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Review

Smart Biosensor-Based Technologies for Horticultural Supply Chains and Post-Harvest Losses Mitigation

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Abstract

Biosensors and complementary sensing technologies are valuable tools for rapid monitoring of horticultural produce because quality deterioration and contamination can occur at any stage of the supply chain. This review discusses different biosensors and complementary sensing technologies to detect pathogens, pesticide residues, heavy metals, spoilage-related compounds, and changes associated with ripening and freshness. It considers their use from pre-harvest production and harvesting to storage, transportation, packaging, retail and consumer-level monitoring. The review also examines the role of nanomaterials and complementary tools such as near-infrared spectroscopy, hyperspectral imaging, electronic noses, machine vision, artificial intelligence, and the Internet of Things. These technologies can support rapid, non-destructive assessment, but many devices have been tested mainly under controlled or laboratory conditions. Wider use is still limited by sample-matrix effects, instability of biological components, calibration challenges, high cost, and limited validation with naturally contaminated produce. Future work should focus on simple, stable, affordable, and multiplexed devices that can be tested under actual supply-chain conditions. With proper validation, integrated sensing systems could improve food-safety monitoring and support post-harvest quality management; however, direct evidence that they reduce horticultural produce losses remains limited.

Keywords: post-harvest quality; biosensors; supply chains; cold-chain management; artificial intelligence

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1. Introduction

The term "biosensor" is a compound word that is derived from two words: bio and sensor. "Bio" refers to the biological component of the device, which is a biological recognition element and can be an enzyme, antibody, or even a microorganism or tissue; and

"sensor" refers to the detector component [1]. The International Union of Pure and Applied Chemistry (IUPAC) defined a biosensor as a device that uses specific biochemical reactions mediated by isolated enzymes, immune systems, tissues, organelles, or whole cells to detect chemical compounds, usually by electrical, thermal, or optical signals. Leland Charles Clark Jr. is considered the father of biosensors [2].

The term "biosensor" was first introduced by Cammann to describe a device that uses a biological recognition element and a transducer to detect a target analyte. Biosensors have undergone many changes, with better sensitivity, specificity and integration of biological components [3]. Biological biosensors are used in monitoring and diagnosis by combining biological sensing materials with signal-transduction systems [4]. They are powerful tools with a very wide range of applications that improve quality of life (Figure 1). The heavy use of pesticides, along with environmental pollution, has caused long-term contamination of food sources. This shows the importance of ensuring food safety and quality [5,6]. In addition, miniaturised biosensor platforms can enable rapid, sensitive, and multiplexed detection of foodborne pathogens and other contaminants, supporting on-site food-safety monitoring [7]. Biosensors are used in the food industry and offer many important features, including detection of heavy metals, toxic components and foodborne pathogens, and help in the detection of pesticide residues. In agriculture, biosensors are used to monitor soil nutrients, to help detect plant diseases, and to support precision farming [4,8,9] (Figure 2). A biosensor has three main parts: a bioreceptor, a transducer and a signal processing and display system [10]. New advancements like nanotechnology, multiplexed detection, and smartphone-based systems have significantly improved biosensor technology [11]. Several types of biosensors are used in agriculture (Table 1) [12–14]. They can overcome the drawbacks of conventional methods by providing fast, sensitive, and on-site detection of food contaminants [15].



Figure 1. Diverse practical applications of modern sensor technologies.

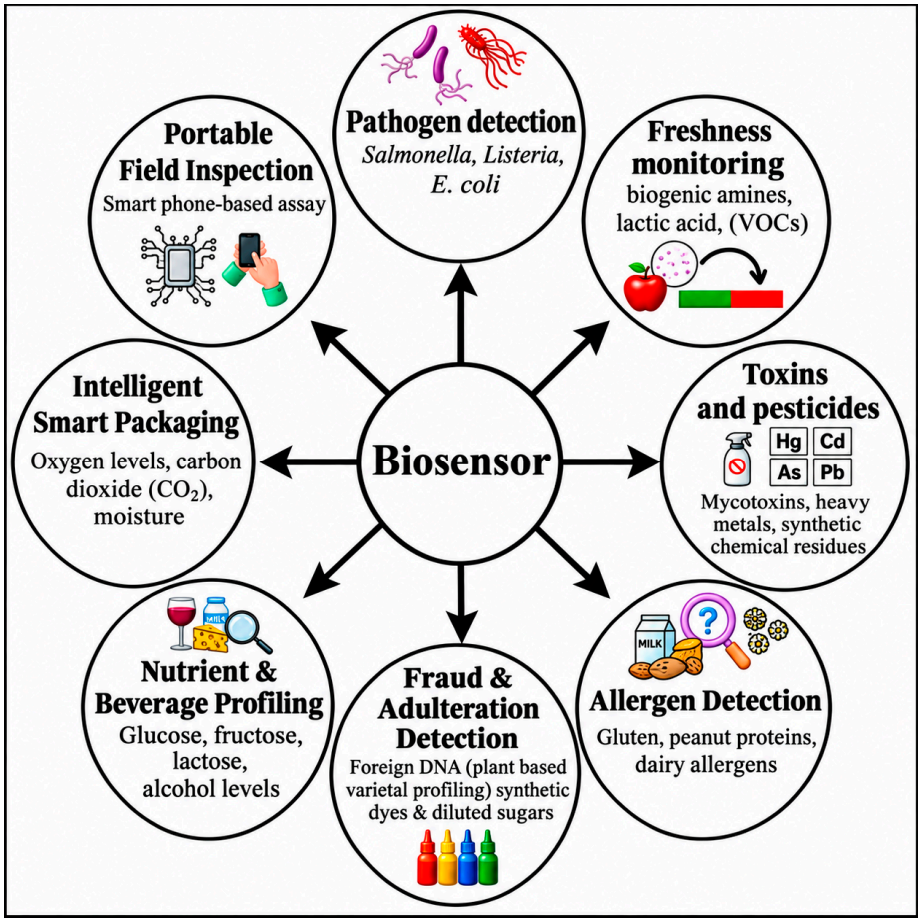

Figure 2. Applications for biosensors in food safety, quality assessment, and intelligent food packaging.

Fruits and vegetables are highly perishable, and quality losses can occur at any stage, including handling, packaging, storage, transportation, and marketing. Biosensors and other sensing technologies have been explored to assess the quality and safety of horticultural produce during post-harvest handling and storage. Better supply-chain coordination, biosensor monitoring, and improved post-harvest practices can help maintain horticulture quality [13,14,16].

Existing reviews typically cover biosensors for a single analyte class (for example, pathogens or pesticides), a single sensing principle, or a single stage of the chain. This review differs in three ways. First, it follows biosensors and complementary sensing technologies across the whole horticultural supply chain, from preharvest production and harvesting through storage, transportation, packaging, and retail to consumer-level monitoring. Second, it covers the main target groups in one framework: pathogens, pesticide residues, heavy metals, spoilage-related compounds, and ripening and freshness indicators. Third, it appraises each technology against practical adoption criteria rather than analytical performance alone. These criteria are validation in real samples, calibration robustness, portability, cost, and suitability for deployment at each supply-chain stage. It also covers optical, spectroscopic, imaging, and electronic-nose approaches where they complement or integrate with biosensor systems, together with digital tools (IoT, AI/machine learning, smart packaging, and traceability). Although these technologies can support rapid, non-destructive assessment and post-harvest quality management, direct quantitative evidence for their independent effect on post-harvest loss reduction under commercial supply-chain conditions remains limited. We therefore identify this evidence

gap and outline priorities for future research: validating these technologies in real supply chains and measuring their effects on spoilage, shelf life, and post-harvest losses.

2. Literature Search and Selection Methodology

We searched Scopus for publications available up to 3 August 2026. The search combined the terms below using Boolean operators. We used different keywords such as (biosensor OR biosensing) AND (horticult OR fruit OR vegetable) AND (post-harvest OR postharvest OR food safety OR quality monitoring OR artificial intelligence OR machine learning. We included review and original research articles that addressed biosensors or complementary sensing technologies (optical, spectroscopic, imaging, and electronic nose) for horticultural quality or safety, supply-chain monitoring, or related digital applications. Reviews were used for background and thematic discussion, and original articles for experimental and sensor-performance data. We excluded studies outside food, agriculture, horticulture, sensing, or supply-chain monitoring. We conducted a literature search in Scopus for publications available up to 2026. Relevant review and original research papers were identified using combinations such as biosensor or biosensing with terms related to horticulture, fruit and vegetable quality, food safety, post-harvest monitoring, pathogens, pesticides, contaminants, cold-chain management, artificial intelligence, machine learning, IoT, smart packaging, digital traceability, nanomaterials, and non-destructive sensing. We included studies that addressed biosensors, complementary sensing technologies, horticultural quality or safety, supply-chain monitoring, or related digital applications. We included optical, spectroscopic, imaging and electronic-nose studies when relevant to horticultural monitoring or integration with biosensor systems. Review papers were used for the background and thematic discussion, whereas the original articles were used for experimental and sensor-performance information. Studies outside the scope of food, agriculture, horticulture, sensing, biosensing or supply-chain monitoring were excluded. We removed duplicate records, then screened the remaining papers by title and abstract, followed by full-text assessment where necessary. The selected literature was organised according to the main themes of the review.

3. Biosensor Working Principles and Components

A biosensor uses a biological element and a transducer to detect a target and produce a measurable signal. The signal may be colour-based, fluorescent, chemiluminescent, or electrical, and smartphones can record and analyse it [17,18]. The recognition element may involve enzymes, antibodies, nucleic acids, microorganisms, or whole cells [19,20]. Biosensors can be classified according to their recognition mechanism or transduction principle, such as electrochemical, optical, thermal, and mass-sensitive systems [20] (Figures 3 and 4).

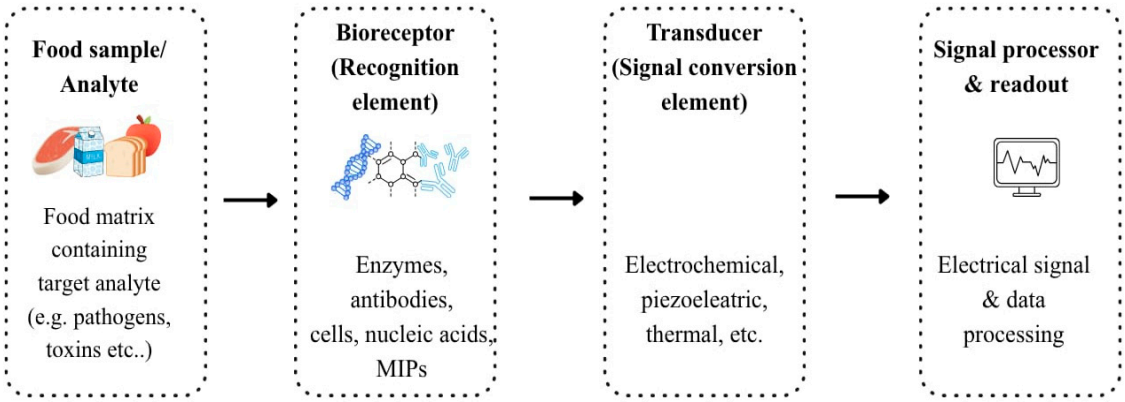

Figure 3. Components of a biosensor.

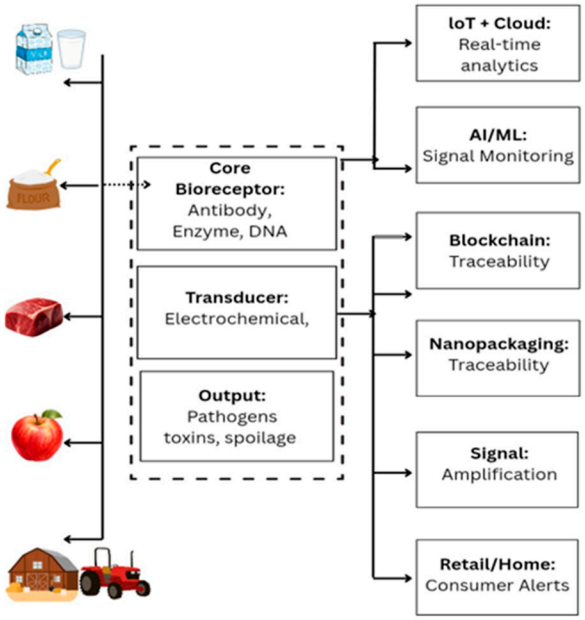

Figure 4. Integrated biosensor framework for food safety and quality monitoring.

A sensing device should not be considered a biosensor solely because of its transducer; the presence of a biological recognition element is a key distinguishing feature [19]. A biosensor contains a biological recognition element, such as an enzyme, antibody, nucleic acid, or cell, together with a transducer. Physical sensors measure parameters such as temperature, pressure, humidity, or light without using a biological recognition element. Chemical sensors detect chemical properties or analytes through chemical interactions. Therefore, the presence of a biological receptor coupled with a transducer distinguishes a biosensor from physical and conventional chemical sensors [4,19].

4. Classification of Biosensors

4.1. Bioreceptor-Based Classification

1. Enzymatic biosensors are widely used. They use enzymes to detect target substances. In the reviewed studies, glucose oxidase-based biosensors were used for fruit-quality assessment. Enzyme-inhibition methods have been reviewed for pesticide detection in vegetable crops. Enzyme-inhibition systems involving acetylcholinesterase were applied to pesticide detection [21–24].
2. Immunosensors: A nanostructured immunosensor was developed for the early and in situ detection of *Xanthomonas arboricola* in agricultural food production [25].
3. Whole-cell biosensors or microbial biosensors use living organisms as biological sensing elements to detect signals related to crop infection [26].
4. Aptasensors are short single-stranded DNA or RNA molecules as recognition elements for target detection [19].

4.2. Transducer-Based Classification

1. Electrochemical biosensors detect target substances by converting the interaction between a bioreceptor and the target into an electrical signal. Potentiometry, voltammetry, impedance, and amperometry are commonly used. Bioreceptors such as antibodies, DNA, aptamers, peptides, enzymes, and bacteriophages have been used to detect food contaminants, including allergens, pesticides, antibiotic residues, toxins, and bacteria. These biosensors can provide rapid and sensitive detection and have

potential for low-cost, miniaturised and on-site food analysis [15]. Recent advances in nanotechnology have improved the design and performance of electrochemical (bio)sensors used for plant and plant-related samples [27].

2. Optical biosensors: They are important for food-quality monitoring. They provide sensitive and specific detection of different food contaminants, allergens and adulterants. Recent developments include the use of nanotechnology, multiplexed detection and smartphone-based biosensors to improve food monitoring [11,28].
3. Piezoelectric quartz crystal microbalances (QCM) are highly sensitive sensors that can detect small changes in mass on the quartz crystal surface. When substances attach to the crystal surface, their resonant frequencies change. The Sauerbrey equation explains this relationship. QCM sensors have been used to detect volatile compounds released by fruits during ripening and to monitor fruit freshness [29] (Table 2).

Importantly, the transduction principle alone does not make a device a biosensor; the presence of a biological recognition element is a defining feature.

Table 1. Major biosensor classification based on transduction principle, biological recognition element, and its application.

Transduction Principle	Biological Recognition Element	Detection Principle	Main Target/Application	Key Features
Electrochemical	Antibody	Antigen–antibody binding is converted into an electrochemical signal	Foodborne pathogens and contaminants	Immunosensors provide high target specificity and have been applied to pathogen detection [19,22,25,30]
Electrochemical	Enzyme	Enzyme reaction or enzyme inhibition generates a measurable signal	Pesticides and glucose-related fruit-quality indicators	Enzyme-based systems are simple and useful for rapid screening; examples include glucose oxidase-based fruit-quality assessment and acetylcholinesterase-based pesticide detection [21,23,31,32]
Electrochemical	Aptamer or DNA probe	Target binding or nucleic-acid hybridisation changes an electrochemical signal.	Pathogens, pesticides, toxins, and other food contaminants	Aptamers are short single-stranded DNA or RNA recognition elements; DNA and aptamers are reported as bioreceptors for electrochemical biosensors [15,19]
Electrochemical	Enzyme, antibody, DNA, aptamer, peptide, or bacteriophage	Bioreceptor–target interaction is converted into an electrical signal	Allergens, pesticides, antibiotic residues, toxins, and bacteria	Potentiometry, voltammetry, impedance, and amperometry are commonly used; electrochemical biosensors can provide rapid, sensitive, low-cost, miniaturised, and on-site food analysis [15,19,20,30]
Optical	Enzyme, antibody, aptamer, or nucleic acid	Target interaction changes light absorption, fluorescence, colour, or another optical signal.	Food contaminants, allergens, adulterants, and foodborne pathogenic bacteria	Optical biosensors provide sensitive and specific detection; recent developments include nanotechnology, multiplexed detection, and smartphone-based systems [11,19,28,30]
Piezoelectric/QCM	Antibody, aptamer, or DNA probe immobilised on the crystal surface	Target binding changes the mass and resonant frequency of a quartz crystal	Foodborne pathogens and other contaminants	QCM sensors are label-free and mass-sensitive; with immobilised bioreceptors they can detect pathogens in food samples [17,29]
Photoelectrochemical	Bioreceptor-based recognition element	Optical excitation generates a photocurrent that is measured electrochemically.	Biological and chemical targets	Combines optical excitation with electrochemical detection [19,30]

AI and machine learning are not independent biosensor classes; they may be integrated with electrochemical, optical, piezoelectric, or other biosensing platforms for signal processing, pattern recognition, and prediction [33].

Table 2. Biosensor and complementary sensing technologies used for horticultural quality and safety assessment.

Crop	Sensing Principle/ Transduction	Target Analyte/ Trait	Recognition Element	AI/ML Processing	Classification	Reference
			Fruits			
Mango	Acoustic sensor & electronic nose with sensor fusion	Ripeness and maturity stage	Not applicable	Sensor fusion	Complementary sensing technology	[34]
Mango	Near-infrared spectroscopy	Mango quality attributes	Not applicable	ML-based sensing	Complementary sensing technology	[35,36]
Fruits	Vis/NIR optical spectroscopy	Internal quality and variety identification	Not applicable	Spectral & chemometric analysis	Complementary sensing technology	[37]
Strawberry	Enzyme-based electrochemical biosensor	Fruit quality/glucose	Glucose oxidase enzyme	Not reported	Biosensor	[21]
Grapes	Electrochemical pattern recognition	Fruit quality analysis	Pattern recognition from sensor array	Pattern-recognition-based analysis	Complementary sensing technology	[38]
Grapes	Headspace volatile detection using a sensor array	Aroma profile or volatiles	Not applicable	Not reported	Complementary sensing technology	[39]
			Vegetables			
Crops	**Sensing Principle/ Transduction**	**Target Analyte/ Trait**	**Recognition/ P rinciple**	**AI/ML Processing**	**Classification**	**Reference**
Onion	Disposable amperometric electrochemical sensing on a screen-printed electrode.	Pyruvic acid/pungency	Pyruvate dehydrogenase enzyme	Not reported	Biosensor	[40]
Tomato and other vegetable crops	Smart disease monitoring system	Disease detection	Not applicable	Deep learning-based visual sensing	Complementary sensing technology	[41]
Tomato	RGB and hyperspectral sensing with ML	Biochemical quality trait	Not applicable	Machine learning-based assessment	Complementary sensing technology	[42]
Vegetable crops/plant tissue	Nanomaterials enable electrical, electrochemical, and optical sensing.	Pathogens and stress biomarkers	Bioreceptor-based recognition	Not reported	Biosensor	[43]
Vegetables and fruits	Biosensors and nano biosensors	Pesticides, mycotoxins, heavy metals	Bioreceptor-based recognition	Not reported	Biosensor	[44]

5. Application of Biosensors in Food Supply Chains

Biosensor technologies have been reviewed for the early detection and quantification of plant pathogens. Advances in biosensing technologies for detection of plant pathogens in sustainable agriculture have also been reviewed [45,46]. Flexible wearable sensors have been reviewed for crop monitoring. Wearable and implantable electrochemical

(bio)sensors have been reviewed for monitoring agrochemicals, phytohormones, plant-growth precursors, and stress biomarkers in plants [47,48] (Tables 3 and 4).

5.1. Electrochemical Biosensors

These sensors can detect disease by measuring even small electrical changes. Electrochemical sensing materials have been reviewed for detecting plant-emitted volatile organic compounds associated with biotic and abiotic stress in potato and tomato plants [49]. For example, DNA-based impedance sensors detect *Pseudomonas syringae.* Lau et al. [50]developed a specific and sensitive isothermal electrochemical biosensor for detecting *Pseudomonas syringae* DNA. The biosensor used recombinase polymerase amplification and colloidal gold nanoparticles as probes. It detected infected *Arabidopsis thaliana* samples before visible symptoms appeared and showed higher sensitivity than conventional PCR followed by gel electrophoresis. Patel et al. [51,52] investigated a label-free, non-faradaic DNA-based impedimetric biosensor for detecting *Ralstonia solanacearum*. The system used micro-sized gold interdigitated electrodes and a pathogen-specific DNA probe, and detected target DNA at concentrations as low as 0.1 ng/µL under the reported experimental conditions. Regiart et al. [25] developed a microfluidic electrochemical immunosensor for *Xanthomonas arboricola* in walnut samples. The study reported that the linear range was from 5 × 102 to 1 × 104 CFU mL^{-1} and showed a detection limit of 1.5 × 10^2 CFU/mL^{-1} [25]. Malecka et al. [53] developed an ion-channel DNA genosensor to detect specific Plum pox virus sequences in plant extracts. The sensor was based on hybridisation between a virus-specific DNA probe and the target sequence, with the response measured electrochemically. The study states that the genosensor could clearly distinguish healthy plant extracts from extracts of infected leaves across the tested concentration range of 10–50 pg/mL. The reported detection limit for DNA from infected plant extracts was 12.8 pg/mL, and the sensor differentiated infected samples from healthy plant extracts.

5.2. Optical Sensors

In wine grapes, field sampling of volatile compounds followed by chemical analysis was used to identify markers associated with *Botrytis cinerea* infection. This method represents a complementary analytical approach for disease assessment rather than a recombinase polymerase amplification-surface-enhanced Raman scattering (RPA–SERS) biosensor [54]. A multiplex point-of-care platform combining RPA-SERS was evaluated to detect *Botrytis cinerea*, *Pseudomonas syringae*, and *Fusarium oxysporum*. The method detected as few as two copies of B. *cinerea* DNA and demonstrated simultaneous detection of the three pathogens in *Arabidopsis thaliana* and commercial tomato crops [55].

5.3. Whole-Cell and Wearable Biosensors

Zanger and Eltzov (2025) [26] developed a genetically engineered, luminescent *Escherichia coli* whole-cell biosensor to detect volatile compounds released by infected potato tubers. The biosensor was evaluated under low-temperature storage conditions for the continuous surveillance of soft rot infections caused by *Pectobacterium brasiliense* [26]. Moreover, flexible wearable plant sensors are being developed for continuous monitoring of physiological and chemical changes in plants, although pathogen-specific validation under field conditions remains limited [50]. Electrochemical sensors have been investigated for detecting pesticide residues in irrigation water, which may support the identification of contaminated water sources. Genetically modified bacterial biosensors have also been explored for detecting heavy metals such as lead and cadmium in soil. Aptamer-based nano sensors have been investigated for detecting fungal pathogens such as *Phytophthora* on rootstock surfaces before visible symptoms appear. These studies

demonstrate the potential of biosensors for detecting agricultural contaminants and plant pathogens; however, further validation is needed to determine their effectiveness under practical field conditions [14,15,30].

Table 3. Application of biosensors in food supply chains.

Stage	Reported Sensing Applications	Key Analytes/Indicators	Sensor Type	Reference
Pre-harvest	Detection of soil pathogens, irrigation contaminants & NPK-related parameters	Soil pathogens, irrigation contaminants, NPK	Aptamer-based electrochemical sensor	[11,30]
Harvesting	Detection of pesticide residues & heavy metals	Pesticide residue, heavy metals	AChE-based electrochemical sensor	[15,18]
Raw material intake	Detection of pathogens & adulterants	Pathogens (*Salmonella*), adulterants.	Immunosensor	[1]
Post-harvest	Assessment of ripening & quality-related parameters	Ethylene, SCC/TA, firmness	QCM & NIR-optical sensing	[17,56]
Cold chain	Monitoring of temperature abuse & microbial growth	Temperature abuse, microbial growth	IoT-TTI & pH sensor (complementary physical/chemical sensing technology)	[14]
Packaging	Monitoring of freshness-related changes & pathogen growth	CO2/pH, pathogen growth	Colorimetric TTI (complementary smart-packaging sensing technology)	[30]
Retail	Assessment of respiration rate & surface pathogens	Respiration rate, surface pathogens	Flexible patches (complementary sensing technology)	[37]
Consumer	Smartphone-based access to QR-linked freshness information	QR-linked freshness information	Smartphone applications	[57]

Table 4. Comparative analysis of biosensor and sensing technologies for food safety and quality assessment.

Sensor System and Target	Recognition, Transduction and Matrix	Analytical Performance, Response Time & Sample Number	Validation and AI	Laboratory/Field & Portability	Limitations	Evidence of Post-Harvest Loss Reduction
Electrochemical biosensor with smartphone integration; Target: organophosphate pesticide	AChE enzyme; Transducer: amperometric electrochemical detection; Matrix: vegetable extract	LOD: 9.8 ng/L Linear range: 10-100 ng/L LOQ, sensitivity, sample number & response time not reported	Spiked-matrix validation; comparison with potentiostat; 85-day stability reported; AI not reported	Laboratory/spiked matrix Portability: portable smartphone prototype No field performance reported	Spiked extract validation and field performance not established	No evidence of post-harvest reduction reported; detection performance only [31]
Microfluidic electrochemical immunosensor; Target: *Xanthomonas arboricola*	Monoclonal anti-*Xanthomonas arboric*ola antibody; Transducer: Electrochemical immunosensing; Matrix: walnut plant sample	LOD: 1.5 × 10^2 CFU/mL, CV ≤ 5% Linear range: linear range: 5 × 10^2–1 × 10^4 CFU mL^{-1} LOQ & sample number: not reported	Selected plant-sample validation; AI not reported	Laboratory/selected plant sample Microfluid platform Limitation: limited naturally contaminated & field validation	Limited naturally contaminated and field validation	No evidence reported; pathogen detection only [25]
AChE electrochemical biosensor; Target: chlorpyrifos	Acetylcholinesterase; Transducer: electrochemical detection; Matrix:	LOD: 3.1 μg/L; LOQ: 12.5 μg/L Linear range: 10–200 μg L^{-1}; Recoveries: 96.67–105.65%;	Matrix-matched recovery testing; AI not reported	Laboratory/food-matrix testing Portability: screen-printed carbon-electrode formate.	Performance limited to tested matrices; broader validation needed	No evidence reported; analytical detection only [23]

	drinking water & orange juice	Response time & sample number: not reported				
Enzyme-based electrochemical biosensor; Target: glucose/strawberry quality	Glucose oxidase; Transducer: electrochemical detection; Matrix: diluted strawberry juice	linear range: 0–10 mM LOD & response time: not reported Ranked 8 cultivars against HPLC	Fruit-juice validation; HPLC comparison	Laboratory/fruit-juice analysis Portability: disposable screen-printed electrode format	Dilution and matrix preparation required; field deployment not evaluated	Indirect evidence only; quality-related measurement reported, but loss reduction not quantified [21]
Disposable screen-printed biosensor array; Target: grape quality	Sensor-array-based recognition; Transducer: electrochemical pattern recognition; Matrix: grape sample	LOD, LOQ, response time & sample number: not reported Pattern-recognition-based analysis	Grape-sample analysis	Laboratory/selected sample analysis Pattern recognition analysis Portability: disposable screen-printed format	No LOD or field validation reported	No evidence reported; grape analysis only [38]
Electronic nose; Target: grape aroma/volatiles	Volatile-responsive sensor array; Transducer: gas-sensing pattern recognition; Matrix: grape berries	LOD, LOQ, response time & sample number: not reported Aroma-profile discrimination	Grape-berry aroma profiling	Laboratory/selected sample analysis Portability: instrument-dependent	No individual-compound quantification or field validation reported	No evidence reported; aroma profiling only [39]
Hyperspectral imaging with machine learning; Target: mango maturity & quality	Not applicable; Transducer: hyperspectral optical imaging; Matrix: mango fruit	LOD, LOQ, response time & sample number: not applicable 100% maturity classification Rp^2: 0.946 firmness, 0.793 SSC 0.825 TA	Model calibration and validation on mango dataset; AI: SVM for maturity; random forest for quality prediction	Laboratory/model-based; non-destructive Portability: imaging system, not handheld in cited study	Dataset- and model-dependent; external field validation needed	Indirect evidence only; quality prediction may support grading, but loss reduction not quantified [36]
RPA-SERS point-of-care platform; Target: *Botrytis cinerea*, *Pseudomonas syringae*, *Fusarium oxysporum*	Nucleic-acid amplification and SERS nanotags; Transducer: surface-enhanced Raman scattering; Matrix: *Arabidopsis thaliana* and commercial tomato crops	LOD: as few as 2 copies of B. *cinerea* DNA LOQ, sample number & response time: not reported	Plant and field-oriented validation; AI not detected Outside-laboratory testing reported	Field-oriented detection; not a post-harvest-loss intervention	Portable SERS readers may be costly; loss-reduction outcome not measured	No evidence reported for post-harvest loss reduction; field/on-site pathogen detection only [55]

Portable acetylcholinesterase (AChE) strips are used to detect pesticide residue. Portable smartphone-assisted sensors have been investigated for on-site screening of organophosphorus pesticide residues in food and agricultural samples [18]. The raw material arrival stage is the first key inspection point, where contaminated consignments can enter the processing line. Conventional laboratory testing, such as culture-based or chromatographic methods, often takes hours to days and requires sample transport and trained personnel. Biosensors offer a faster alternative, with reported detection times from minutes to a few hours depending on the target and platform. They have been developed for pathogens, toxins, pesticide residues, and quality indicators in food and horticultural samples [1]. In principle, such methods could support rapid screening of incoming lots at or near the receiving area. However, most reported systems have been validated on prepared or spiked samples under controlled conditions. Evidence for their operation

directly on conveyor belts or at intake hoppers is limited, and in-line use would need further validation for sampling representativeness, matrix interference, throughput, and robustness in industrial environments.

A smartphone-integrated electrochemical sensor was developed for on-site detection of organophosphate pesticides. Chaudhary et al. developed a smart on-site electrochemical organophosphate pesticide sensor plugged into a mobile app, which offers a low detection limit (9.8 ng L^{-1}) and broad detection range (10–100 ng L^{-1}) [31]. These results demonstrate analytical performance under the reported experimental conditions; however, they should not be generalised to all pesticide residues or untreated field samples. An acetylcholinesterase-based electrochemical biosensor using a Cu nanowire/reduced graphene oxide nanocomposite was reported for chlorpyrifos detection. The study reported a linear range of 10 μg/L–200 μg/L and a detection limit of 3.1 μg L and a limit of quantification of 12.5 μg/L, with application to drinking water and orange juice samples [23]. Such studies demonstrate the potential of enzyme-based electrochemical sensors for rapid contaminant screening, while also highlighting the importance of sample matrix and validation conditions when interpreting detection limits. These performance results are from individual studies under specific experimental conditions (Table 5).

5.4. Flavour and Quality Analysis Using Biosensors

Food quality is assessed using several factors, including texture, taste, colour, nutrient content, microorganisms, pH, and water activity. Biosensor-based methods have been explored for measuring selected compounds related to food freshness, composition, and contamination [32].

5.5. Cell-Based Biosensors for Taste Detection

Cell-based biosensors have been investigated for evaluating taste-related responses, including sweet, bitter, and umami compounds. However, their use is limited by short cell life, unstable signals, and difficulties in large-scale production. Cell immobilisation techniques and AI-driven data processing have been investigated to improve the biosensor longevity and prediction accuracy of cell-based biosensors [57].

5.6. Biosensor Methods for Metrics Assessment

Cell-based biosensors and nano biosensors have been reviewed for food-flavour evaluation and food-safety applications. Biosensors have also been developed for food analysis. However, the reported applications and performance depend on the sensing system and the target being measured [57–59] (Table 5).

Tropical fruits experience post-harvest losses due to ethylene-induced ripening and decay due to microbial activity. Piezoelectric quartz crystal microbalance sensors have been investigated for detecting ethylene and other volatile compounds associated with fruit ripening. These sensing approaches provide opportunities for rapid monitoring of fruit freshness and quality during storage and distribution. Such technologies can support timely quality assessment and management of fresh fruits throughout the supply chain [17]. Near-infrared (NIR) spectroscopy is mostly applied for non-destructive mango grading purposes. NIR and hyperspectral sensing combined with machine-learning approaches have been investigated for non-destructive prediction of fruit quality parameters. Reported coefficients of determination and prediction errors depend on the crop, cultivar, dataset, spectral range, pre-processing method, and validation strategy. Therefore, a single prediction value should not be generalised to all fruit-quality applications [35,36].

5.7. Cold-Chain Monitoring and Transport Protection

Cold-chain monitoring and transport-related sensing have been discussed as approaches for tracking quality changes and deterioration of fresh food during storage and distribution. These approaches are relevant to maintaining product quality throughout the supply chain; however, the cited literature does not provide a consistent numerical comparison of sensor performance or post-harvest loss reduction under commercial cold-chain conditions [16,17] (Figure 5).

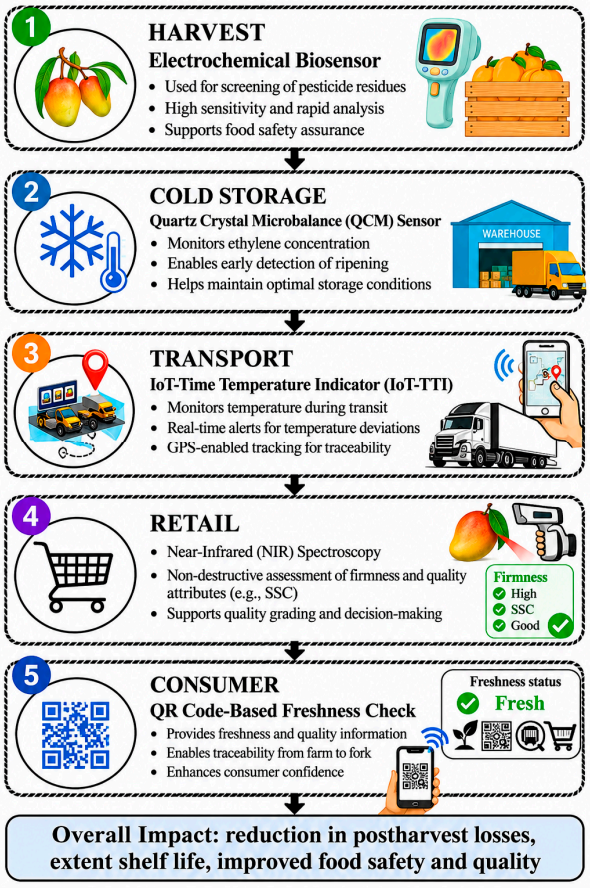

Figure 5. Biosensor and sensor-enabled cold-chain monitoring system for horticultural crops.

5.8. Freshness Assurance

Freshness labels can provide visual information about the deterioration status of packaged food without opening the package. Bio-based sensors have also been investigated for monitoring freshness and quality changes in perishable food products. These applications support freshness assessment during distribution and retail, but the cited references do not report a standardised numerical reduction in post-harvest losses [17,60,61].

5.9. Smart Packaging

Intelligent packaging can incorporate biosensors, sensors, and tags for monitoring food-related conditions such as temperature, humidity, gases, pH, package integrity, freshness, and traceability. These systems provide information relevant to food-quality and food-safety monitoring; however, the existing references do not establish a common quantitative value for shelf-life extension or post-harvest loss reduction across horticultural products [60–62].

5.10. Retail

At the retail stage, non-destructive sensing methods can support fruit-quality assessment and sorting, while freshness labels can communicate the deterioration status of packaged food without opening the package. These functions may assist quality evaluation and handling decisions, but the cited literature does not provide standardised numerical evidence of reduced retail losses.

5.11. Supply-Chain Integration

Biosensors, freshness labels, intelligent packaging, and traceability systems can be integrated to collect and communicate information about food quality, food safety, freshness, and product movement through the supply chain. The cited studies support these monitoring and traceability applications, but they do not report a specific percentage reduction in post-harvest losses resulting from such integration [30,61–63].

Table 5. Comparative synthesis of biosensor, sensing technologies and validation conditions.

Criteria	**Electrochemical Biosensor**	**Optical Biosensor**
Sensitivity	Depends on the bioreceptor, electrode material, assay design, and sample matrix [15,25,31,51,53]. Reported LODs: 3.1 μg/L chlorpyrifos (AChE/CuNWs–rGO sensor; linear range 10–200 μg/L) [23]; 9.8 ng/L organophosphates (smartphone-interfaced sensor) [31]; 1.5 × 10^2 CFU/mL Xanthomonas arboricola (immunosensor; linear range 5 × 10^2–1 × 10^4 CFU/mL) [25].	Depends on the recognition element, optical format, signal, and background [11,28,55]. Reported LOD: as low as 2 copies of Botrytis cinerea DNA (SERS/RPA assay) [55].
Selectivity	Mainly determined by antibodies, enzymes, aptamers, or DNA probes [19,20,25,51,53].	Determined by the recognition element and optical signal-generation method [11,28,55].
Matrix interference	Food components may affect electrode reactions and receptor binding [15,63,64]. Tested in drinking water and orange juice with high recoveries and no interference [23]	Colour, turbidity, scattering, autofluorescence, and background signals may interfere [11,28,55].
Portability	Screen-printed and smartphone-integrated formats support portable testing [15,31]. A smartphone-interfaced sensor remained stable for 85 days [31].	Depends on the light source, detector, optics, and reader [11,28,55].
Cost	Depends on electrodes, reagents, nanomaterials, and electronics [15,63,65].	Depends on optical components, labels, substrates, and readers [11,28,55].
Response time	Depends on preparation, binding, incubation, amplification, and measurement [25,31].	Depends on labelling, incubation, amplification, acquisition, and processing [28,55].
Calibration requirements	Requires electrode calibration, receptor stability, and control of operating conditions [63,64].	Requires instrument/background calibration and signal normalisation [11,28].
Biosensors versus NIR/hyperspectral imaging		
Criteria	**Biosensor**	**NIR/hyperspectral imaging**
Destructive versus non-destructive analysis	May require contact, extraction, swabbing, juice, or tissue, depending on the assay [23,25,31,51,53].	Generally supports intact, non-destructive assessment of fruit quality [35,37,56].
Single-analyte versus multiple-attribute assessment	Usually targets one analyte or a limited group of analytes [23,25,31,51,53].	Can predict several attributes, such as maturity, firmness, SSC, and TA, from calibrated spectral models [35,36]. Example: SVM classified three mango maturity stages with 100% accuracy, and RF predicted firmness, SSC, and TA with Rp^2 = 0.946, 0.793, and 0.825, respectively [36].
Laboratory versus field deployment	Portable formats are possible, but broad field validation remains limited for many platforms [15,31,65].	Field use requires instrument control, calibration transfer, and testing under variable conditions [35,36,56].

Calibration requirements	Requires receptor and sensor calibration, stability testing, and control of assay conditions [63,64].	Requires reference measurements, pre-processing, calibration models, and independent validation [35,36].
AI dependence	AI may assist interpretation but is not essential for every biosensor [33].	Machine learning is commonly used for classification and prediction [35,36].
Cost and infrastructure	Requires electrodes or optical readers, reagents, and sometimes sample-preparation tools [15,31,63].	Requires imaging equipment, controlled illumination, computing, reference data, and a prediction model [35,36,56].
Laboratory and field validation		
Criteria	**Laboratory validation**	**Field validation**
Sample preparation	Often uses standards, extraction, dilution, filtration, or spiked samples [23,25,31,51,53].	Uses more heterogeneous samples with less control over preparation [56,63,65].
Environmental variation	Often uses standards, extraction, dilution, filtration, or spiked samples [23,25,31,51,53].	Temperature, humidity, illumination, handling, and storage vary during use [35,36,56.
Sensor or model drift	Drift can be monitored under stable and controlled conditions [63,64].	Drift may increase because of ageing, fouling, environmental changes, instrument variation, or changing samples [35,36,56].
Validation	Demonstrates analytical feasibility under defined conditions, often with selected or prepared samples [23,25,31,51,53].	Demonstrates performance under realistic agricultural or supply-chain conditions using representative samples [63,66,67].
Reproducibility	Usually assessed under controlled conditions and selected samples [63,65]. Example: within- and between-assay CV below 5% [25].	Must be demonstrated across samples, operators, locations, seasons, devices, and batches [36,56,67].
Robustness	Shows whether the method works under optimised conditions [63,65].	Shows whether performance is maintained despite matrix and environmental variation [35,36,56,67].

Electrochemical and optical biosensors are mainly targeted analytical platforms, whereas NIR and hyperspectral imaging are generally non-destructive, model-based platforms for broader quality assessment. Their performance cannot be universally ranked because the studies use different targets, matrices, calibration procedures, datasets, and validation conditions. Laboratory feasibility should therefore be distinguished from field robustness, where matrix heterogeneity, environmental variation, drift, reproducibility, and independent validation are critical.

6. Challenges and Limitations

Although biosensors have considerable potential for food safety and quality monitoring, several limitations still need to be addressed before their wider practical application.

6.1. Complex Food Matrices and Sensor Performance

Food samples contain many components that can interfere with the interaction between the target analyte and the sensing element. This interference can change the response of the sensor and affect the measurement reliability [63]. A sensor that performs well with a simple test solution may therefore give different results when it is used in a real food sample.

6.2. Stability and Calibration

Biological sensing materials may lose activity during the time of storage or repeated use. Sensor responses can also change when temperature, humidity or any other operating

conditions vary. Therefore, regular calibration is needed to maintain consistent results [64].

6.3. Validation Under Real Conditions

Many biosensors have shown good results under laboratory experiments, but fewer have been tested extensively with genuine food samples or under supply-chain conditions [65]. Differences in sample composition and the surrounding environment can influence the performance of the sensor. Testing with naturally contaminated and commercially relevant samples is therefore necessary before practical adoption.

6.4. Cost and Commercialisation

The cost and complexity of a biosensor can limit its use outside the laboratory. Practical devices should be affordable, easy to operate, and suitable for large-scale production. Nanomaterials may improve sensitivity, but their use can also increase fabrication complexity and manufacturing cost [63,65,66].

6.5. Limited Datasets

AI models may be affected by small or narrowly sampled datasets and limited external validation. Larger, more diverse datasets are needed before practical deployment.

6.6. Environmental and Matrix Conditions

Changes in environmental conditions, sensor signals and food-matrix composition may reduce model performance. Independent testing under different real-sample conditions is therefore necessary [67].

Overall, the major challenges include matrix interference, stability, calibration, validation under practical conditions and cost. Addressing these limitations is important for improving the reliability, affordability, and practical applicability of biosensors in food safety and quality monitoring. (Table 6).

Table 6. Comparative limitations of biosensors and complementary sensing technologies used in the horticultural supply chain.

Technology	Limitation Supported by the Cited Reference	Reference
Electrochemical biosensors	Complex food matrices can interfere with the interaction between the target analyte and the sensing element, affecting measurement reliability.	[63]
Enzyme-based biosensors	Enzyme-inhibition methods are mainly applicable to organophosphorus and carbamate pesticides; matrix and sample-extraction conditions require careful consideration in vegetable samples.	[24]
Immunosensors	Foodborne-pathogen biosensors require validation in relevant food matrices before practical application.	[22]
Whole-cell biosensors	Whole-cell biosensor performance depends on maintaining viable cells under appropriate operating and storage conditions.	[26]
QCM sensors	QCM-based fruit-freshness sensing depends on the selection of sensitive materials and operating conditions for VOC detection.	[29]
NIR and hyperspectral imaging	Prediction performance depends on crop and cultivar, dataset, spectral range, pre-processing method, and validation strategy.	[35]
RGB and hyperspectral imaging with machine learning	Performance depends on the sensing data and the machine-learning approach used for quality prediction or classification.	[42]
AI/ML-assisted sensing	Data heterogeneity, matrix interference, and limited external validation can affect the reliability of AI-assisted sensing.	[67]

7. Integration with Emerging Technologies

Biosensors are being investigated as part of smart food-monitoring and traceability systems. Biosensor technologies have been reviewed for food safety and quality monitoring, including their possible use in food traceability systems [30]. Smart food-packaging research has also discussed biosensors for real-time monitoring and spoilage detection and the use of the Internet of Things (IoT) to improve traceability and transparency in the food supply chain [68] (Figure 6).

7.1. Artificial Intelligence and Machine Learning

Artificial intelligence (AI) and machine learning (ML) are being integrated with biosensors and other sensing technologies for food-safety and quality assessment. AI applications have been reported for electrochemical, optical, and piezoelectric biosensors for foodborne-pathogen detection, with machine-learning and deep-learning methods used for biosensor data interpretation [33,67]. The application of different AI models depends on the sensing data and analytical objective. Hyperspectral imaging (HSI) combined with support vector machine (SVM) classification was used to discriminate three mango maturity stages, while a random forest (RF) model was applied to predict firmness, soluble solids content (SSC), and titratable acidity (TA). The SVM model achieved 100% classification accuracy, while the RF model produced Rp^2 values of 0.946, 0.793, and 0.825 for firmness, SSC, and TA, respectively [36]. The hyperspectral imaging example represents AI-assisted complementary sensing rather than AI-assisted biosensing, because hyperspectral imaging does not use a biological recognition element. AI and ML can support the interpretation of signals from both biosensors and complementary sensing technologies. Although AI-assisted biosensors have been reported for foodborne-pathogen detection, evidence from externally validated applications under real horticultural supply-chain conditions remains limited. However, the reliability of AI-assisted sensing can be affected by data heterogeneity, matrix interference, and limited external validation. These factors have been identified as important challenges in the application of AI for foodborne-pathogen detection [69].

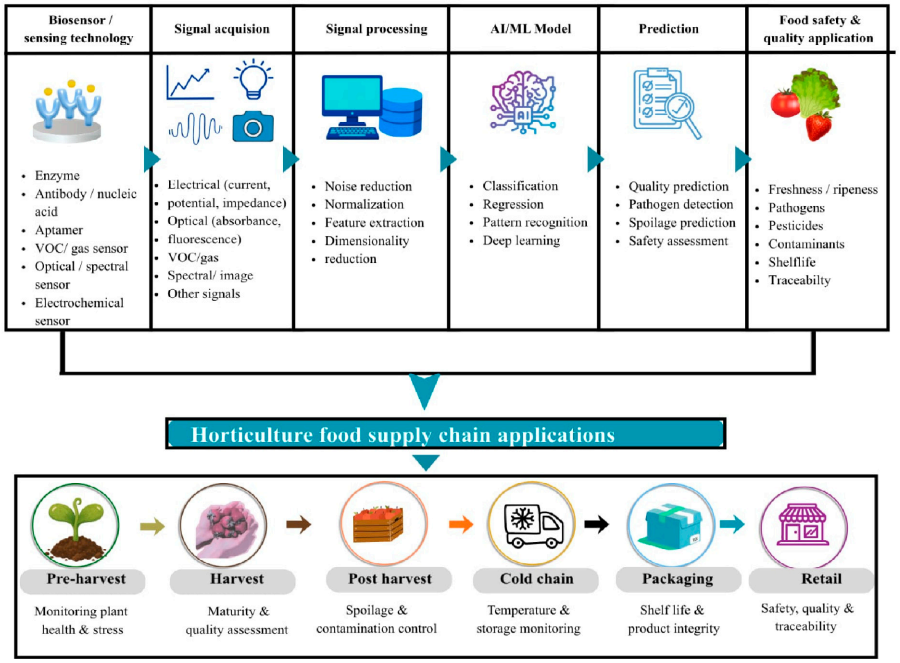

Figure 6. Conceptual workflow of biosensor-based sensing, signal processing and artificial intelligence for food safety and quality assessment of horticultural crops.

7.2. Internet of Things and Intelligent Monitoring

The Internet of Things provides a means of connecting sensing technologies with digital systems. In smart food-packaging research, IoT has been discussed in relation to the transfer and management of information and to improving traceability and transparency within the food supply chain [68]. Biosensors have also been discussed as components of smart food traceability systems for food safety and quality monitoring [30]. The food safety concept connects biosensors with the Internet of Things, smartphones, QR codes, and cloud-based systems. These connections can support continuous monitoring, data sharing, traceability, and faster responses to food-safety risks [32]. Wearable and implantable electrochemical (bio)sensors have been reviewed for monitoring agrochemicals, phytohormones, plant-growth precursors, and stress biomarkers in plants. These sensor configurations support in vivo monitoring of plant health and have potential applications in precision agriculture [70]. In fresh fruits and vegetables, intelligent supply-chain research includes sensing technologies, imaging, smart indicators, wireless sensor networks, and data-driven approaches. The use of IoT and other digital technologies has also been discussed for improving monitoring and management of fresh-produce supply chains [69].

7.3. Digital Traceability and Data Management

Biosensors can provide information related to food safety and quality, while digital traceability systems can be used to manage information associated with food products and their movement through the supply chain. The use of biosensors in smart food traceability systems has been reviewed in relation to food safety and quality monitoring [30]. For fresh fruits and vegetables, digital supply-chain research has discussed data carriers, indicators, wireless sensor networks, IoT, cloud processing, and blockchain in relation to data-driven tracing and supply-chain management [69].

7.4. Integrated Approach for Horticultural Supply Chains

The integration of biosensors with digital technologies can connect food-safety or quality measurements with information-management systems. Biosensors have been investigated for food safety and quality monitoring and smart traceability, while IoT has been discussed for connecting sensing and information systems [30,68,71]. AI and ML are additionally being investigated for analysing data obtained from different sensing approaches, including biosensors [67]. For fresh fruits and vegetables, intelligent monitoring systems have been reviewed across the supply chain using sensing, imaging, smart indicators, wireless networks, and data-driven technologies [69]. However, the practical application of AI-assisted sensing systems requires appropriate validation because data heterogeneity, matrix interference, and differences between internal and external validation can affect reported performance [67].

Although biosensors, AI/ML, IoT, smart packaging, and digital traceability have been discussed as complementary components of food-monitoring systems, evidence from experimentally validated end-to-end integration remains limited. Many studies address biosensing, AI-based data analysis, IoT connectivity, or traceability separately, rather than evaluating a fully integrated system under real horticultural supply-chain conditions. Therefore, further studies should validate integrated systems across practical supply-chain stages, including sensor performance, data transfer, calibration, external validation, and real-sample conditions. Future development of biosensor technologies for food safety should focus on improving the sensing capabilities and integrating biosensors with emerging digital technologies. Multiplex detection is an important direction because it allows a single sensing platform to detect multiple contaminants simultaneously. Such approaches have been investigated for the detection of different food contaminants and

may also provide more comprehensive information from a single sample. The development of multiplexed sensing platforms is therefore relevant for food-safety monitoring where different contaminants may need to be assessed [72,73]. Biosensors have been discussed as components of smart food-traceability systems. For fresh fruits and vegetables, intelligent supply-chain approaches incorporate sensing technologies, smart indicators, wireless sensor networks, and data-driven technologies for supply-chain monitoring and management [69].

Future research should therefore move beyond laboratory-scale demonstrations toward stable, low-cost, and field-validated systems for horticultural supply chains. Priority should be given to standardised calibration and validation protocols, testing with naturally contaminated and commercially relevant samples, and evaluation under real storage, transport, and retail conditions. Integrated systems should connect biosensors with complementary sensing technologies, AI-based data analysis, IoT connectivity, and digital traceability, while also considering cost, usability, interoperability, and regulatory requirements for practical adoption (Figure 7).

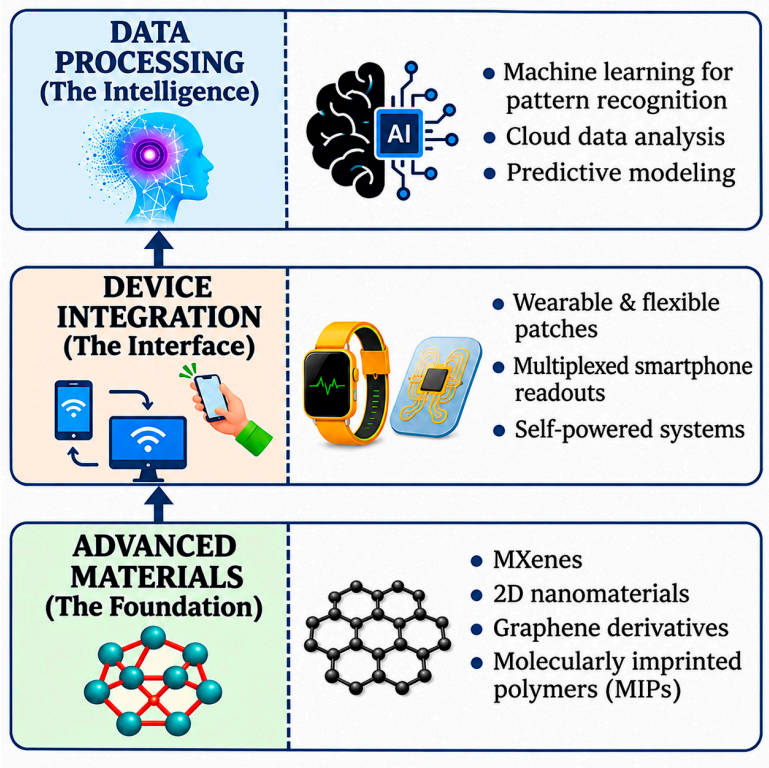

Figure 7. Next-generation smart sensing ecosystem integrating biosensors, complementary sensing technologies and digital traceability for horticultural supply chains.

8. Conclusions

This review provides an integrated overview of sensing technologies, signal processing, artificial intelligence (AI), and digital tools for food safety and quality assessment across horticultural supply chains. These technologies were evaluated based on practical factors such as real-sample validation, calibration, portability, cost, and suitability at different supply-chain stages. The reviewed studies show that these technologies can rapidly detect contaminants, pathogens, spoilage indicators, and changes in fruit ripening and freshness, often without damaging the samples. Early detection can help reduce post-harvest losses through timely sorting, improved storage, and removal of contaminated products. However, most studies focus on detection accuracy and speed rather than actual reductions in spoilage, shelf life, or post-harvest losses. No reviewed study directly

measured the impact of these technologies on post-harvest losses under commercial supply-chain conditions. Their practical application is still limited by testing under controlled conditions, poor validation with real samples, sensor instability, calibration issues, high costs, and limited integration of AI, IoT, and traceability systems.

Future research should focus on four key areas: 1. Measure actual outcomes: conduct field trials to determine the effects of sensor-based technologies on spoilage, shelf life, rejected produce, and post-harvest losses. 2. Real-condition validation: test technologies using naturally contaminated samples under actual storage, transportation, and retail conditions. 3. Improve reliability: develop standardised datasets, robust calibration methods, and explainable AI models to improve accuracy and reproducibility. 4. Develop integrated systems: combine sensors, AI, IoT, and digital traceability, while considering cost, usability, compatibility, and regulatory requirements. Overall, these technologies offer promising opportunities to improve food safety and quality monitoring. However, their actual contribution to reducing post-harvest losses needs to be demonstrated through commercial-scale validation and field-based studies.

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