vanoli et al. 2020). In this context, several works examine modeling techniques for predicting the ideal harvest time and non-destructive methods for assessing fruit freshness (Zaborowicz et al. 2017). These predictions are based on spectroscopic and/or imaging methods that quantify the color and/or spectral characteristics of fruits, reflecting changes in their molecular makeup during ripening. The functions and applications of non-destructive method techniques are discussed in Table 2, providing a comprehensive understanding of the strengths and limitations of both destructive and non-destructive approaches. By critically examining the latest research and technological advancements in this field, we aimed to contribute to the ongoing development and implementation of innovative practices in the fruit industry.

Visible / Near Infrared Spectroscopy (NIRS)

NIRS is founded on the fundamental principles of spectral absorption and reflection, where near-infrared light interacts with the chemical composition of fruits. This interaction is governed by the vibrations of chemical bonds in organic molecules, with each compound exhibiting characteristic absorption bands in the NIR spectrum. The heart of NIRS lies in its calibration models, constructed through the relationship between known chemical compositions and measured spectral data during a training process. The electromagnetic spectrum's range from 780 to 2500 nm is covered by NIRS (Gupta et al. 2022a). Utilizing mathematical algorithms, NIRS quantitatively analyzes fruit samples, providing rapid and non-destructive estimations of critical parameters like sugar content and moisture levels. This non-invasive nature of NIRS, coupled with its ability to reveal the chemical makeup of fruits, makes it an invaluable tool in fruit maturity estimation, ensuring the quality and integrity of fruit produce while supporting efficient agricultural and food industry practices (Pandiselvam et al. 2022).

NIRS finds wide-ranging applications in the realm of maturity determination due to its non-destructive and rapid analytical capabilities. One primary application lies in the assessment of fruit ripeness. NIRS can accurately determine key indicators of maturity, such as sugar content, acidity, and moisture levels, without the need for invasive sampling. This information is invaluable for growers and producers as it helps them determine the optimal harvest time, ensuring fruits reach their peak flavor and nutritional value. Moreover, NIRS is instrumental in quality control during post-harvest handling and processing. It enables the quick sorting and grading of fruits based on their maturity, allowing for the segregation of ripe fruits from those that need more time to ripen. This not only reduces food waste but also enhances the efficiency of supply chains. Additionally, NIRS facilitates the monitoring of fruit quality during storage and transportation, helping to prevent spoilage and maintain product integrity. In sum, the application of NIRS in maturity determination empowers the agricultural and food industries to make informed decisions that improve both product quality and overall operational efficiency (Pandiselvam et al. 2022).

It helps in fruit sorting and grading and is more suited to practical application. This technique measures the skin tone of fruits like bananas, apples, tomatoes, and mangoes to assess fruit maturity (Fig. 2). The skin colour is influenced by how much chlorophyll is found there. The changes in pigmentation can be used to gauge the maturity of fruits. As the fruit ripens the chlorophyll content starts decreasing (Chauhan et al. 2017). Ravindran et al.

Table 2 Non-destructive methods to determine quality characteristics of fruits and vegetables (Zhang et al. 2014; Dhiedt et al. 2021; Gupta et al. 2022a)

Non-destructive technique	Quality characteristics	Function	Advantages	Limitations
Impact test	Firmness and internal damage	The primary function of an impact test is to assess the toughness and resilience of materials, especially metals and polymers	Relatively simple and standardized testing procedures are available for various materials	It may not capture the complete behavior of a material under dynamic loading conditions
NMR	Maturation, freeze burn, heat injury worm infestation, sugar content, moisture, and oil content	NMR spectroscopy measures the interaction of atomic nuclei with magnetic fields	NMR can determine the 3D structure of molecules, making it invaluable for identifying compounds and elucidating molecular structures	NMR can determine the 3D structure of molecules, making it invaluable for identifying compounds and elucidating molecular structures
MRI	Freeze burn, morphology,core breakdown and insect infestation	MRI, or Magnetic Resonance Imaging, is a medical imaging technique that uses strong magnetic fields and radio waves to create detailed images	MRI does not involve ionizing radiation, making it safer than some other imaging methods	MRI machines are expensive to purchase and maintain, making the procedure relatively costly
X-ray	Moisture content, freeze burn, enzymatic browning, bruises, tissue damage and insect infestation	The primary function of X-ray is to check tissue damage, insect infestation, enzymatic browning etc	X-ray imaging is generally quick, providing rapid results for medical and industrial applications	Incorrect use or overexposure to X-rays can be harmful, so proper safety measures are crucial
NIR	Total soluble solids, firmness, acidity, sugar content, freeze burn,post-harvest damage, fat and protein content	NIR spectroscopy is a non-destructive analytical technique that utilizes the near-infrared region of the electromagnetic spectrum (typically 780–2500 nm) to analyze the composition of materials	NIR spectroscopy allows for the analysis of samples without altering or damaging them	NIR spectroscopy is surface-sensitive and can only analyze the outer layer of a sample, limiting its use for certain applications
Acoustic	Firmness, internal defects, and cavity detection	Acoustic technology refers to the use of sound waves to transmit, receive, or process information. It has various applications across different fields	Acoustic technology can operate in various media, including air, water, and solids. This versatility allows it to be applied in diverse fields and environments	The resolution of acoustic imaging systems may not be as high as some other imaging modalities like MRI
UV–VIS spectroscopy	Carotene, chlorophyll, and tannin	It involves measuring the absorption of ultraviolet (UV) and visible (VIS) light by a sample to obtain information about its electronic structure, concentration, and chemical composition	UV–VIS spectroscopy is versatile and can be applied to a wide range of compounds, including organic and inorganic molecules, ions, and biomolecules	High-quality UV–VIS spectrophotometers can be expensive, which can be a limitation for some laboratories
Fluorescence spectroscopy	Freshness, ripeness, and surface blemishes	In fluorescence spectroscopy, a sample is exposed to a specific wavelength of light (the excitation wavelength), typically from an external light source such as a laser or lamp	Fluorescence spectroscopy is highly sensitive and can detect even trace amounts of fluorescent compounds in a sample	One of the significant limitations of fluorescence spectroscopy is that the sample must contain fluorescent molecules or be labeled with fluorescent probes. Not all compounds exhibit fluorescence
Ultrasound	Maturity defects,sugar content, firmness moisture and oil content	Ultrasound in food processing is a technology that utilizes high-frequency sound waves to manipulate, analyze, or process food products	Ultrasound is generally more cost-effective compared to other imaging techniques like MRI	Ultrasound may have lower resolution compared to other imaging modalities like MRI or CT, making it less suitable for detailed imaging of certain structures

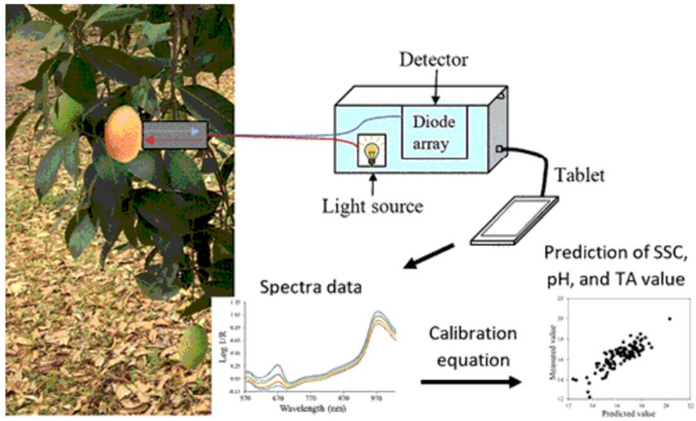


Fig. 2 Measurement of plum fruit quality using VIS/NIR (Source: Posom 2020)

(2015) had used NIR approach to test fruit firmness and find output whether if there are any obvious flaws. Using this method, it is possible to test soluble solid content, dry matter, hygroscopicity, hardness, sugar content, acidity, etc. without the need for any special equipment.

Lan et al. (2020) conducted a study on apple quality, utilizing spectral details to predict various parameters, including viscosity, cell wall content, dry matter, soluble solids content (SSC), and puree product titratable acidity (TA) (Lan et al. 2020). The spectral measurements encompassed a range of 800–2,500 nm and employed an automatic sampling wheel with 18 different positions. However, it was noted that methods utilizing six optical fibers or manual positioning appeared to be more realistic and accurate, possibly due to the consistency of the sampling wheel setup. Notably, SSC determination yielded a high R^2 value of 0.92, underscoring the method's effectiveness in assessing puree product homogeneity (Lan et al. 2020).

Further investigations into NIRS applications revealed its efficacy in predicting parameters like soluble solids, glucose, malic acid, and dry matter in calçot onions and apple purees (Lan et al. 2021; Sans et al. 2018). These studies highlighted the successful use of spectral analysis for quality evaluation of purees. Khodabakhshian et al. extended NIRS analysis to pomegranates, employing both transmittance and reflectance modes in the 400–1,100 nm range, and employed pretreatments such as standard normal variate (SNV) and multiplicative scatter correction (MSC) to account for morphological variations in pomegranate varieties (Khodabakhshian et al. 2019).

Hu et al. (2019) conducted an extensive study on SSC determination in Hami melons, exploring various measuring configurations, variable selection algorithms, and classification models. The calyx model emerged as the most effective, likely due to higher SSC content in the calyx region. This underscores the importance of precise measurement location for accurate predictions. A similar study on apples incorporated multiple orientations, with the stem-calyx vertical orientation with the stem upward proving optimal (Xia et al. 2019). Various combinations of variable selections and prediction algorithms indicated that the Monte Carlo–uninformative variable elimination–successive projections algorithm (MC-UVE-SPA) achieved the best results for SSC determination (Rp > 0.8) (Hu et al. 2019). Xia et al. (2019) found that competitive adaptive reweighted sampling-subwindow permutation analysis-partial least square (CARS-SPA-PLS) performed well for SSC prediction in apples, with a low root mean square error of prediction (RMSEP) of < 0.573° brix. They also emphasized the importance of determining effective wavelengths from a global model to mitigate orientation effects.

Texture assessment, a critical factor in evaluating agricultural product quality, involves parameters like firmness and penetrometer readings (Camps and Gilli 2017; Sharma and Sirisoomboon 2019). Some studies have explored additional parameters such as fracture force, hardness, and compressive energy (Mohammadi-Moghaddam et al. 2018). These parameters can distinguish between varieties, making them essential for quality evaluation. Firmness, for instance, correlates with maturity and oil content in olives (Cirilli et al. 2016). Prediction of firmness, although complex, has yielded promising results, such as R^2 values at peak regions using PLS regression in olives (Cirilli et al. 2016) and a high R^2 value of 0.966 in cherry tomatoes using an extreme learning machine algorithm (Feng et al. 2019). Compression and penetrometer tests were performed concurrently on tomatoes, with the compression test demonstrating superior prediction performance ($R^2 = 0.85–0.97$) (Camps and Gilli 2017). Additionally, a study on juicy stone fruits emphasized the significance of the compression test as the fruit matures (Labaky et al. 2020). Clustering of data may contribute to improved R^2 values, although RMSE values may exhibit less variation (Camps and Gilli 2017).

The integration of NIRS in fruit maturity testing has laid a solid foundation for future advancements. To further enhance its capabilities, multi-sensor fusion with other sensing technologies, advanced machine learning algorithms, and the development of portable NIRS devices for field applications are critical directions. Standardization and calibration across diverse fruit types, the implementation of online monitoring systems, and the creation of user-friendly consumer applications can ensure the widespread adoption of NIRS. Additionally, addressing environmental considerations and promoting sustainability in NIRS deployment will be essential. These future directions collectively hold the potential to not only refine fruit maturity assessment but also empower growers, producers, and consumers to make informed decisions, reduce food waste, and contribute to more efficient and sustainable fruit production and consumption practices.

Nuclear Magnetic Resonance Techniques (NMR)

NMR spectroscopy, NMR relaxometry, and magnetic resonance imaging are all components of the nuclear magnetic resonance imaging (MRI). NMR spectroscopy operates on the principles of nuclear spin and magnetic resonance. In the context of fruit maturity testing, the principle involves the interaction of hydrogen nuclei (protons) within the water molecules present in the fruit tissue with a strong magnetic field and radiofrequency pulses (Chauhan and Singh 2012; Surya Kiran and Niranjana 2019). Protons possess a magnetic moment, and when placed in a magnetic field, they align with or against the field. When radiofrequency pulses are applied, they cause these protons to temporarily deviate from their alignment. As these protons return to their equilibrium state, they emit radiofrequency signals, which are detected and analyzed. The NMR instrument measures the time it takes for these signals to decay, known as relaxation times (T1 and T2), and the intensity of the signals. These relaxation times and signal intensities provide information about the physical and chemical properties of the fruit, including water content, mobility, and molecular interactions (Ebrahimnejad et al. 2018).

This method can be used to determine a sample's water and oil content. Although the pace of measurement is slow, MRI may produce high resolution images of the internal architecture of intact fruit. The assessment of water and oil is impacted by the presence of other dietary elements in the sample. The ice crystals created in food limit the spatially situated NMR signals, making them useful in determining the freeze damage caused during storage (Newton et al. 2017; Yodh 2017).

NMR spectroscopy is widely employed for assessing fruit maturity by determining key parameters without causing sample damage. One critical parameter in fruit maturity assessment is water content, which changes as fruits ripen. NMR enables precise and non-destructive measurements of water content variations during ripening stages. Additionally, NMR facilitates the measurement of sugar content and soluble solids, including sugars and organic acids, which tend to increase as fruits mature. This information serves as a valuable indicator of maturity. Furthermore, NMR can assess fruit texture and firmness by analyzing alterations in the molecular structure and mobility of water in fruit tissues, correlating with changes in fruit texture. This aids in pinpointing the optimal harvest time. Importantly, NMR's non-destructive nature preserves sample integrity, making it suitable for quality control and research applications where destructive methods are unsuitable. It can seamlessly integrate into quality control and sorting systems, ensuring the selection of ripe, high-quality fruits for distribution, ultimately reducing food waste and elevating product quality (Nicolai et al. 2007; Borba et al. 2021).

In a similar study, the authors aimed to explore the potential applications of Low-Field Nuclear Magnetic Resonance (LF-NMR) and MRI techniques in the study of water dynamics and the measurement of quality parameters in fruits and vegetables. The methodology involved an extensive literature review to gather insights from existing research, followed by conducting LF-NMR and MRI experiments on various fruit and vegetable samples. The acquired data allowed for the analysis of water dynamics within these samples, revealing correlations between relaxation times and physiological changes during ripening and aging. Furthermore, LF-NMR and MRI demonstrated their capability to measure critical quality parameters, such as moisture content, sugar levels, texture, and firmness, offering non-destructive and accurate assessments. This study concluded that LF-NMR and MRI hold substantial potential for enhancing the understanding of water behavior within agricultural produce and improving the assessment of their quality. Future objectives include refining methodologies, diversifying applications, integrating artificial intelligence, and promoting industry adoption of these technologies for more efficient quality control in the agricultural and food sectors (Kamal et al. 2019).

In summary, NMR spectroscopy leverages nuclear spin and magnetic resonance principles to provide insightful information about fruit maturity. Its non-destructive capabilities and proficiency in measuring water content, sugar levels, and fruit texture position it as a powerful tool for fruit maturity testing and quality control within the agricultural and food industries.

Time-resolved Reflectance Spectrometry (TRS)

TRS is founded on the principle of measuring the time delay between a short light pulse's emission and the detection of the reflected or transmitted light. This delay, known as the time-of-flight, is influenced by the interaction of light with the internal structure of fruit samples. TRS operates based on the concept that different tissue structures and compositions within fruits will scatter light in unique ways, affecting the time it takes for light to travel through the sample. By analyzing these time-resolved measurements, TRS can provide valuable insights into the internal properties of fruits, including water content, pigmentation, and tissue density, which are critical indicators of fruit maturity (Zerbini et al. 2009; Vanoli et al. 2011; Rizzolo et al. 2015).

In the context of fruit maturity assessment, TRS has diverse applications. Firstly, it can be utilized to non-invasively determine water content, a parameter that changes during fruit ripening. As fruits mature, water content often diminishes due to various physiological processes (Rizzolo et al. 2015). TRS can precisely quantify these changes, aiding in the accurate assessment of fruit ripeness. Additionally, TRS can provide information about pigment composition and concentration within fruits, helping to assess attributes like color development and anthocyanin levels, which are indicative of maturity (Vanoli et al. 2011). Furthermore, TRS can be used to evaluate the density and structural properties of fruit tissues, such as cell wall integrity and firmness, offering valuable data for assessing the overall quality and ripeness of fruits. In summary, TRS is a powerful optical technique that can non-destructively assess various parameters related to fruit maturity, contributing to improved fruit quality and efficient harvesting practices (Zerbini et al. 2006).

In a study conducted by Zerbini et al. (2006), the research aimed to assess the potential of TRS as a non-destructive tool for evaluating nectarine maturity at harvest and developing a predictive model for nectarine softening during storage. The methodology involved TRS measurements on nectarine samples at various ripeness stages during the harvest season. Key parameters such as water content, pigment composition, and tissue density were analyzed using TRS. These measurements were then correlated with traditional destructive methods and sensory evaluations to establish a comprehensive dataset for model development. The observations demonstrated that TRS accurately assessed nectarine maturity at harvest and predicted their softening behavior during storage. This research concluded that TRS holds significant promise as a valuable tool for optimizing harvest timing and post-harvest handling in the fruit industry. Future objectives include refining predictive models, expanding application to other fruit varieties, and integrating TRS into commercial fruit management practices to enhance quality and reduce waste.

Similarly, Zerbini et al. (2009) aimed to investigate the practical application of TRS as a management tool within the fruit supply chain, specifically in an export trial involving nectarines. To achieve this, a comprehensive methodology was implemented. Nectarine samples at different ripeness stages underwent TRS analysis to assess parameters like water content, pigment composition, and tissue density. These TRS measurements were taken at critical points along the export supply chain, including pre-harvest, post-harvest, and transportation. Observations revealed that TRS provided real-time insights into fruit maturity, facilitating precise timing for harvest and post-harvest decisions. The study concluded that TRS could significantly enhance fruit quality and ripeness management in the export supply chain. Future objectives include further refining TRS methodologies for a wider range of fruit varieties and integrating real-time data analysis to optimize fruit quality and minimize losses during export (Zerbini et al. 2009).

Recently, a study was undertaken to explore the non-destructive determination of ripeness in melon fruit utilizing TRS. The methodology involved conducting TRS measurements on melon samples at various stages of ripeness. Key optical parameters, including fluorescence decay times and reflectance spectra, were collected and analyzed using TRS techniques. These measurements were then correlated with traditional destructive methods, such as firmness and soluble solid content assessments, to establish a comprehensive dataset for model development. The observations indicated a strong correlation between TRS-derived optical parameters and melon fruit ripeness. The study concluded that TRS could effectively serve as a non-destructive tool for determining ripeness in melon fruit. Future objectives include refining the TRS models, expanding the application to different melon varieties, and integrating TRS into quality control processes to enhance fruit quality assessment and reduce waste (Vanoli et al. 2023).

Despite its promise, TRS also presents challenges. It requires specialized equipment and expertise, making its implementation costly and complex. Additionally, TRS models may need further refinement to accommodate a broader range of fruit varieties and conditions, including different ripening patterns and textures.

Looking ahead, the future scope of TRS in fruit maturity assessment is promising. Refinement of TRS methodologies, integration of real-time data analysis, and its application to a wider range of fruit varieties are essential goals. By addressing these challenges and objectives, TRS has the potential to revolutionize fruit quality management in the agricultural and food industries, leading to improved fruit quality, reduced waste, and enhanced consumer satisfaction.

X-ray

X-ray radiography is a non-destructive technology that offers valuable insights into the internal properties of fruits by displaying density differences using grayscale levels. This enables the identification of healthy fruits and those with pest damages while classifying them without the need for destructive sampling (Abdshaib et al. 2017; Diels et al. 2017). The varying densities inside fruits, influenced by factors such as water content, hard tissues, insect pest holes, hollowness, and corruption, are represented by different grayscale levels. X-ray radiography has found practical applications in fruit quality classification and disease detection, particularly in citrus fruits. Additionally, it has been utilized for sorting mature lettuce heads, assessing mango and tomato ripening based on tomography, and detecting surface defects in fruits using appearance images (Lenker et al. 1971; Barcelon et al. 2000; Brecht et al. 1991; Hernández-Sánchez et al. 2016). Furthermore, X-ray radiography plays a role in fruit quarantine by capturing and analyzing fluoroscopy images to identify problematic areas (Iqbal et al. 2018; Jiang et al. 2008). However, it is important to note that while X-ray radiography can provide valuable qualitative analyses of fruit surfaces and internal structures, it primarily yields 2D and 3D images, unlike x-ray computed tomography (CT scanning) (Chauhan et al. 2017). With its ability to detect variations in density and water content, X-ray radiography holds promise for assessing fruit maturity and identifying internal flaws associated with physiological anomalies, ultimately contributing to enhanced fruit quality and reduced waste in the agricultural and food industries. The objective of the study by Hsiao et al. (2021) was to assess and investigate the feasibility of using X-ray imaging and information visualization for the ripeness assessment of lemons (Fig. 3). The methodology involved acquiring X-ray images of lemon samples at different ripeness stages and employing image processing techniques to extract relevant information. This information, including internal features and density variations within the lemons, was visualized and analyzed to determine the correlation between X-ray images and lemon ripeness. The results indicated that X-ray imaging combined with information visualization showed promise as a non-destructive method for assessing lemon ripening, with the capability to distinguish between different ripeness stages based on internal characteristics. However, a drawback of the study was the limited sample size, and future directions may involve expanding the research to a larger dataset, refining the image analysis algorithms, and exploring the application of this approach to other fruits for broader implications in the fruit industry.

Acoustic Impulse Response Method (AIRM)

The AIRM is based on the principle of analyzing sound wave propagation through fruits to assess their internal properties, which can provide valuable information about fruit maturity. This non-destructive technique involves sending an acoustic impulse or pulse, typically in the form of a brief sound wave, into the fruit (Yamamoto et al. 1980). As the sound wave travels through the fruit, it interacts with the internal structures and properties, including density, moisture content, and texture. These interactions cause the sound wave to be reflected or refracted in different ways, resulting in a unique acoustic response or signature. By analyzing this impulse response, it is possible to gain insights into the fruit's internal characteristics, such as ripeness, firmness, and moisture content. The AIRM finds applications in various aspects of fruit maturity assessment. One primary application is the determination of fruit firmness, which is a crucial indicator of maturity and quality. As fruits ripen, their firmness often changes due to alterations in cell structure and water content. The method can accurately measure this parameter by analyzing the speed and attenuation of sound waves passing through the fruit. Additionally, the method can be used to assess moisture content in fruits, which is another key factor in determining maturity. By evaluating the acoustic properties related to water content, it becomes possible to monitor the fruit's moisture levels as it ripens.

In the acoustic impulse response method utilized by Fathizadeh et al. (2019) and Yamamoto et al. (1980), a ball weighing 2 g and 8.5 g, respectively, is employed as an impactor. When this ball impacts the fruit, the resulting sound is captured by a microphone. Subsequently, Fourier transformation is applied to the captured sound data, allowing for the identification of the largest resonant frequency. This prominent frequency is then utilized to calculate the firmness index, a key parameter indicative of fruit quality. The schematic representation of the test apparatus used for implementing the acoustic impulse response method, illustrating the setup and components involved in this non-destructive technique for assessing fruit firmness.

The acoustic impulse resonance frequency (AIF) technique utilises the natural frequencies of the whole fruit, which are obtained by recording the sound made by striking the fruit, and then applying a Fourier transformation

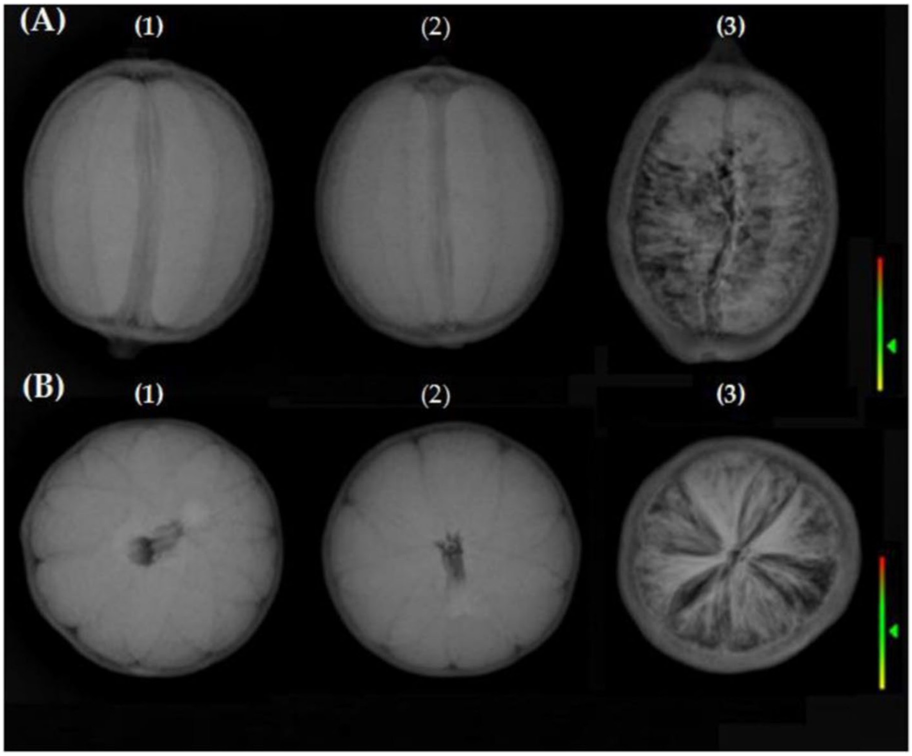


Fig. 3 X-ray radiographic images of (1) fresh, (2) mature, and (3) overripe lemons acquired at **A** median-plane and **B** axial-plane of the lemons. (Source: Hsiao et al. 2021)

to the recorded signal (Muramatsu et al. 2015). The frequency and mass of the fruit can be used to compute the stiffness factor for spherical fruit. This method includes measuring the resonance frequency that fruits produce, which changes as the fruits grow. Assessing the interior quality and ripeness of fruits involves calculating the impact response the fruit produces when a force is applied. The outcomes are delicate and rely on different characteristics (Chauhan et al. 2017).

Similarly, a non-destructive method for assessing the internal quality of fruits, specifically apples and watermelons, using the acoustic impulse response technique. The methodology involved subjecting intact fruits to an acoustic impulse and measuring the resulting vibrational response. By analyzing the natural frequency derived from these acoustic responses, the researchers aimed to correlate this parameter with the internal quality attributes of the fruits. The results indicated that the natural frequency obtained through the acoustic impulse response method was a promising indicator of fruit quality. It demonstrated sensitivity to variations in fruit texture and internal attributes, such as firmness and juiciness. However, a drawback of the study may have been the need for specialized equipment and calibration procedures, which could limit its practical application. Future directions in this research could involve further refinement of the method, including the development of user-friendly tools and protocols for wider implementation in the fruit industry. Additionally, exploring the method's applicability to a broader range of fruit types and sizes would enhance its utility in non-destructive quality assessment (Yamamoto et al. 1980).

Fathizadeh et al. (2020) developed a nondestructive method for predicting the firmness of apple fruits using acoustic vibration response, as firmness is a crucial quality parameter in apples. The methodology involved sample preparation with apples of varying ripeness levels, employing an acoustic vibration system to induce surface vibrations on the fruits and recording their acoustic responses using sensors. Data analysis comprised extracting features like frequency and amplitude from the acoustic data. A calibration model was constructed, correlating these acoustic features with reference firmness values obtained through traditional destructive testing. Validation confirmed the model's potential in accurately predicting firmness nondestructively. While promising, this approach should address sample variability and undergo further validation on a broader range of apple samples. Future directions may focus on enhancing accuracy, real-time applications, multimodal approaches, and automation, offering significant improvements in fruit quality assessment practices.

Ultrasonic

The evaluation of fruit ripeness and maturity is paramount for optimizing harvesting, transportation-marketing, and consumption (Chauhan et al. 2017; Magwaza and Tesfay 2015). However, ripe fruit is highly susceptible to mechanical damage, microbiological decay, and physiological deterioration. In this context, the application of ultrasonic technology emerges as a promising nondestructive solution (Cao et al. 2010). Ultrasonic methods offer several advantages, such as cost-effectiveness, robustness, reliability, and safety for fruits, making them a preferred choice among nondestructive techniques (Kim et al. 2009; Morrison et al. 2014; Valente et al. 2013; Lee et al. 2013).

Ultrasonic measurement relies on changes in the attenuation and velocity of ultrasonic waves, which are sound waves with frequencies higher than the human hearing limit. These waves interact with matter through absorption and scattering, and these interactions can be correlated with internal fruit factors (Awad et al. 2012). Parameters like acidity, viscosity, and sugar content can be evaluated through ultrasonic methods, with velocity and attenuation being dependent on the physical properties of the fruit and the frequency of sound propagation within the fruit (Mizrach 2004; Mizrach 2008; Kuo et al. 2008). While ultrasonic methods have proven fast, accurate, and nondestructive for fruit quality evaluation, existing ultrasonic systems have limitations, particularly in non-laboratory and field applications. Furthermore, these systems are typically designed for specific fruit species, lacking versatility. To address these issues, a custom-designed ultrasonic system was developed, enabling users to adjust frequency, amplitude, pulse repetition frequency, and the number of pulses in a burst. Notably, this system offers a broader frequency range from 10 kHz to 10 MHz, in contrast to market devices that often start at 500 kHz. This flexibility is crucial for monitoring fruit quality in various scenarios, including picking, storing, packaging sites, as well as laboratory-based applications.

Nevertheless, nondestructive ultrasonic methods alone are insufficient for comprehensive fruit quality assessment. To obtain a holistic understanding, it's essential to acquire physical characteristics such as size, shape, and volume. By combining a custom-designed ultrasonic system with a non-contact physical measurement unit, superior fruit quality assessment can be achieved. Yildiz et al. (2019) aimed to create a complete nondestructive quality evaluation system using (a) ultrasonic testing and (b) volume estimation through automatic machine vision techniques. This approach involved programmable ultrasonic components, piezoelectric probes, an oscilloscope, and computer-based systems for ultrasonic testing (Fig. 4). Additionally, a machine vision system captured multiple fruit images for volume calculation. This method demonstrated the potential for highly accurate quality assessment (Yildiz et al. 2019). Mizrach (2000) developed a nondestructive ultrasonic measurement system to assess transmission parameters related to the maturity, firmness, and quality of avocado and mango fruits. Low-frequency probes measured ultrasonic signal attenuation, which changed as the fruit ripened and softened. Statistical analysis revealed quantitative relations between ultrasonic parameters and fruit quality attributes, such as oil content, dry weight percentage, and firmness. These findings open avenues for nondestructive assessment of fruit maturity and firmness, eliminating the need for invasive methods (Mizach, 2000). In another study, the characteristics of fruit tissue and its maturity stage were determined by measuring the attenuation coefficient and wave velocity of ultrasonic waves as they passed through the fruit. The study focused on Tabrizi variety peaches at different ripeness stages. Results showed strong correlations between attenuation coefficient and hardness, as well as wave velocity and pH and acidity. This research provides valuable insights into nondestructive methods for assessing fruit quality and maturity (Abolghasemi et al.2009). In conclusion, non-destructive ultrasonic methods, when combined with physical measurements and advanced technologies, offer a promising approach for evaluating fruit quality and maturity. These techniques not only enhance our understanding of fruit characteristics but also provide practical solutions for the industry's needs, from harvesting to storage and beyond.

Image processing

Color perception is a critical sensory attribute influencing consumer acceptance of food products. Ensuring consistent color and appearance in food items relies on accurate color measurement techniques. Recent advancements in computer vision technology, driven by camera-computer systems, have enabled automated detection systems for agricultural and food products. Computer vision involves image capture, processing, and analysis, providing an objective and non-destructive approach to assess visual quality in food products. Owing to hardware and software advancements, cost-effective solutions have emerged, leading to the increased adoption of computer vision systems within the food industry. These systems offer non-destructive and cost-efficient means for sorting and grading

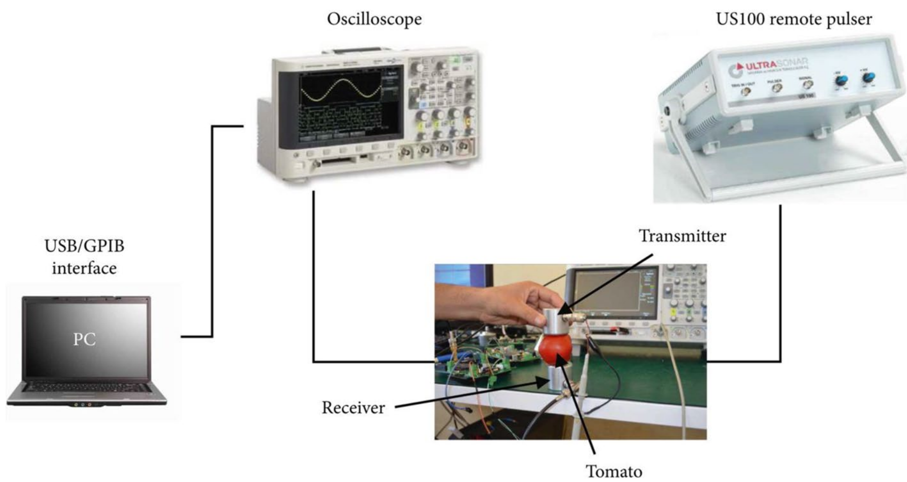


Fig. 4 The schematic view of the ultrasonic measurement experimental setup. (Source: Yildiz et al. 2019)

agricultural and food products during processing and for commercial applications (Xiao et al. 2023).

The process of quality inspection for fruits and vegetables using image processing techniques generally comprises five steps: Image acquisition, Pre-processing, Image segmentation, Feature extraction, and Classification (Fig. 5). Image acquisition is a critical initial step, as the quality of the acquired image significantly affects subsequent processing outcomes. Various tools, including cameras, ultrasound, MRI, electrical tomography, and computed tomography (CT), are employed for image acquisition. Digital images are generated using complementary metal oxide semiconductor (CMOS) and charged coupled device (CCD) image sensors (Bhargava et al. 2021).

A typical computer vision system consists of five fundamental components: lighting, an image capture board (digitizer or frame grabber), a camera, computer hardware, and software. In fruit and vegetable analysis, lighting systems are categorized as front and back lighting. Front lighting assesses surface quality attributes such as color, texture, and skin defects, while back lighting is utilized for evaluating boundary quality attributes like size and shape. Conventional, spectral, and hyperspectral computer vision systems have been extensively studied for quality analysis of food and agricultural products (Bhargava et al. 2021).

Color is a vital factor impacting consumers' decisions regarding fruits and vegetables. It indirectly reflects quality attributes such as freshness, desirability, variety, maturity, and safety, influenced by physical, chemical, biochemical, and microbial changes occurring during growth, ripening, and postharvest processing. Color features are essential for image retrieval and indexing, with the RGB color space, hyperspectral imaging (HSI) color space, and CIE-LAB color space being commonly used. Various color features, including color correlogram, color coherence vector, color moments, and color histogram, have been proposed for color extraction. Among these, color moments, such as mean, standard deviation, and skewness, are widely utilized. While the RGB color model is popular for image capture, it lacks linearity with human vision and requires transformation techniques to standardize values. In contrast, the HSI color space is preferred for color-based algorithms, closely resembling human perception (Kuswandi et al. 2011; Gupta et al. 2022a). However, it is less suitable for evaluating color transformations during processing. The CIE-LAB color space, designed as a device-independent model, offers cognitive uniformity, representing color differences perceived by humans as Euclidean distances in the CIE-LAB space. This makes it a suitable method for assessing object color (Table 3).

Hyperspectral imaging technique

Hyperspectral imaging technique was used to classify the background and growth stages of blueberry fruit. Four information theory-based band selection methods alongwith machine and deep learning were applied to assess the performance of the selected bands by the four methods. The selected bands attain 88% and higher accuracies of classification. Therefore, the maturity stages of blueberry fruit can be detected using the band selection methods, which are capable of reducing the volume of the hyperspectral data and constructing a multispectral imaging system (Yang et al. 2014). A similar study was investigated by Munera et al. (2017), where the hyperspectral images of unripe, mid-ripe, and ripe strawberries were used to extract spectral

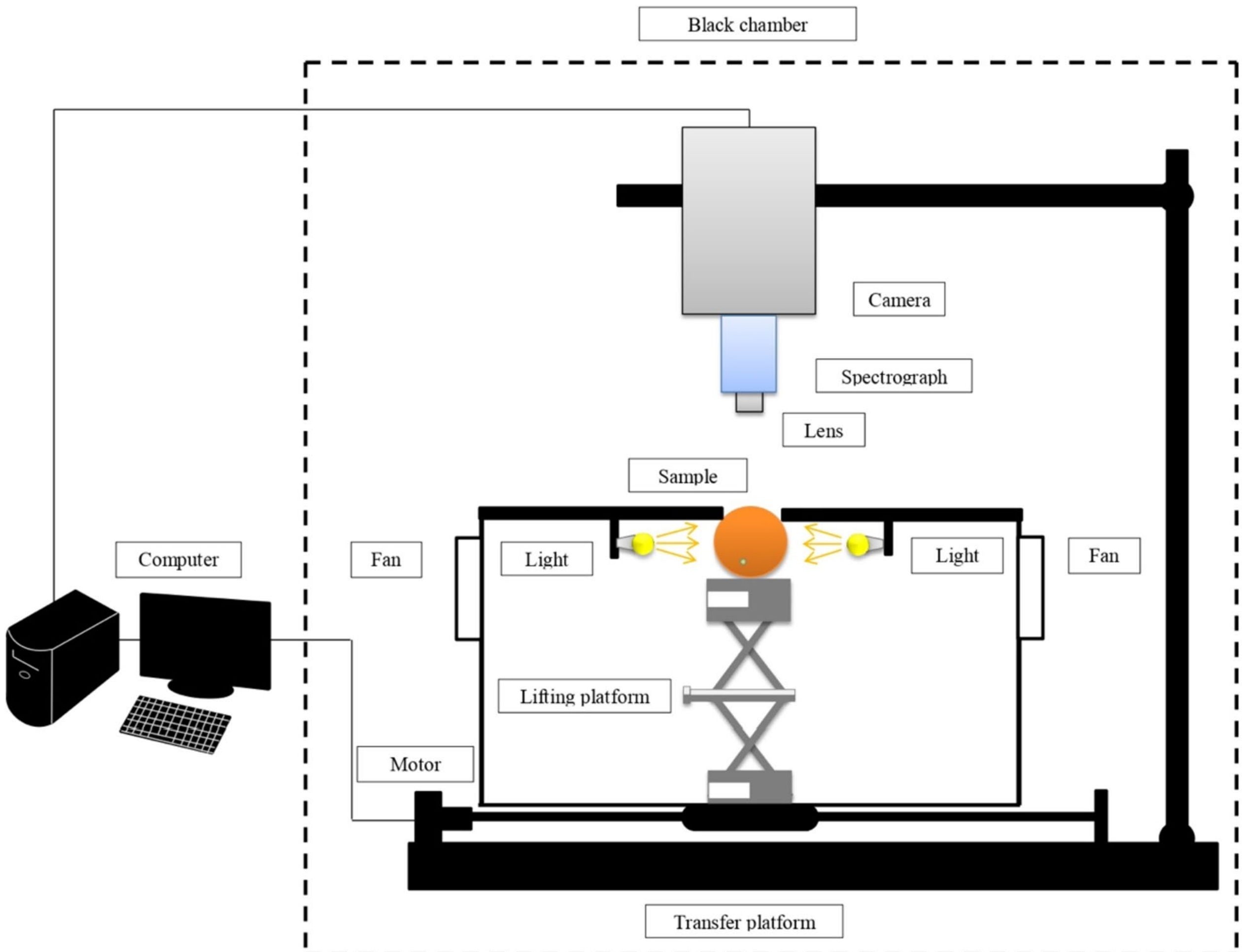


Fig. 5 A classical computer vision system. (Source: Wei et al. 2017)

Table 3 Comparison summary of intelligent systems in fruit packaging container

Technology	Purpose	Advantages	Disadvantages
Electrochemical Ethylene Sensor	Determine the quality of fruit produce Determine the rate of respiration and ripening in fruits by detecting ethylene concentrations released by the fruit	Ethylene sensitive Can be used in individual and bulk packaging Less expensive than NDIR	Susceptible to chemical interference (can be internally mitigated) More costly than indicators
Capacitive Humidity Sensor	Determine the package environment's quality Determine the relative humidity of the package	Accurate and can be used in bulk packaging	Individual packaging is expensive and impractical
RFID	Identify and convey package details Package data should be sent to an exterior processing unit	Scalable, simple to read and real time monitoring system	Active tags can be costly External infrastructure is required
Freshness Indicators	Determine the quality of the packaging environment and the fruit produce Detect the passage of various factor threshold limits (temperature, gas composition disruption)	Scalable, simple to read	Neither quantifies data nor used as sensors

data for evaluation of ripeness of strawberry using hyperspectral imaging. The optimal wavelengths were acquired between spectra of 441.1–1013.97 and 941.46–1578.13 nm by loadings of PCA. The images obtained were used to extract optimal wavelengths and pattern texture features such as contrast, correlation, homogeneity and entropy. To build classification models on full spectral data, texture features, optimal wavelength and the combined dataset of texture features, and optimal wavelengths, respectively, support vector machine (SVM) was used. Among all datasets, SVM models using combined datasets performed the best. The SVM models using datasets from hyperspectral images at 441.1–1013.97 nm gave a better performance with 85% or more classification accuracy. Munera and co-worker assessed the efficacy of hyspectral reflectance imaging for the evaluation of internal quality and sensorial attributes by means of Ripening Index (RPI) and the Internal Quality Index (IQI) of 'Big Top' and 'Magique' nectarines (*Prunus persica* L. Batsch var. nucipersica). During the ripening of fruit under controlled conditions, the hyperspectral images of the whole fruits were taken, and their physicochemical properties were also determined. The correlation coefficient was found higher than 0.87 for the two cultivars and indices. The partial least square (PLS) models and IQI have shown promising results for further monitoring of the nectarine maturity in industrial setups (Munera et al. 2017). In a similar study, HI was examined by Yan et al. (2017) in fresh cut celeries to calculate soluble dietary fiber (SDF) and insoluble dietary fiber (IDF) contents and visualize their spatial distribution during 28-day of storage periods. A superior techniques, Genetic synergy interval partial least square (GA-Si-PLS) algorithm and Si-PLS were developed to establish a calibration model to achieve the highest prediction performance. The developed GA-Si-PLS models were then applied pixel-wise to visualize the spatial distribution of IDF and SDF contents during storage successfully. The study determines that HSI could be helpful in real-time IDF and SDF contents monitoring in industry and vegetable research. Recently, the maturity and ripening stages of fruits has been productively examined by thermal imaging (TI). Fresh palm fruit was successfully classified into five stages using two TI camers and different approaches were selected designate the relation between the stages of maturity of palm fruits (Zolfagharnassab et al. 2016).

Hongwiangjan et al. (2015) evaluated pomelo maturity using peel optical properties and characteristics. A multivariate classifying model with the discriminant analysis is developed using optical parameters and peel related variables. The accuracy of classifying all samples into mature, late-mature, early-mature, and immature groups was 83.3%. A variation of green color between the oil gland and the peel surface was the most distinctive difference between a group of the immature and the early-mature pomeloes from a group of the late-mature and mature pomelos.

Artificial intelligence

AI techniques have gained significant traction in the horticultural, agricultural, and food industries, offering opportunities for the development of intelligent systems, particularly with the introduction of machine learning (ML). ML, a subset of AI, employs algorithms to discern patterns in data and make informed decisions (Nturambirwe & Opara 2020). With the increasing affordability and accessibility of computing power, the integration of AI and ML in hyperspectral imaging system research is witnessing a surge. The success of AI in hyperspectral imaging can be attributed to its advantages over RGB imaging. AI techniques applied to hyperspectral imaging data can uncover correlations with quality parameters that may elude the naked eye due to the richness of spectral and spatial data in a single image. This synergy between hyperspectral data and advanced AI techniques opens new avenues for enhancing the quality control of fresh produce.

Efforts to discover effective food assessment methods are centered on enabling efficient control and evaluation of food products. In this context, artificial intelligence methods supported by computer analysis prove invaluable for various decision-making processes and tasks related to food processing and preservation. Non-invasive technologies with minimal costs are imperative for ensuring high-quality food products, and image processing technology has gained increasing popularity in this context. Computer vision technology, a pivotal component of image processing, finds diverse applications, encompassing the identification, dimensioning, and quality assessment of kernels, tubers, vegetables, and fruits. It is also instrumental in pest identification, the evaluation of muscle and joint health, analysis of drying processes, fruit color and classification, as well as leaf area measurement. Researchers have developed various image processing-based systems, such as the Liming and Yanchao strawberry classification system, which categorizes fruits based on their size, shape, and color (Al-Sammarraie 2022). While commercial software can assist in data analysis, its limitations may impede scientific progress. Researchers are increasingly turning to new algorithms and data analysis workflows, often developed using free programming environments like Python or Octave. Open-source projects like Orange data mining software provide standardized data processing workflows for various machine learning problems, streamlining data processing and analysis (Nakhle et al. 2021).

The potential of artificial intelligence systems has piqued the interest of scientists for future applications. An example is the use of artificial neural networks to non-invasively recognize orange flavor based on a color space model. A study conducted by Al-Sammarraie et al. (2022) explored the relationship between RGB values of orange fruits and their sweetness, determining the algorithm with the highest prediction accuracy. This interdisciplinary research bridges the gap between AI, image processing, and food science, presenting exciting prospects for future advancements in quality assessment and flavor recognition.

The integration of hyperspectral imaging with artificial intelligence techniques holds immense promise in revolutionizing the evaluation of fruit and vegetable quality. By harnessing the power of AI and machine learning, researchers and industries can unlock the potential of non-destructive and cost-effective methods for assessing produce attributes, ultimately enhancing freshness, flavor, and overall consumer satisfaction. As the fields of computer vision, image processing, and AI continue to advance, we can anticipate further innovative solutions that will drive the food industry towards more efficient and accurate quality control measures. With a growing emphasis on data analysis, open-source platforms like Orange data mining software offer invaluable resources for researchers to develop and implement cutting-edge algorithms. The pursuit of artificial intelligence systems in food science represents a significant leap forward in addressing the challenges of modern food assessment and holds immense potential for shaping the future of quality evaluation in the agricultural and food sectors (Lu et al. 2017).

Artificial Neural Network (ANN)

ANN is employed for the detection of fruit samples' shape, size, and color. To ensure widespread usability, the android mobile platform was chosen, making the proposed model accessible to numerous users. This image-based computer vision approach allows for non-destructive assessment and grading of fruit and vegetable quality. For evaluating the quality of oranges, SVM was utilized. Similarly, the firmness of kiwifruit is predicted using ANN and linear regressions to determine its quality. The effectiveness of image-based grading using various machine learning algorithms is demonstrated and explained. An Android app is developed to distinguish between naturally and artificially ripened fruits. Additionally, an image processing-based approach is implemented to count calories based on extracted features from an image. Furthermore, vegetable quality is measured using an ANN-based technique. These advancements in artificial intelligence and image processing hold great promise for enhancing the accuracy and efficiency of quality assessment in the fruit and vegetable industry. The utilization of ANNs in the evaluation of fruit and vegetable quality has gained significant attention in recent years. ANNs are powerful machine learning algorithms capable of learning complex patterns from data, making them well-suited for tasks such as detecting the shape, size, and color of fruit samples. By employing ANNs, researchers and industries aim to develop efficient and accurate grading systems that can assess the quality of produce with minimal human intervention (Zhou et al. 2023).

To ensure the widespread adoption of such systems, the importance of a user-friendly platform cannot be overstated. Recognizing the popularity and accessibility of Android mobile devices, researchers have opted for this platform to implement their fruit and vegetable grading applications. This mobile-based approach empowers end-users, including farmers, distributors, and consumers, to conveniently and effortlessly assess the quality of produce. This convenience and accessibility render the proposed model highly appealing to a broad spectrum of users, potentially revolutionizing the grading and trading of fruits and vegetables in the market (Miranda et al. 2023).

For instance, SVMs have been effectively employed in determining the quality of oranges based on various parameters, facilitating efficient sorting and grading of oranges for diverse markets or processing purposes. Similarly, ANN and linear regression models can predict the firmness of kiwifruit, a crucial quality attribute, ensuring optimal ripeness and market suitability. Furthermore, this research delves into the effectiveness of different machine learning algorithms in grading fruits and vegetables. By comparing and analyzing the performance of various algorithms, researchers can pinpoint the most suitable method for specific produce and quality attributes. These insights contribute significantly to the development of robust and accurate grading systems tailored to the distinctive characteristics of different fruits and vegetables (Wieme et al. 2022).

Beyond grading, the application of artificial intelligence and image processing extends to various facets of the fruit and vegetable industry. Researchers have developed mobile applications capable of distinguishing between naturally and artificially ripened fruits, instilling consumer confidence in the produce they purchase. Moreover, through the extraction of features from images, AI-powered apps can estimate calorie content, aiding individuals in making healthier dietary choices. The continuous evolution and integration of artificial intelligence, machine learning, and image processing technologies hold immense promise for the transformation of the fruit and vegetable industry. From enhanced quality control to an improved consumer experience, these advancements contribute to more efficient, sustainable, and economically viable fruit and vegetable production and distribution processes. As researchers persist in exploring novel algorithms and approaches, the future of AI-driven fruit and vegetable quality assessment shines brightly, offering exciting possibilities for the entire agricultural and food sectors (Wieme et al. 2022).

The integration of artificial intelligence, machine learning, and image processing technologies into the evaluation of fruit and vegetable quality signifies a significant stride forward for the agricultural and food industries. These cutting-edge approaches, encompassing artificial neural networks and support vector machines, enable precise, non-destructive, and real-time grading of produce attributes, ushering in a revolution in how fruits and vegetables are assessed, traded, and consumed. These proposed models have the potential to captivate a wide range of users, from farmers to consumers, by leveraging the power of mobile-based applications and user-friendly platforms, thus enhancing the accessibility and efficacy of quality assessment across the supply chain. The triumph of these AI-driven methods ushers in fresh opportunities for research and development in fruit and vegetable quality control, with exciting prospects for elevating freshness, ripeness, safety, and overall consumer satisfaction. As these technologies continue to evolve and researchers explore additional applications, the future of fruit and vegetable quality assessment stands on the cusp of transformative advancements, shaping a more sustainable and technology-driven agriculture and food industry (Ben Ayed & Hanana 2021; Wieme et al. 2022).

Convolutional neural network

The effectiveness of CNN models in comparison to other machine learning techniques was established through extensive experimentation with a diverse dataset comprising various fruits and vegetables. In the model training phase, once the dataset was curated, a series of preprocessing steps were employed to enhance image quality and remove extraneous information. These preprocessing techniques played a pivotal role in improving classification accuracy. Initially, standardization of images reduced data loss, followed by data augmentation to expand the dataset and enhance model performance. Subsequently, image characteristics encompassing color, shape, size, and texture were extracted. These extracted features were then utilized to train the classifier. Figure 6 illustrates the CNN system, a deep learning algorithm, which effectively serves as a classifier for image recognition by processing pixel grids (Naranjo-Torres et al. 2020).

In a recent study conducted by Azadnia et al. (2023), an automated machine learning-based algorithm was developed to assess the maturity level of hawthorn fruits, a critical parameter influencing their suitability for various applications. The research involved assembling a comprehensive dataset of hawthorn images captured at distinct maturity stages, each exhibiting unique colors and textures. Image preprocessing techniques were meticulously applied to standardize and enhance image quality. Machine learning algorithms, notably CNNs, were employed to train a model capable of categorizing hawthorns into distinct maturity levels based on their visual attributes. The results unequivocally demonstrated the algorithm's exceptional accuracy in classifying hawthorns by maturity level. Nevertheless, a notable drawback of the study pertained to the dataset's limited size, which could potentially impact the model's robustness and general applicability. To further advance this research, future endeavors may encompass dataset expansion, the incorporation of spectral imaging for deeper analysis, and the integration of the automated algorithm into hawthorn sorting and processing systems. These steps aim to bolster quality control measures and enhance decision-making processes during hawthorn harvesting and processing operations.

Application of AI in fruits and vegetables

Disease diagnosis Image pre-processing is an essential step in segmenting leaf images, distinguishing background, non-diseased portions, and diseased areas. This segmentation facilitates the efficient transmission of diseased portions to remote laboratories for further examination. Furthermore, image pre-processing enables real-time pest identification, detection of nutrient deficiencies, and disease diagnosis recommendations. These advancements contribute significantly to reducing pesticide losses, minimizing soil and groundwater contamination, and mitigating the risk of pesticide residues in the human food system. Additionally, the automation and efficiency brought about by image pre-processing address labor shortages in agricultural practices (Subeesh and Mehta 2021).

Figure 7 provides a comprehensive view of citrus fruit images, specifically highlighting various peel conditions. These images encompass healthy fruits and fruits affected by five distinct types of blemishes, including Huanglongbing (HLB), black spot, melanosis, canker, and scab. Each condition is carefully selected and depicted for clarity and reference. In Fig. 7A, we see a

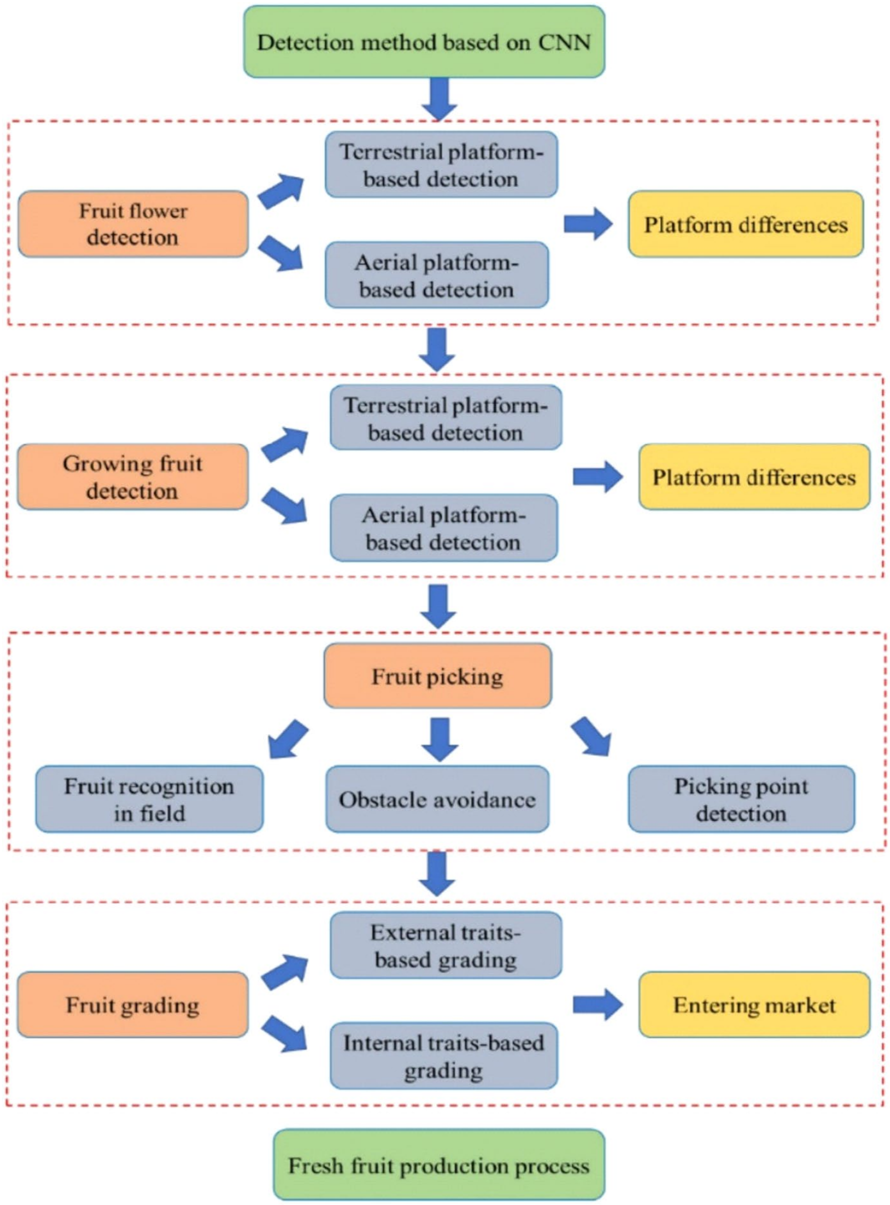


Fig. 6 Model of CNN. (Source: Wang et al. 2022)

citrus sample with a healthy peel condition, serving as a reference point for comparison. In Fig. 7B, we observe HLB, a disease caused by Candidatus Liberibacter asiaticus, associated with stunted growth, improper fruit coloring, leading to green and misshapen fruits with a curved central core, deformities, and cracking (Doh et al. 2019). Figure 7C showcases black spots on fruits, with diameters ranging from 0.12 to 0.4, which may appear small and circular but carry significant implications (Chen et al. 2021). Melanose, induced by Diaporthe citri, is displayed in Fig. 7D, characterized by scattered, raised brown to black blotches (Trivedi et al. 2021). Figure 7E depicts citrus scabs, fungal infections more severe in regions with frequent wetting, resulting in tiny, gritty, irregularly shaped dots (Khan et al. 2021). Finally, in Fig. 7F, we observe canker with fruit spot diameters ranging from 1 to 10 mm, covered by water-soaked, yellow, curvilinear blemishes (Poongodi et al. 2022).

In a recent study by Dhiman et al. (2023), a precise fruit disease identification model, known as "PFDI," was developed, leveraging context data fusion techniques within an edge computing environment. The primary objective

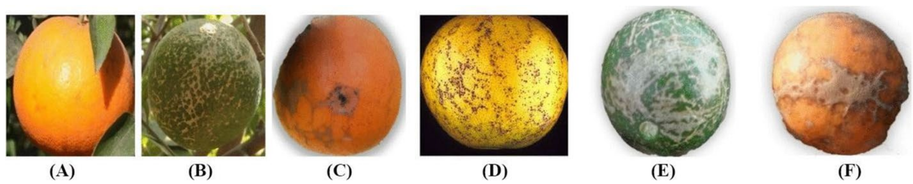


Fig. 7 Healthy and infected citrus fruit images. (Source: Dhiman et al. 2023)

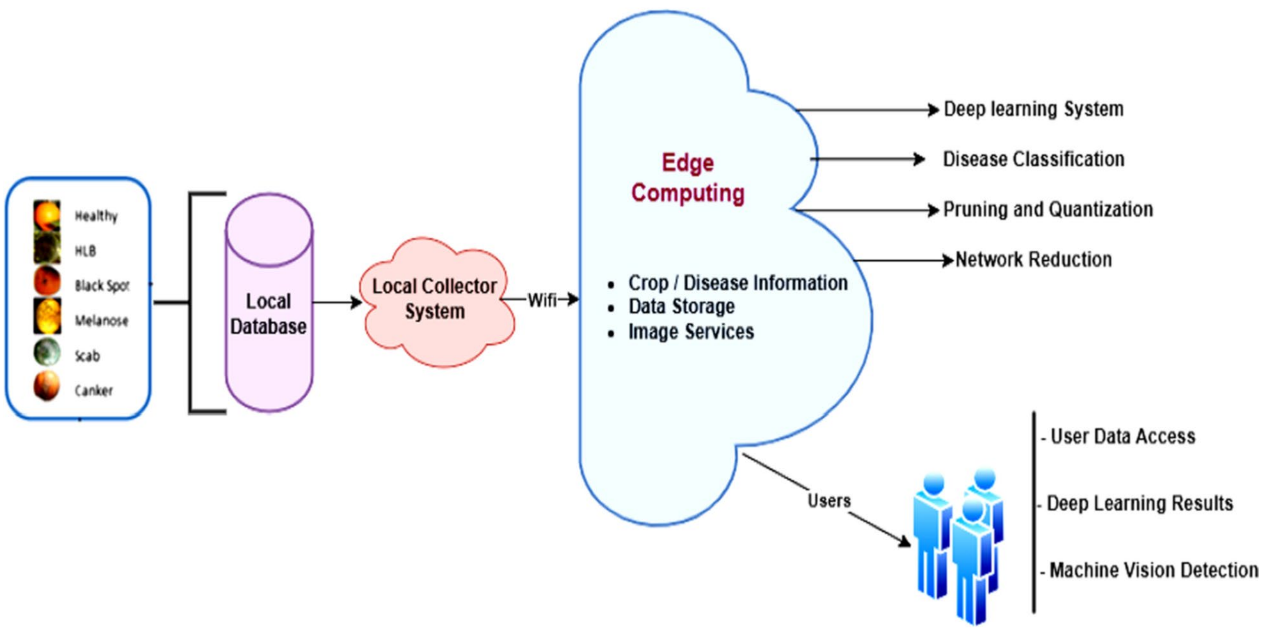


Fig. 8 Overall edge computing architecture. (Source: Dhiman et al. 2023)

of this research is to create an accurate, efficient, and dependable model for the detection of fruit diseases, which is a vital component of autonomous food production on a robotic edge platform. This study delves into the analysis and investigation of four distinct Citrus fruit diseases using CNN deep learning models, intended for use as edge computing solutions. Initially, a sequential model is employed to identify Citrus diseases, including cankers, black spots, greening, scab, melanosis, and healthy citrus fruits (as depicted in Fig. 7). This identification process begins without pruning and then proceeds with varying levels of sparsity following pruning, followed by post quantization. Figure 8 provides an overview of the Edge computing architecture within the proposed model. This architecture comprises four primary modules, each serving specific functions: 1) Collector nodes, 2) Deployment of web services or edge computing, 3) Prediction processes, model pruning, and quantization, and 4) User applications. The third module plays a pivotal role by bridging the gap between locally-based and remote functions within the platform. Initially, data is collected from the public domain at the local level. However, as the data is initiated, edge services come into play for processing and computational tasks.

In this study, a transfer learning approach is employed to fine-tune the model for fruit disease detection by integrating visual data from two sources: Near-Infrared (NIR) and RGB. Authors evaluated early and late data fusion techniques for effectively integrating information from both NIFR and RGB models. The results of this approach are promising, with the proposed model achieving impressive accuracy rates for various diseases, including canker disease at 97%, scab at 95%, melanosis at 99%, greening at 97%, black spot at 97%, and healthy at 97%. The authors compared and evaluated the results of the proposed model with different sparsity levels, ranging from 50 to 80%, 60% to 90%, 70% to 90%, and 80% to 90% pruning. Additionally, the study examined the outcomes of post-quantization at each sparsity level. The findings indicate that by utilizing 60% to 90% pruning, the model's size can be significantly reduced without a substantial loss of accuracy. Moreover, post-quantization further reduces the model size, enhancing both precision and efficiency. An important advantage of this approach is its reduced dependence on pixel-level annotations, requiring only bounding box annotations for the implementation of new fruit disease detection methods.

While the study presents promising results, it is worth noting a potential limitation related to the dataset's size and diversity, which may affect the model's adaptability to different fruit types and disease conditions. Future research directions may involve expanding the dataset to encompass a broader range of fruit species and disease manifestations, fine-tuning the model's architecture, and optimizing edge computing resources to enhance overall efficiency and applicability. The PFDI model represents a significant advancement in fruit disease identification, offering precise and real-time insights that have the potential to revolutionize disease management practices in agriculture (Dhiman et al. 2023).

In a recent study, Azgomi et al. (2023) developed an effective system for diagnosing apple fruit diseases by combining image processing techniques and ANNs. The research aimed to create a comprehensive dataset of apple fruit images, including those with symptoms of common diseases like apple scab, apple rot, and healthy apples for reference. The image preprocessing phase was meticulously carried out to standardize image quality and extract pertinent features, with a focus on attributes such as color, texture, and shape. CNNs, a subtype of ANNs, were employed for image classification. The dataset was partitioned into training and testing sets to evaluate the model's accuracy in distinguishing healthy apples from those affected by specific diseases, thus facilitating early disease detection and management. The study demonstrated the efficacy of this approach in diagnosing apple fruit diseases accurately. However, future directions for this research include expanding the dataset to encompass a broader range of diseases and environmental conditions, optimizing ANN architectures, and integrating real-time disease diagnosis into practical orchard applications (Azgomi et al. 2023).

Identifying crop maturity Images of various crops are captured under white/UV-A light to determine the proper stage of maturity of fruits. Farmers can create different maturity grades based on crop/fruit category and stack them separately before sending them to market, especially for highly perishable horticulture crops, and harvesting at proper maturity will increase post-harvest shelf life. In a study, an automated deep learning-based system was developed to accurately detect tomato maturity. The methodology involved collecting a comprehensive dataset of tomato images at different ripeness stages, categorizing them into specific classes. CNNs served as the core of the system, and the dataset was divided into training and testing sets for model development and evaluation. Data augmentation techniques were applied to enhance dataset diversity, and the CNN model was trained to recognize ripeness-related features. The results showcased the system's efficiency in precisely classifying tomatoes by ripeness, reducing the need for manual sorting and inspection in agriculture and food processing. Despite its success, potential limitations included dataset diversity and sensitivity to environmental conditions, which could be addressed in future research by expanding the dataset and improving robustness under varying scenarios. Future directions may also involve integration with food industry sorting systems and application to other fruits and vegetables for maturity detection (Mutha et al. 2021).

Similarly, the objective of another research endeavor was to employ a machine and deep learning approach using multispectral data to predict crucial agricultural parameters in soybean cultivation, including days to maturity, plant height, and grain yield. The methodology involved collecting multispectral data from soybean fields, covering various spectral bands, which were then utilized to develop predictive models. Traditional machine learning and deep learning techniques were both harnessed to create models capable of forecasting days to maturity, plant height, and grain yield. The results demonstrated the effectiveness of these models in providing accurate predictions for these vital agricultural attributes, facilitating precision agriculture practices. However, one potential drawback of the study was the requirement for substantial computational resources when implementing deep learning approaches. Future directions in this research area may involve optimizing computational efficiency, expanding the dataset to encompass diverse environmental conditions, and integrating these predictive models into real-world farming applications to enhance soybean cultivation and overall crop management (Teodero et al. 2021).

Fruit grading In recent years, the application of image processing in fruit grading has gained prominence due to its pivotal role in the post-harvest process. Fruit grading involves the categorization of fruits based on parameters such as disease severity, defects, and contamination, a task traditionally executed manually, known for its time-consuming and error-prone nature. Consequently, the need for an automated and faster grading system became evident. One such reliable solution is the application of automatic image processing techniques for fruit sorting and grading. Numerous studies have concentrated on harnessing the power of ML techniques, including SVM and ANN, to train models for the automatic classification and sorting of fruits like dragon fruits, based on attributes such as size, color, and ripeness. The outcomes of these studies have showcased the feasibility of this approach, boasting high accuracy in grading and sorting dragon fruits, effectively reducing manual labor and ensuring consistent fruit quality throughout the agricultural supply chain. However, a potential drawback of these studies lies in their limited generalization to varying environmental conditions and diverse fruit varieties. To address these limitations, future directions in this field may encompass refining the algorithms for enhanced robustness, scalability to handle larger datasets, and integration with real-world fruit sorting systems to further augment the efficiency and accuracy of dragon fruit grading and sorting (Patil et al. 2021).

Additionally, Menon et al. (2021) have made significant strides in advancing digital fruit grading and sorting techniques through the application of cutting-edge technologies like computer vision, machine learning, and image processing. Their research underscores the efficiency and accuracy of these automated systems, presenting a notable advantage over traditional manual sorting methods. To ensure broader adoption across the fruit industry, future directions should prioritize efforts to enhance the scalability and affordability of these technologies, particularly catering to the needs of smaller producers. Furthermore, research endeavors should explore the integration of hyperspectral imaging and advanced machine learning algorithms to enable more comprehensive fruit quality assessment. Additionally, addressing sustainability concerns and investigating applications related to food waste reduction and supply chain optimization present critical avenues for future research in this domain. Collaboration among academia, industry stakeholders, and policymakers will undoubtedly play a pivotal role in advancing these innovations and ensuring their successful implementation throughout the fruit industry, promising more efficient and effective fruit grading and sorting processes in the future.

Biosensors

Biosensors play a vital role in assessing fruit maturity and ripeness, offering a non-destructive and real-time method for evaluating fruit quality (Ma et al. 2016). These innovative devices utilize biological components, such as enzymes or antibodies, to detect specific molecules or compounds related to fruit maturation processes. One common biosensor application in fruit maturity assessment is the detection of ethylene gas. Ethylene is a natural plant hormone responsible for triggering fruit ripening processes. As fruits mature, they release ethylene gas, and its concentration can be a reliable indicator of the fruit's ripeness. Biosensors equipped with ethylene-sensitive elements can accurately measure ethylene levels in the fruit's vicinity, allowing growers and producers to determine the optimal harvest time (Gupta et al. 2022a; Gupta et al. 2023; Medhi et al. 2022).

Additionally, biosensors can target other biochemical markers that change during fruit maturation, such as sugars, acids, and volatile compounds responsible for flavor development. For example, certain enzymes or receptors can be integrated into the biosensor to detect the levels of specific sugars like glucose and fructose, which increase as the fruit ripens. The use of biosensors in fruit maturity assessment offers several advantages (Senapati et al. (2022). Firstly, they provide real-time data, enabling timely harvesting to ensure fruits are picked at their peak quality (Gupta et al. 2022a). This not only enhances consumer satisfaction but also reduces post-harvest losses. Secondly, biosensors are non-destructive, meaning they do not harm the fruit during measurement, making them ideal for quality control in large-scale fruit processing facilities. The development of biosensors for fruit maturity assessment is an ongoing area of research, and advancements in nanotechnology and biotechnology continue to enhance their sensitivity, specificity, and ease of use (Yumnam et al. 2022). Moreover, the integration of biosensor data with artificial intelligence and machine learning algorithms allows for more accurate and precise predictions of fruit ripening trends, enabling optimized supply chain management and distribution (Kuswandi et al. 2022).

Hawari et al. (2012) fabr icated the molecularly imprint polymer (MIP) based sensor to determine the mango aroma volatiles. In the MIP technique, molecules possess the ability of molecular recognition at low interference level. For decades, MIP has been effectively used to produce the material having more selective adsorption towards a particular molecule. The basic concept of MIP development includes the pre-arrangement of a functional monomer and a template, followed by polymerization using a cross-linker at a certain temperature. Once the template is removed, it leaves a cavity that is selective to the targeted template only MIP was fabricated by pre-arranging the functional monomer (methacrylic acid) and template followed by polymerization using cross-linker, which will form the MIP complex at a certain temperature. The template used is the imprinting molecule, which forms a receptor site with binding features according to the morphology of the molecule and spatial orientation of the peripheral functionality. When the templates are removed, it forms a cavity having selective nature. Computational aids such as computer software were employed for designing the MIP, which is both time and cost-effective. In the understanding of the intermolecular interaction in the molecular system, *HyperChem* software simulation was used. It helps to retrieve essential information that lead to stable MIP such as the Binding Energy (ΔE) between the template and the functional monomer. In this study, different array MIPs template, including α-pinene, β-pinene and limonene were designed and fabricated onto the surface of quartz crystal microbalance (QCMs). Then, polymerize the coated MIPs, followed by the removal of templates molecules that would leave the cavity of selective templates. The synthesized QCM arrays were able to make a clear distinction between different terpenes gases due to its sensitivity and selectivity properties and quickly identified the gases released from the mangoes during the ripening. The optimal plucking time of fruits and may help in ensuring the quality and standards of the cultivar using the MIP technology.

It is important to distinguish between maturation and ripening, as they represent different qualities in the fruit's growth process. Maturation pertains to the biological growth rate of the fruit, whereas ripening refers to the development that brings the fruit to a desirable stage for consumption. This stage is often assessed based on color and physical texture, as well as the attainment of the desired fruity aroma and flavor. Certain fruits exhibit climacteric and non-climacteric characteristics, which impact their post-harvest ripening behaviour. Climacteric fruits, like bananas, continue to ripen after being picked, and their freshness is closely tied to ripeness and ethylene emission. On the other hand, non-climacteric fruits, like strawberries, do not undergo significant ripening after being harvested. The freshness of climacteric and succulent fruits is strongly linked to their ripening process and ethylene levels, while non-climacteric and aggregate fruits' freshness depends on factors like time, temperature, and potential spoilage indicators such as pH and color.

Recent advances in agricultural science and technology have led to more precise methods for monitoring and managing fruit maturation and ripening (Lino et al. 2008). Techniques like spectroscopy, hyperspectral imaging, and smart sensing devices provide real-time data on fruit quality parameters, enabling better harvesting decisions and reducing food waste. Additionally, research on post-harvest treatments, such as controlled atmosphere storage and ethylene regulation, is continually improving to prolong fruit shelf life and enhance consumer satisfaction. The ongoing efforts in understanding and optimizing the maturation and ripening processes in fruits are crucial in ensuring a steady supply of high-quality, flavorful, and nutritious produce to meet the demands of the ever-growing global population. Overall, biosensors have become invaluable tools in the fruit industry, providing growers, producers, and consumers with valuable information to ensure the delivery of high-quality, flavorful, and nutritious fruits while minimizing food waste and optimizing the fruit supply chain. As technology continues to evolve, biosensors are expected to play an increasingly significant role in fruit maturity assessment, contributing to a more sustainable and efficient agricultural ecosystem.

Electronic Nose (E-Nose) and Electronic Tongue (E-Tongue)

The use of E-Nose technology has revolutionized various aspects of the fruit industry, including grading, sorting, determining the timing of fruit harvest, transportation, storage handling, and final selection. By characterizing aromatic compounds, E-Nose provides valuable insights into the quality and ripeness of fruits (Beghi et al. 2017; Liu et al. 2020). E-Nose utilizes different types of gas sensors, with four commonly employed in commercial applications: Metal oxide semiconductors (MOS), Metal oxide semiconductor field-effect transistors (MOSFET), Conducting organic polymers (CP), and piezoelectric and Quartz crystals microbalance (QCM) (Table 4).

An electronic nose consists of several key components: a) a sample delivery system, b) sensor arrays, c) a signal processing unit, d) an information processing unit, e) software with analytical algorithms, and f) a reference-library database. The sample can be delivered through an automated or flow-based system, which may include sample concentration modulation (Electronic Nose 2019). The sensor array is composed of various sensors that respond to different chemical classes across a wide range, enabling them to distinguish between different combinations of potential analytes. These sensors carry chemical-sensitive layers, chosen based on the type of samples being analyzed. The signals from the sensor array undergo various processing operations, including offset subtraction, concentration modulation by time, signal ratioing between sensors, signal averaging for noise compensation, signal normalization to account for aging effects, and range compression of sensory input. Through these processes, the outputs are collected and combined to create a distinctive digital response pattern, which is then recognized through its distinct aroma signature for identification and categorization. Before analyzing the sample, a reference digital library is used to create aroma signature patterns for known samples. The detection of odors relies on identifying unknowns based on their

Table 4 Application of E-nose in fruits and vegetables maturity

E-nose application	Commodity	Species	Specific aim	Sensors	References
Ripeness Evaluation	Apple	*Malus domestica Borkh*	Cultivar discrimination and prediction of the optimal harvest date	QMB (Libra Nose)	Saevels et al. 2003
			Quality indices assessment and maturity evaluation	CPs (Cyranose 320)	Pathange et al. 2006
	Apple, pear and Peach	-	Fruit ripeness monitoring	MOS (Prototype)	Brezmes et al. 2000
	Mandarin	*Citrus reticulata*	Maturity Monitoring	MOS (PEN 2)	Gómez et al. 2006b
	Mandarin and Orange	*Citrus unshiu* and *Citrus sinensis*	Quality Detection	MOS (PEN 2)	Qiu and Wang 2015
	Peach and nectarine	*Prunus persica*	Sensorial Properties investigation	QMB (Libra Nose)	Di Natale et al. 2001a
	Peach	*P. persica*	Cultivar discrimination and quality assessment	QMB (Libra Nose)	Di Natale et al. 2002
	Peach	*P. persica*	Quality indices evaluation	MOS (Prototype)	Zhang et al. 2008a
	Peach and nectarine	*P. persica*	Cultivar Discrimination and quality evaluation	MOS (EOS 835)	Infante et al. 2011
	Peach	*P. persica*	Quality indices prediction	MOS (Prototype)	Zhang et al. 2012
	Mango	*Mangifera indica*	Maturity assessment	MOS (FOX 4000)	Lebrun et al. 2008
			Maturity assessment	CPs (Cyranose 320)	Zakaria et al. 2011
	Apricot	*Prunus armeniaca*	Cultivar discrimination	MOS (FOX 4000)	Solis-Solis et al. 2007
			Cultivar discrimination	MOS (PEN 2)	Parpinello et al. 2007
	Pear	-	Quality indices prediction	QMB (Prototype)	Zhang et al. 2008b
	Cherry	*Prunus avium*	Cultivar discrimination and ripeness evaluation	MOS (PEN 2)	Benedetti et al. 2010
	Tomato	*Lycopersicum esculentum*	Maturity assessment	MOS (PEN 2)	Gómez et al. 2006a
	Spring onion	*Allium spp.*	Quality evaluation	CPs (AromaScan)	Abbey et al. 2005
	Garlic	*Allium sativum L*	Cultivar discrimination	MOS and QMB (Prototype)	Trirongjitmoah et al. 2015
Shelf-life assessment of fresh products	Apple	*M. domestica Borkh*	Storage time prediction	MOS (Prototype)	Guohua et al. 2013
	Apple	*Malus sylvestris*	Quality Assessment during shelf life	QMB (Libra Nose)	Saevels et al. 2004
	Apple	*M. domesticaBorkh*	Shelf life evaluation	MOS (Prototype)	Brezmes et al. 2000
	Mandarin	*C. reticulata*	Shelf life evaluation	MOS (PEN 2)	Gómez et al. 2007a
	Banana	*Musa acuminata*	Quality assessment	MOS (Prototype)	Sanaeifar et al. 2016
	Peach	*P. persica*	Quality changes during cold storage	MOS (PEN 3)	Rizzolo et al. 2013
Shelf life assessment of ready to eat products	Apple	*M. domestica Borkh*	Quality and shelf life of fresh cut slices	MOS (Fox 4000)	Bai et al. 2004
		Malus communis	Shelf life of fresh cut slices	MOS (PEN 2)	Siroli et al. 2014
		-	Shelf life modelling of fresh cut slices	MOS (PEN 3)	Correa 2015

aroma attribute patterns that exhibit similarities with pattern databases in the reference library (Beghi et al. 2017). The continuous advancements in E-Nose technology and its integration with artificial intelligence and machine learning algorithms have expanded its capabilities and applications in the fruit industry. As research progresses, E-Nose is expected to play an increasingly significant role in optimizing fruit quality assessment, supply chain

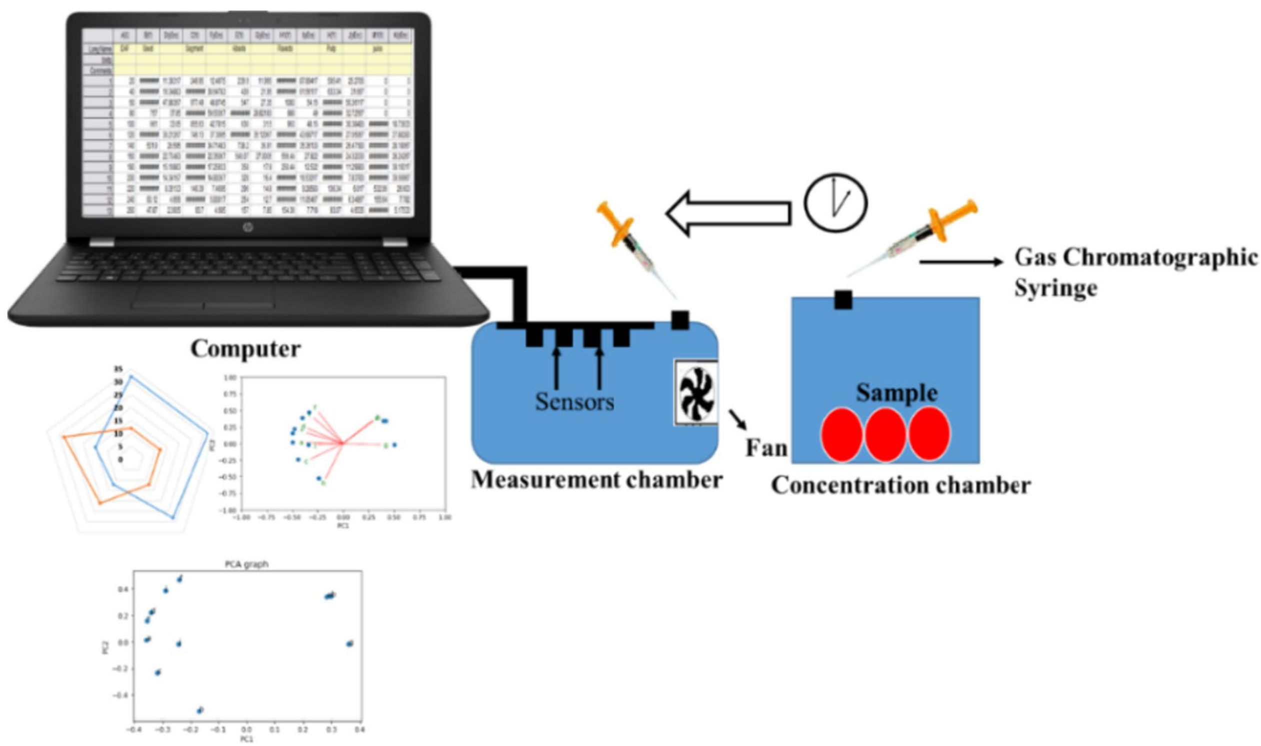


Fig. 9 Schematic diagram of E-Tongue. (Source: Liu et al. 2020)

management, and overall consumer satisfaction. By harnessing the power of electronic noses, the fruit industry is poised for greater efficiency, reduced waste, and improved fruit quality throughout the entire value chain.

E-Tongue imitates human tongue by using a variety of sensors to react the taste characteristics such as salty, sweet, sour, bitter and umami and then send signals through computer for elucidation, the mostly used sensors are voltametric and potentiometric, this hybrid technology combines both methods shown in Fig. 9 (Liu et al. 2020). E-Tongue widely used for beer fermentation analysis, milk fermentation, in meat industry to determine the amount of curing agents. This makes better and efficient sensory analysis gives output corelating the sensorial analysis by experts and consumer preferences. In determining the ripening stage, e-nose as well as comparing the variations between the cultivars, and the work based on the maturity levels cluster analysis is applied to measure their maturity indices (TA, total soluble solids, and color) (Liu et al. 2020).

The E-nose has found effective application in monitoring changes in aroma during the ripening process of climacteric fruits like apple (Brezmes et al. 2000; Saevels et al. 2003; Pathange et al. 2006), peach (Brezmes et al. 2000; Di Natale et al. 2001a, b and 2002; Infante et al. 2011; Zhang et al. in 2012), mango (Lebrun et al. 2008; Zakaria et al. 2011), pear (Brezmes et al. 2000), apricot (Parpinello et al. 2007), and tomato (Gómez et al. 2006a). However, there is limited information available regarding the application of the E-nose on non-climacteric fruits like cherry (Benedetti et al. 2010), mandarin (Gómez et al. 2006b; Qiu and Wang 2015), and orange (Qiu and Wang 2015). Additionally, some literature has also utilized the E-nose for purposes of cultivar discrimination and classification (Beghi et al. 2017). To enhance selectivity and increase the detection limits of target molecules, employing different types of sensing elements in the sensor array proves advantageous. Hu et al. (2013) have pioneered a method to incorporate an array of single nanowires (NWs), including materials like polyaniline (PANI), palladium (Pd), polypyrrole (PPy), and zinc oxide (ZnO), representing metal, metal oxide, and conducting polymer categories, onto a single chip. This involved cutting a 4-inch wafer with patterned electrodes and nanochannels into smaller slices, with four distinct single nanowires grown onto electrochem-chips using varying electrolyte solutions. A probe station equipped with three probes facilitated direct contact with the electrodes. The growth of Pd, PPy, and PANI single nanowires occurred through electrochemical deposition, while ZnO nanowire growth involved electrochemical deposition followed by a hydrothermal treatment. The chip containing these four distinct single nanowires underwent rinsing in DI water and subsequent drying before stabilization. This innovative nanowire array on a single chip has demonstrated its efficacy in detecting and identifying four target gases, including hydrogen, methanol, carbon monoxide, and nitrogen dioxide. One notable limitation is the limited application of E-Nose technology on non-climacteric fruits like cherry, mandarin, and orange, indicating potential challenges in effectively assessing aroma changes in these fruit types due to differences in volatile organic compounds. Additionally, there is a need to enhance the selectivity of E-Nose technology, particularly in terms of distinguishing between specific target molecules and reducing cross-sensitivity issues. The complexity of developing sensor arrays with multiple sensing elements, such as nanowires made of different materials, poses manufacturing and maintenance challenges. Looking ahead, future research directions should aim to expand the application of E-Nose technology to non-climacteric fruits, broadening its utility in the fruit industry. Enhancing selectivity remains a critical goal, which may involve the development of more specialized sensor arrays or advanced data analysis techniques. Researchers could also explore ways to simplify sensor arrays without compromising accuracy. The integration of E-Nose technology with artificial intelligence and machine learning algorithms offers potential for more advanced and automated applications. Furthermore, efforts to expand the range of gases and compounds that E-Nose technology can detect and identify could open up new applications across various industries, extending its impact beyond fruit quality assessment. In summary, addressing limitations and exploring innovative directions are crucial for the continued growth and effectiveness of E-Nose technology in the future.

Nanosensor

Nanotechnology and nanoscale materials represent innovative and burgeoning fields of research. Nanoparticles, owing to their minuscule size and exceptional properties, hold vast potential for the development of novel devices with unprecedented applications in diverse fields, including optics, mechanics, pharmaceuticals, and food safety (Rabbani et al. 2020). Nanosensors, in particular, have emerged as indispensable tools, enhancing health, environmental quality control, and numerous global applications.

These sensors extend their utility beyond medicine and pharmaceuticals, proving invaluable in the realm of food safety and security. Conventional methods often suffer from time constraints and high costs, making the development of nanosensors a game-changing advancement. Many such sensors have been created with a focus on cost-effectiveness and scalability, improving agricultural efficiency, soil quality, food processing, packaging, food shelf life, and pathogen analysis (Ansari et al. 2023).

For instance, Sarkar et al. (2020) engineered a ZnO Nanostructured ethylene gas sensor, a critical indicator of fruit ripening. Their optimized sensor exhibited heightened sensitivity, promising significant benefits in ethylene gas detection during fruit ripening, thereby enhancing quality control and reducing food wastage. Similarly, Fahim et al. (2020) crafted a chitosan-graphene nanocomposite-based sensor with varying concentrations, manifesting unique gas-sensing capabilities through both mechanical and electrical means. Additionally, Dalal et al. (2017) developed a nanosensor to detect malic acid in tomatoes, a marker of ripeness. They immobilized malic enzyme on a carboxylated-multiwall carbon nanotubes electrode, characterizing it through SEM and FTIR analysis. Their study underscored the nanosensor's rapid and accurate potential in determining tomato ripeness by detecting malic acid levels.

The pre-determination of fruit maturity holds paramount importance, offering crucial insights into harvesting and selling priorities and preservation conditions. In this context, nanotechnology demonstrates promising potential, enabling precise and timely maturity assessment. This technology stands to significantly impact agricultural practices and market outcomes, offering the advantage of efficiency and accuracy. However, it's essential to consider potential disadvantages such as the need for specialized equipment and expertise, as well as the cost of implementing nanotechnology-based solutions. Looking ahead, the future scope of nanosensors in agriculture and food safety is vast, with potential advancements in scalability, cost-effectiveness, and broader adoption in the food industry. Further research and development in this field will continue to drive innovation and improve the sustainability of agricultural practices worldwide.

Freshness sensors

Fruit ripeness, firmness, and freshness are essential parameters monitored by freshness sensors or indicators, providing valuable insights into the quality of fruits. Conversely, smart sensors or smart packaging systems encompass embedded electronic components alongside electrochemical or electro-optical sensors strategically placed in close proximity to packaged fruits (Gómez et al. 2006; Kuswandi et al. 2013). These systems facilitate continuous monitoring of fruit quality, beginning from the moment the shipment leaves the processing plant until it reaches consumers, as depicted in Fig. 10. It is worth noting that the efficacy of fruit freshness sensors is contingent on the specific fruit type and its distinctive

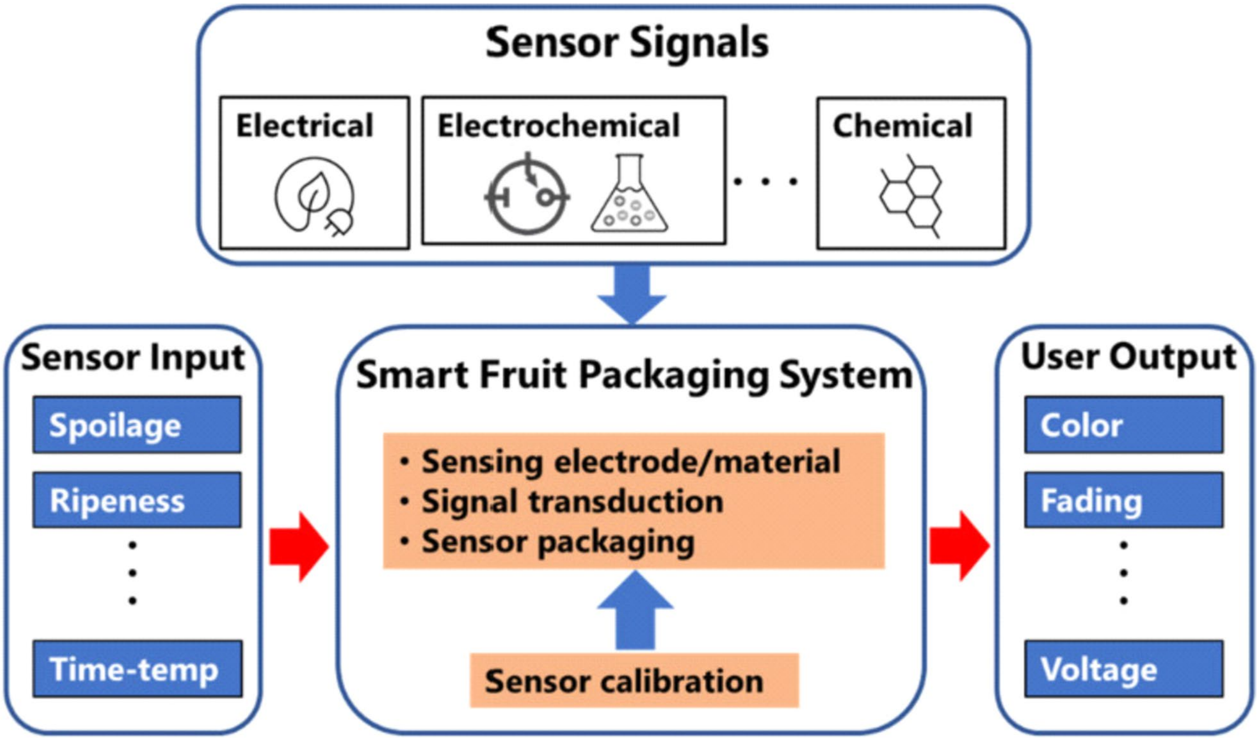


Fig. 10 Illustration of smart food packaging system. (Source: Alam et al. 2021)

physiological attributes (Alam et al. 2021). Consequently, understanding the physiology of the fruit is imperative in the development and implementation of freshness sensors and smart packaging systems, as elaborated in the following sections.

Freshness sensors can be broadly classified into two categories: direct sensors and indirect sensors. Direct freshness sensors directly detect specific analytes present in the fruit, serving as direct indicators of food freshness (Kuswandi et al. 2013). In contrast, indirect freshness sensors operate by detecting signs of fruit deterioration attributed to freshness factors, such as temperature and/or time (El-Ramady et al. 2015). These sensors are meticulously designed to monitor various stages within the food distribution chain, including consumer packages displayed on store shelves. Importantly, these sensors must accurately gauge the rate of fruit freshness deterioration (Alam et al. 2021).

The design and functionality of freshness sensors vary based on the specific monitoring stage within the food distribution chain or the consumer package on the shelf. Regardless of the stage, these sensors must effectively track the degradation rate of fruit freshness (Beshai et al. 2020). A diverse array of concepts for fruit freshness sensors or indicators has been developed, encompassing parameters such as aldehyde (Kim et al. 2018, Vo et al. 2007), volatile organic compounds (VOC) (Mustafa et al. 2018), ethanol (Boerman et al. 2016), hydrogen sulfide (H_2S) (Hu et al. 2012), pH (Guo et al. 2007b, Park et al. 2019), and CO_2 (de Almeida Teixeira et al. 2018). These sensors or indicators are seamlessly integrated into food packaging as visible indicators, labels, or tags, undergoing discernible color changes in response to variations in freshness markers and/or analytes. Freshness sensors can be configured as single sensors, dual sensors, or multiple sensor arrays. The majority of commercially available freshness sensors employ a single sensor, enabling monitoring of a single freshness parameter at a time, such as pH or time–temperature. Dual freshness sensors utilize two sensors that reference each other during the sensing process while simultaneously providing insights into food freshness. Moreover, dual and multiple sensor array configurations are currently under development in laboratory settings and are expected to be introduced to the market soon. Figure 11 illustrates various types of fruit freshness sensors based on both direct and indirect sensing methods.

Direct fruit freshness sensors have the capability to detect and assess the freshness level of fruits based on distinctive markers or compounds. Traditional forms of direct fruit freshness sensors encompass indicators for

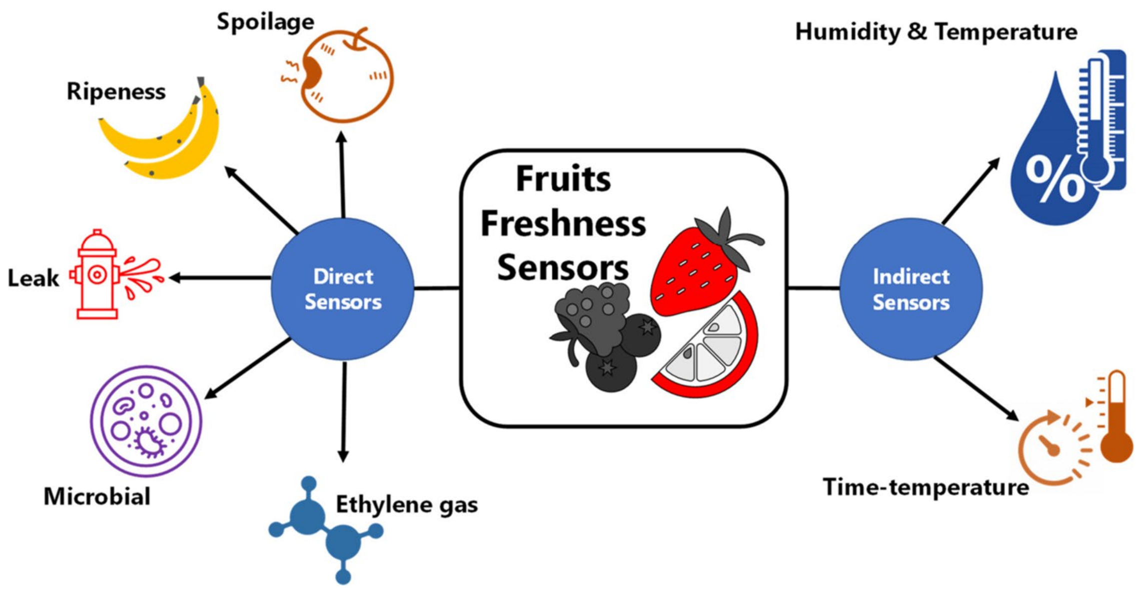


Fig. 11 Classifications of sensors for monitoring freshness of fruits. (Source: Alam et al. 2021)

spoilage, ripeness, leakage, microbial pathogens, ethylene, and senescence. These sensors often incorporate a color indicator for straightforward visual assessment of freshness levels by the naked eye. The indicator undergoes a color change, and the rate of this change corresponds to the rate of food deterioration, which is closely linked to temperature fluctuations and time elapsed during food distribution cycles and shelf storage (Kuswandi et al. 2017).

Direct freshness (Ripeness detecting sensors) Ripeness, a crucial factor in assessing fruit freshness, often presents a challenge for consumers in their estimation. This predicament frequently leaves customers uncertain about the optimal time to purchase, store, or consume fruits. To address this issue, several commercial ripeness indicators have been developed, offering practical solutions. Notably, ripeSenseTM, a company based in New Zealand, has introduced a promising approach (https://product.statnano.com/product/6730/ripesense). Their sensor responds to the aromatic cues emitted by ripening fruit, undergoing a color transformation from red (crisp) to orange (firm) and eventually to yellow (juicy) as the fruit ripens further. Consumers can easily gauge the fruit's ripeness state by simply observing the color of the sensor, facilitating informed decisions. Moreover, the utilization of such sensors can potentially mitigate fruit damage and shrinkage resulting from consumer handling and inspection. These sensors are typically housed in recyclable polyethylene terephthalate (PET) clamshell packaging, aligning with the trend toward more hygienic and environmentally conscious packaging solutions. ripeSenseTM sensors effectively monitor the ripeness of various fruits, including pears, kiwifruit, melons, mangoes, and avocados. Furthermore, different stages of fruit ripening may release volatile compounds, a phenomenon studied using electronic noses (e-noses). For instance, e-noses have been employed to assess the ripeness of tomatoes (Gómez et al. 2006).

In another study, a straightforward, cost-effective, on-package color indicator was developed using methyl red (MR) for the detection of ripeness in non-climacteric fruits, such as strawberries (Kuswandi et al. 2013). In this case, an increase in pH in the package headspace triggered the release of volatile acids, gradually diminishing the presence of MR immobilized onto a bacterial cellulose membrane. This enzymatic process resulted in the formation of esters during ripening, causing the indicator's color to transition from yellow to red–purple, signifying over-ripeness. A high correlation was observed between the color changes and strawberry ripeness levels. Consequently, real-time ripeness monitoring of strawberries was effectively demonstrated using this on-package color indicator, applicable in both ambient and refrigeration conditions.

Ripeness sensors offer several advantages, including the provision of real-time data on fruit quality, assisting in timely decisions for harvesting, packaging, and distribution. This helps reduce food waste and ensures consumers receive high-quality produce. The integration

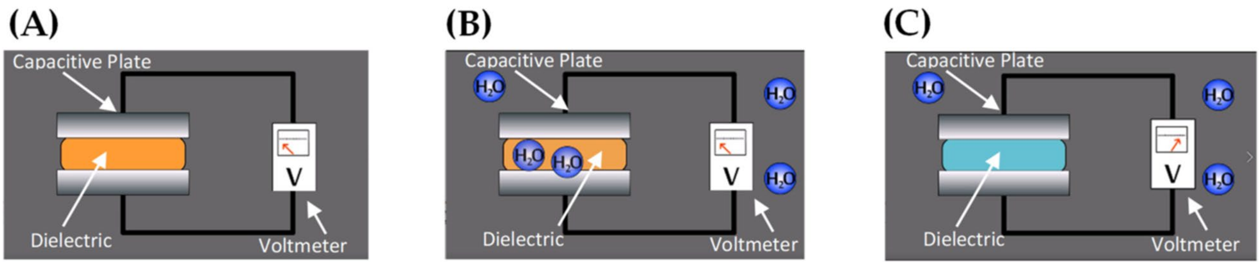


Fig. 12 Working principle for a capacitive humidity sensor. **A** The initial setup of the capacitive sensor indicating no detectable voltage across the plates. **B** The introduction of water vapor in the atmosphere. (C) The change in the permittivity of the dielectric because of the water vapor, generating a detectable voltage across the plates. (Source: Alam et al. 2021)

of these sensors into smart packaging systems allows for precise monitoring and control of fruit storage and transportation conditions. However, limitations exist, including variations in sensor effectiveness based on fruit type, necessitating customization for specific varieties. Calibration and maintenance are vital for sustained accuracy, and cost considerations may limit adoption, especially for small-scale growers and producers. Future developments aim to enhance sensor accuracy and versatility, with advancements in multi-sensor arrays holding potential for improved fruit quality assessment. Efforts to reduce sensor costs may increase accessibility. Overall, ripeness sensors continue to evolve, contributing to the enhancement of fruit production and distribution (Alam et al. 2021).

Indirect freshness The indirect assessment of fruit freshness relies on using indirect freshness indicators like temperature, storage duration, and technologies such as RFID (radio frequency identification). These indirect freshness sensors mimic the alterations in specific quality parameters of food when subjected to the same conditions as the indirect freshness indicators (Kuswandi et al. 2013). The rate of change in these sensors should correspond to the rate of degradation in the packaged food due to fluctuations in temperature and humidity during transportation, distribution, and storage over time. These indirect sensors should provide indications of freshness by means of alterations in color and electronic signal output when exposed to abnormal storage temperatures and/or humidity levels (Mahajan et al. 2014).

Humidity sensor

A capacitive humidity sensor, a type of hygrometer, relies on changes in capacitance to gauge relative humidity levels. This sensor consists of a pair of slender metal surfaces or electrodes separated by a dielectric material film, typically a metal oxide (as depicted in Fig. 12). These electrodes form a parallel plate capacitor with a specific capacitance value. As the moisture content in the surrounding air varies, the permittivity of the dielectric film also undergoes changes. These alterations result in fluctuations in capacitance between the two electrodes. The shift in capacitance generates a noticeable analog voltage difference across the electrodes, which can be quantified and employed to ascertain the relative humidity level in the environment (Alam et al. 2021). These sensing devices are designed to operate within a temperature range of -20 °C to 85 °C, encompassing the temperature fluctuations encountered during fruit transportation and storage (https://www.ti.com/tool/TIDA-00972).

While capacitive humidity sensors offer an extensive range and are among the most accurate humidity sensors available, they come with certain drawbacks. They are relatively costly and may experience long-term stability issues. Consequently, it is crucial to recalibrate or replace these sensors when they approach their recommended operational lifespan, particularly when they are reused for different batches of produce during transportation and packaging (Liu and Zhang 2021). Furthermore, the performance of capacitive humidity sensors can be constrained by challenges related to saturation, hysteresis, or prolonged exposure to high humidity conditions (Lamberty and Kreyenschmidt 2022).

In addition to their benefits, capacitive humidity sensors do have drawbacks. They can be relatively expensive and may suffer from long-term stability problems, necessitating recalibration or replacement after a certain lifespan, especially when used for various batches of produce during transportation and packaging. Furthermore, these sensors may face limitations related to saturation, hysteresis, or extended exposure to high humidity conditions, which can affect their accuracy and performance (Lamberty and Kreyenschmidt 2022). Looking toward the future, there is potential for advancements in capacitive humidity sensor technology. Researchers and engineers are actively working on improving the long-term stability of these sensors and addressing issues related to saturation and hysteresis. Additionally, efforts are underway to make these sensors more cost-effective, which could broaden their applications in various industries, including the monitoring of fruit transportation and storage. As technology evolves, capacitive humidity sensors are likely to become more reliable and accessible tools for ensuring the quality and freshness of fruits and other products during their journey from farm to table.

Time–temperature indicators (TTIs)

It serve as indirect freshness sensors that operate through various chemical, physical, and biological mechanisms (Maschietti 2010). Chemical and physical mechanisms involve reactions or changes influenced by alterations in time and temperature, such as acid–base reactions, melting, and polymerization. Biological mechanisms are linked to shifts in biological activity, including microorganisms, spores, or enzymes, in response to changes in time and temperature. TTIs primarily rely on color changes when exposed to temperatures beyond recommended storage conditions for extended periods, indicating alterations as the product approaches the end of its shelf life. Consequently, TTIs offer a means to monitor the physical, chemical, and biological attributes of fruits, providing precise indications of freshness in terms of quality, safety, and shelf life.

Irrespective of the detection method, essential specifications for TTI datasheets encompass threshold temperatures and runout times. Threshold temperatures specify the indicator's operational range, defining the maximum and minimum temperatures required to trigger recording. Runout time represents the minimum duration at a temperature outside the operating range necessary for the entire indicator to change color. While TTIs provide reasonably accurate estimates of exposure to unfavorable temperatures, they are not as precise as conventional temperature sensors. However, their straightforward operation, user-friendliness, and suitability for commercial fruit smart packaging systems make them an ideal choice (https://www.3m.com/3M/en_US/company-us/all-3m-products/~{}/MONMARK-3M-MonitorMark-Time-Temperature-Indicators/?N=5002385+3293785721&rt=rud).

Numerous commercial TTIs have been developed and are widely utilized for monitoring perishable goods, including fruits. Examples of such TTIs include Fresh-Check®, Monitor MarkTM, OnVuTM, eO®, Timestrip®, Checkpoint®, and Tempix® (Beshai et al. 2020). These commercial indicators primarily rely on chemical and enzymatic reactions and are frequently applicable to fruit packaging. For instance, Fresh-Check® is a self-adhesive chemical indicator based on polymerization, exhibiting a visual color change and providing a full history of temperature exposure. Monitor MarkTM, on the other hand, is a partial-history TTI that offers temperature vs. time history through the diffusion of blue-dyed fatty acid esters. The OnVuTM indicator operates on a photochemical reaction principle, signaling exposure to elevated temperatures over time. eO® is a microbial-based TTI that changes color in response to variations in the pH of deteriorating food products. Timestrip® functions on diffusion, where dye melting and migration occur through the porous membrane when temperatures exceed the reference temperature. Checkpoint® indicator operates through enzymatic reactions, resulting in color changes. Tempix® is another diffusion-based TTI where activation liquid diffuses into a barcode in the event of temperature breaches. Due to their diverse mechanisms, commercial TTIs can be effectively used for assessing the freshness of various fruit types based on their specific degradation mechanisms and time–temperature breaches (Alam et al. 2021).

Ethylene detecting sensors

Ethylene is released by fruits to initiate respiration, which generates energy for internal biochemical processes. As this process continues, the plant's flavour, texture, and nutrition change; as a result, a continual respiration rate can cause this same fruit to ripen quickly and eventually decline. After harvest, some fruits do not ripen; instead, they enter the senescence stage. Due to their climacteric property, bananas, for example, are exceedingly sensitive to outside ethylene. To avoid the fast, this same quantity of ethylene now must obviously be monitored. It is obvious that the amount of ethylene present must be monitored in order to avoid fruit's rapid decomposition (Iqbal et al. 2017). Consequently, ethylene is commercially used in storage facilities to control fruit ripening. Fruits at different stages of ripening stored close together may also have a limited lifetime due to ethylene excretion from fresh fruits. Thus, ethylene scavenging and monitoring are strongly recommended to preserve fruit freshness. Ethanol scavenging helps to reduce fruit product loss due to ethylene overproduction. Potassium permanganate ($KMnO_4$) is a common ethylene scavenger that oxidises ethylene to ethylene glycol. Moreover, ethylene glycol can be oxidised further to CO_2 and H_2O, resulting in dark brown MnO_2. Granules of $KMnO_4$ on clay particles or activated carbon Low temperature oxidation above a platinum catalyst (Vermeiren et al. 1999) is a commercial ethylene scavenger at 0 °C on mesoporous silica capable of removing 50 ppm ethylene. Another study measured the amount of ethylene gas released by using the metal organic framework base, fruits were measured, possess an olefin detector. An electrochemical ethylene sensor was created using a semiconductor electrode made of

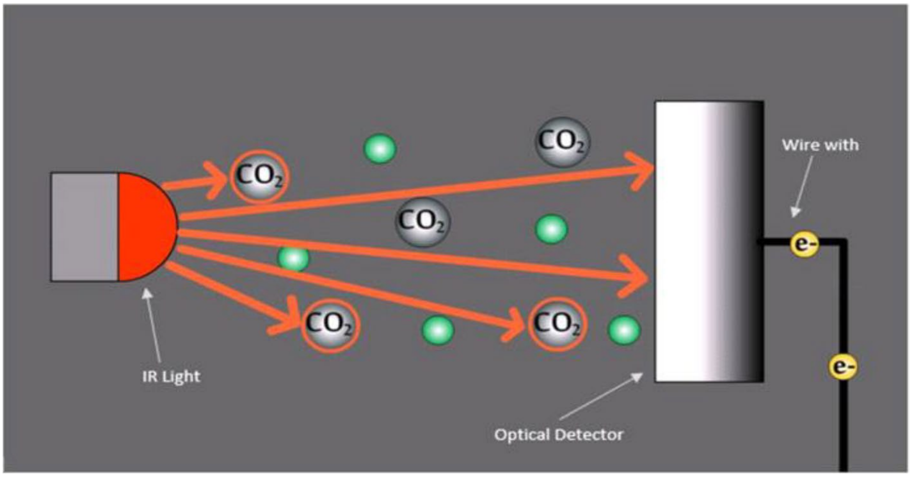


Fig. 13 Setup of the NDIR sensor. The infrared (IR) light with a wavelength of 700 nm to 1 µm is partially absorbed by carbon dioxide and partially transmitted through to the detector. (Source: Alam et al. 2021)

C60 and zeolite. It is built to track the ethylene gas for a variety of concentrations in order to describe how a fruit ripens and a new gas sensor was made that looked at various signal patterns created using the graphite line patterning technique this created sensors are an economical way to track the fruit ripening was additionally observed without causing damage, using E-nose was employed to gauge the evolution of ethylene a sensor for chemicals array built on TiO_2 was introduced.

Infrared thermal emission techniques are also used to develop an ethylene sensing device. A high-sensitivity silicon temperature detector was connected to an infrared heat source adjusted to the 10.6 m wavelength. The 10.6 µm IR waves were absorbed by the addition of ethylene into the wave path between the IR source and temperature detector, which also lowered the surface temperature of the detector. The output was next transformed into an electrical signal (in mV) that provided a precise measurement of the amount of ethylene. These sensors may be used for fruit ripening applications on site and in field as well as fruit screening (Kathirvelan and Vijayaraghavan 2017). The sensor works on the principle of resistance variation in the presence or absence of analyte. The TiO_2-WO_3 dispersion was transformed into a gel using the sol–gel technique, which was applied to the substrate's surface and implanted with gold electrodes using a brush coating technique. When fruit interacts with the constructed sensor, ethylene is produced, is oxidised into ethylene oxide, and subsequently releases electrons and re-enters the sensor element, resulting in a reduction in resistance. Because the reactions are reversible, the created sensor has a higher sensitivity and may be reused. The manufactured sensor was reasonably priced, and its baseline resistance changed less over time (Kathirvelan et al. 2017).

Carbon dioxide non-dispersive infrared sensor

Modified consumer packaging, which alters the atmospheric conditions, plays a crucial role in ensuring the freshness and quality of fruits. By maintaining higher carbon dioxide levels and reducing oxygen levels, packaging creates an environment that slows down respiration, controls ripening, and prevents premature decay (Esser et al. 2012). However, excessive reduction in oxygen levels can lead to cell death and accelerate decay. To maintain the appropriate packaging conditions, NDIR sensors are employed to monitor atmospheric gases effectively (Fig. 13). NDIR sensors utilize infrared light absorption to quantify specific gases present in the atmosphere. The sensor emits a beam of light with wavelengths between 700 nm to 1 µm, passing through the target gas-containing air to an optical detector. Atmospheric gases selectively absorb certain wavelengths of light while allowing others to pass through unaffected. The amount of light absorbed or transmitted is measured by the optical detector, and this data is used to determine the quantity of specific gases present in the atmosphere (https://www.co2meter.com/blogs/news/6010192-how-does-an-ndir-co2-sensor-work).

In smart packaging systems for fruits, carbon dioxide is a crucial target gas used to control the atmosphere's composition during the transportation and storage of produce. When the packaging seal is broken, external oxygen seeps in, and carbon dioxide disperses, accelerating the fruit's ripening process. NDIR sensors, operating at 4300 nm infrared wavelength, easily detect carbon dioxide, as it does not interfere with oxygen absorption (Vanderroost et al. 2014).

In fruit packaging, the measuring range, accuracy, and precision of NDIR sensors are essential considerations. The measuring range indicates the percentage of carbon dioxide in the air that the sensor can detect. Standard NDIR sensors can detect a range of 0–20 percent carbon dioxide gas with an accuracy of approximately ± 0.5% and a sensitivity of about 0.05%. These sensors offer long lifespans, allowing for reuse in multiple fruit shipments and requiring minimal maintenance. However, there is a risk of external spectroscopic interference affecting the optical detector, leading to inaccurate light detection. The use of optical filters can mitigate this issue (Dinh et al. 2016). NDIR sensing is particularly suitable for system-level smart packaging, where the sensor is placed outside the food package and provides feedback to system actuators to optimize storage conditions. This technology's advantages lie in its ability to create an environment that prolongs fruit freshness, enhances shelf life, and reduces food waste, contributing to more sustainable packaging solutions for the fruit industry.

Radio Frequency Identification (RFID)-based sensor system

The focus of most sensing systems discussed earlier is on assessing the quality of fruits or fruit products. However, valuable information can also be gathered from the containers used to store citrus fruits. Active packaging utilizing RFID technology can monitor and identify product quality during storage and transportation in containers. RFID tags, similar to electronic barcodes, are affixed to pre-packed units and store data that can be accessed later through a network as required. These systems consist of an RFID tag with an antenna, an RFID scanner, and radio waves to communicate data to a network. The tag contains an integrated circuit and an antenna enclosed in a protective covering. When scanned, the RFID tag transmits package information to the reader via the antenna, and the receiver converts the radio waves emitted by the tag into the appropriate data format (Alam et al. 2021). These RFID scanners can function independently or in conjunction with a central network for storing, processing, and distributing data. For instance, in refrigerated fruit storage, wireless sensing technologies like RFID and wireless sensor networks (WSN) were used to monitor temperature and humidity. The combination of RFID and WSN devices in commercial wholesale chambers enabled the creation of 3D temperature maps and psychrometric simulation models to calculate changes in latent heat and absolute water content in the air. By utilizing RFID and WSN sensor networks, energy consumption in cold storage, water loss from products, and the detection of water condensation on stored commodities could be estimated (Badia-Melis et al. 2015). One of the significant advantages of RFID technology is its ease of detection on carrier containers or storage shelves. The reading range of RFID can be adjusted based on the operation frequency and power supply transmission line unit, making it more flexible than traditional barcode technology, that requires a clear line of sight and proper orientation for reading. Moreover, RFID scanners can read multiple tags simultaneously, allowing for efficient scanning of single containers or bulk quantities. As this technology continues to evolve, the future scope includes further improvements in accuracy, range, and integration with smart packaging systems, enhancing the monitoring and control of fruit storage and transportation, ultimately reducing food waste and ensuring better product quality for consumers.

A study was performed to detect the freshness of vegetables focusing on oxygen and carbon dioxide concentration in which a monitoring system based on an RFID tag was developed. The criteria behind the development of the sensor was that the concentrations of these two gases are related to freshness and affect the food. The RFID system can be comparatively managed easily. The used sensors were programmed accordingly to the use, and the RFID tag was prepared. The prepared tags kept inside the vegetable packets and study was carried out at several days to check the concentration of both the gases and to determine the freshness level. However, this research is still in the initial stages, where only two gases were detected. Further motivation is to develop the smart RFID tag and to produce more precise data on the freshness of fruit and vegetables (Eom et al. 2012). To address the problems of fruits and vegetable freshness, a sensor was developed which works with the principle of measurement of change in ion concentration in fruit and vegetables. The prototype was composed of four different circuits, such as processor supply circuit, liquid crystal display circuits, the measurement circuit. These circuits were designed by using a circuit design program called Dip Trace after the test was done manually by using circuit test boards. Notably, the measurement circuit was designed using sensitive and low tolerated resistors to increase the sensitivity of performed measurements. Three different critical intervals were chosen for each sample to determine their freshness. By stabbing these electrodes to sample freshness measurement can be done by using information about the ion concentration of the sample. If the value is in the first interval, it means the sample is fresh, if the measurement result is in the second interval it means the sample is about to lose its freshness, and for the values, in the third interval the result will be written: "the sample is rotten and cannot be consumed". This developed prototype was used for different fruit varieties such as citrus variety, apple, pear, and strawberries to determine the freshness, and it was observed that as the fruit decays, the ion concentration of the fruit gets decreased. The prototype was successfully applied in the initial measurement and is still required modification to make it advance (Kemiklioglu and Ozen 2018). Recently, polyvinyl alcohol and red cabbage (Brassica oleracea L.) extract based electrospun nanofiber mat was fabricated to analyze the pH. The nanofibers were subjected to pH sensitivity test applying a sequence of different pH solutions and using a colorimeter, the color spectrum of nanofiber mats were calibrated at different pH values. As per the results found, it could be said that the designed mat can be convenient as a pH sensor and show pH values within the range of 2–12. The color changes of the mat were reversible with respect to the change in the pH value, and thus the monitoring of transient changes could be performed efficaciously (Maftoonazad and Ramaswamy 2019).

In conclusion, RFID technology offers numerous advantages in packaging applications, particularly in the context of fruit monitoring and logistics. RFID tags enable efficient inventory management through reader placement at storage entrances, offering simplicity in tag detection even within carrier containers or storage shelves. Their adjustable reading range, based on operation frequency and power supply, surpasses the limitations of traditional barcode technology, which demands line of sight and proper orientation for scanning. RFID scanners excel in reading multiple tags simultaneously, facilitating both single-item and bulk scanning. However, challenges exist, such as susceptibility to interference, especially when surrounded by materials like metal, and higher installation costs compared to conventional barcodes, which is a consideration in mass production. Nonetheless, RFID tags are cost-effective when applied to reusable containers or packages, delivering benefits in food quality monitoring. Integration of freshness sensors with RFID tags enables the monitoring of various factors including humidity, temperature, light exposure, pressure, and pH, safeguarding food safety and quality by identifying potential cold chain disruptions. Looking ahead, future directions in food quality monitoring involve the continued development and refinement of wireless sensor technologies. In one study, real-time temperature and humidity monitoring for small cold storage units of fruits and vegetables was demonstrated using an Arduino microcontroller-based system, showcasing high measurement accuracy and ease of use. This approach holds promise for enhanced remote monitoring in various storage scenarios. Additionally, in the case of the banana supply chain, modelling and validation of transport from Costa Rica to Europe revealed the potential for automated warning messages based on temperature and humidity variations, enabling remote monitoring of the ripening process within containers. These advancements underscore the growing potential of wireless sensor technologies to revolutionize food quality monitoring practices, ensuring the safety and integrity of our food supply.

Future scope

Expansion of application areas

The advancements in computer vision techniques for determining maturity indices in the food processing sector are expected to extend their application to other industries as well. Industries such as pharmaceuticals, cosmetics, and textiles may benefit from similar automated processes for the quality assessment and maturity determination of their products. Research and development in these areas could lead to the creation of new and innovative applications for computer vision technologies.

Development of specialized hardware

As the demand for more efficient and accurate maturity index determination increases, there is likely to be a focus on the development of specialized hardware tailored to the specific needs of various industries. This could include the design of portable and cost-effective devices equipped with integrated biosensors and AI capabilities, making the technology more accessible and practical for different settings.

Integration of advanced AI techniques

The use of artificial intelligence in conjunction with computer vision techniques is expected to evolve further. Researchers may look into how to combine deep learning algorithms, CNNs, and other cutting-edge AI methods to improve the accuracy, speed, and adaptability of maturity index determination. Such developments could lead to real-time, on-site analysis and decision-making, reducing the time and resources required for quality assessments.

In-field automation and precision agriculture

The application of computer vision techniques for maturity index determination has the potential to revolutionize agriculture. With the integration of autonomous drones, robotic systems, and smart sensors, farmers can efficiently monitor crop maturity in real-time, enabling precise harvesting and resource management. This implementation could improve crop yields, reduce waste, and optimize agricultural practices.

Standardization and regulation

As the adoption of computer vision techniques for maturity index determination becomes more widespread, there will likely be a need for standardization and regulation. Bodies like the Food and Drug Administration (FDA) and other relevant authorities may establish guidelines and criteria for the use of these technologies in different industries to ensure consistent and reliable results.

Collaboration and interdisciplinary research
Future research in this domain will likely require collaboration between experts in various fields, including computer vision, agriculture, food science, and engineering. Interdisciplinary efforts can lead to more comprehensive solutions and novel approaches that address complex challenges in maturity index determination.

Environmental impact assessment
The integration of computer vision techniques in agriculture and food processing can potentially reduce waste and improve resource utilization. Future studies may focus on conducting comprehensive environmental impact assessments to quantify the benefits of these technologies, contributing to sustainable practices and promoting eco-friendly solutions.

Data privacy and security
As computer vision-based systems collect and analyze vast amounts of data, ensuring data privacy and security will become paramount. Future research will need to address these concerns and develop robust protocols to safeguard sensitive information and prevent unauthorized access.

Global adoption and technological transfer
To fully realize the potential of computer vision techniques in maturity index determination, efforts to promote technology transfer and global adoption will be crucial. This could involve knowledge-sharing initiatives, capacity building in developing regions, and fostering international collaboration to ensure equitable access to these advancements.

In a nutshell, the future scope of computer vision techniques in maturity index determination is promising and diverse. The continued research and development in this area have the potential to transform various industries, improve product quality, optimize resource management, and contribute to sustainable practices on a global scale.

Conclusions
In conclusion, this review underscores the significant impact of recent computer vision advancements in determining the maturity indices of fruits and vegetables in the food processing sector. Techniques such as NMR, NIR, and thermal imaging show promise in replacing labor-intensive manual methods, offering more efficient and accurate assessments. These methods, whether destructive or non-destructive, exhibit versatility and potential for automation. Integrating biosensors and AI enhances precision, expanding their application across industries. Beyond food processing, these technologies hold promise in pharmaceuticals, textiles, and more, with potential hardware and AI advancements on the horizon. In agriculture, they enable real-time monitoring and resource management, fostering sustainability. However, standardization, data privacy, and security remain crucial considerations, necessitating interdisciplinary collaboration for responsible adoption. In summary, computation techniques have transformative potential, revolutionizing industries, promoting sustainability, and advancing automation and efficiency, with continued research and collaboration essential for their responsible and beneficial integration into various sectors.

Abbreviations

AIF	Acoustic Impulse Resonance Frequency
AIRM	Acoustic Impulse Response Method
AI	Artificial Intelligence
ANN	Artificial Neural Network
AOAC	Association of Official Analytical Chemists
NDIR	Non-Dispersive Infrared
CARS-SPA-PLS	Competitive Adaptive Reweighted Sampling-Subwindow Permutation Analysis-Partial Least Square
CCD	Charged Coupled Device
CMOS	Complementary Metal Oxide Semiconductor
CP	Conducting Organic Polymers
CNN	Convolutional Neural Networks
E-Nose	Electronic Nose
E-Tongue	Electronic Tongue
FDA	Food and Drug Administration
GA-Si-PLS	Genetic Synergy Interval Partial Least Square
HPLC	High-Performance Liquid Chromatography
HIS	Hyperspectral Imaging
HLB	Huanglongbing
IDF	Insoluble Dietary Fiber
LF-NMR	Low-Field Nuclear Magnetic Resonance
ML	Machine Learning
MRI	Magnetic Resonance Imaging
MOSFET	Metal Oxide Semiconductor Field-Effect Transistors
MOS	Metal Oxide Semiconductors
MIR	Mid-Infrared
MIP	Molecularly Imprint Polymer
MC-UVE-SPA	Monte Carlo–Uninformative Variable Elimination–Successive Projections Algorithm
MSC	Multiplicative Scatter Correction
NIRS	Near-Infrared Spectroscopy
NMR	Nuclear Magnetic Resonance
Pd	Palladium
PLS	Partial Least Square
PPT	Parts per trillion
PANI	Polyaniline
Ppy	Polypyrrole
$KMnO_4$	Potassium Permanganate
PFDI	Precise Fruit Disease Identification Model
PCA	Principal Component Analysis
QCM	Quartz Crystal Microbalance
RFID	Radio Frequency Identification

RPI	Ripening Index
RMSEP	Root Mean Square Error of Prediction
SDF	Soluble Dietary Fiber
SSC	Soluble Solids Content
SNV	Standard Normal Variate
SVM	Support Vector Machine
IQI	Internal Quality Index
TI	Thermal Imaging
TRS	Time-Resolved Reflectance Spectrometry
TA	Titratable Acidity
UV	Ultraviolet
VOC	Volatile organic compounds
WSN	Wireless Sensor Networks
ZnO_2 Zinc	Oxide

Acknowledgements
Not applicable.

Authors' contributions
Anjali, Ankita Jena, Ayushi Bamola, Ishika Jain, Nandini Pathak, Nishita Sharma, Nitiksha Joshi, Renu Pandey, Shakshi Kaparwal, Vinay Yadav, Sadhna Mishra: Writing-original draft preparation, Avinash Kr Jha, Sarvesh Rustagi, Bindu Naik, Manpreet Singh Preet, Vijay Kumar, Saurav Bhatt, Saamir AkhtarResources, Reviewing and Editing, Arun Kumar GuptaConceptualization, Supervision, Resources, Reviewing and Editing.

Funding
Not applicable.

Availability of data and materials
Data sharing is not applicable to this article as no datasets were generated or analysed during the current study.

Declarations

Ethics approval and consent to participate
Not applicable.

Consent for publication
Not applicable.

Competing interests
No competing interest with present submission.

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Received: 21 July 2023 Accepted: 5 November 2023
Published online: 29 February 2024

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