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REVIEW PAPER

Rapid electronic sensing technologies for ensuring food safety against pesticide residues: a comprehensive review

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Abstract
The persistence of pesticide residues in the global food supply chain requires rapid, reliable, and continuous measurement methods to ensure consumer safety and regulatory compliance. Conventional analytical techniques provide exceptional precision. However, their destructive nature, high operational costs, and strict reliance on laboratory environments make them unsuitable for real-time screening in food processing facilities. This review examines the latest advancements in non-destructive electronic sensing technologies specifically designed for characterizing pesticide residues in post-harvest food matrices. The analysis focuses on the analytical capabilities of electrochemical sensors, biosensors, electronic nose (e-nose) platforms, and optical measurement systems, while critically evaluating how these platforms handle complex food matrix interferences, particularly background volatile organic compounds (VOCs), moisture fluctuations, and matrix-dependent signal variability. Particular attention is given to signal analysis and processing strategies, including spectral preprocessing, chemometric modelling, feature extraction, pattern recognition, sensor-drift compensation, and machine learning (ML)-based classification of pesticide signatures. Furthermore, the deployment of edge computing architectures is analyzed for its role in enabling decentralized, real-time signal processing directly on the production line. To establish practical viability for the food industry, the limits of detection achieved by various electronic configurations are benchmarked against international maximum residue limits. Finally, the paper addresses persistent hardware and methodological limitations, including sensor drift, calibration transferability, and reproducibility under highly humid food storage environments. By synthesizing these engineering challenges with food quality requirements, this review provides a comprehensive roadmap for implementing next-generation measurement systems in smart food supply chains.

Keywords Food safety monitoring · Pesticide residue detection · Food matrix characterization · Smart food supply chain

Introduction

Agricultural production has played a central role in sustaining human societies throughout history. However, ensuring both the sufficiency and the safety of the global food supply has become a critical modern challenge. Driven by rapid global population growth, climate change, and the continuous reduction of arable land, agricultural systems have increasingly shifted toward intensive production practices that rely heavily on chemical inputs to maintain yield stability. While these inputs are vital for food security, their widespread use introduces severe food safety risks due to the accumulation of toxic residues in the food chain. When agricultural commodities are harvested and transferred to processing facilities, trace amounts of these chemical agents often remain embedded in or on the food matrices, posing severe long-term health risks to consumers [1–3]. To mitigate these adverse effects, international regulatory bodies and food safety authorities have established stringent Maximum Residue Limits (MRLs) for various food categories. Ensuring compliance with these strict legal thresholds

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requires rigorous and continuous quality control measures during the post-harvest, storage, and packaging stages [4–6]. Consequently, the food industry faces an urgent demand for reliable analytical strategies capable of screening pesticide residues directly on food products before they reach the consumer market.

Among the chemical inputs used in agriculture, pesticides are indispensable for protecting crops against insects, weeds, fungi, and other biological threats that can significantly reduce yield and compromise crop quality [7, 8]. Their widespread application has enabled higher productivity and yield stability, playing a crucial role in supporting global food security, particularly in intensive agricultural systems. However, a substantial fraction of applied pesticides does not reach target organisms and instead persists as residues directly on or within harvested agricultural products and food matrices [9]. These residues can accumulate over time, posing serious risks to human health through long-term exposure, bioaccumulation, and contamination of food chains. To address these concerns, rapid and reliable pesticide residue analysis is now vital for post-harvest quality assurance and regulatory compliance amid tightening safety standards.

Conventional analytical techniques, such as Gas Chromatography (GC) and Liquid Chromatography (LC) coupled with Mass Spectrometry (MS), are widely considered as the gold standard for pesticide residue analysis due to their high sensitivity, selectivity, and quantitative accuracy [10, 11]. These methods enable precise identification of pesticide residues and remain indispensable for regulatory compliance and confirmatory analysis. However, the practical deployment of these techniques is largely restricted to centralized laboratory environments, as they typically require costly instrumentation, trained personnel, and complex, destructive sample preparation workflows [12, 13]. In high-throughput food processing and packaging facilities, where rapid assessment and timely decision-making are critical for quality control, additional constraints such as sample transportation, logistical delays, and operational costs severely reduce their effectiveness. These challenges become particularly important in modern food supply chains, where continuous screening of large sample volumes is impractical using time-consuming laboratory methods. Consequently, although liquid chromatography-mass spectrometry (LC-MS) and gas chromatography-mass spectrometry (GC-MS) techniques offer unmatched analytical performance, their inherent operational limitations render them poorly suited for large-scale, real-time, and non-destructive pesticide monitoring directly on food production lines.

In response to these limitations, the concept of the Smart Food Supply Chain has emerged as a data-driven paradigm that integrates sensing technologies. The Smart Food Supply Chain addresses these bottlenecks by integrating Internet of Things (IoT) devices and intelligent data processing to improve traceability [14]. Embedding sensor networks into post-harvest environments enables the uninterrupted monitoring of chemical contaminants, including pesticide residues. This continuous data acquisition facilitates early risk detection and supports immediate analytical interventions [15]. This shift from periodic, laboratory-based inspection to continuous data acquisition has the potential to significantly enhance consumer protection while improving decision accuracy on the production line. However, the deployment of such systems in real-world food processing and storage facilities presents several practical challenges related to network connectivity, data latency, large data volumes, and energy consumption. These challenges are particularly critical in complex, high-throughput food distribution networks, where unreliable communication and limited processing capabilities constrain the scalability and reliability of smart sensing solutions.

Recent advances in electronic and sensor-based detection technologies have introduced promising alternatives to conventional analytical approaches for pesticide monitoring, particularly in applications requiring rapid and on-site assessment [16–18]. Optical sensing methods, electrochemical sensors, biosensors, and e-nose systems have attracted increasing research interest due to their potential for non-destructive operation, reduced analysis time, and compatibility with portable platforms. Among these approaches, e-nose systems stand out by exploiting characteristic Volatile Organic Compound (VOC) patterns associated with pesticides and their degradation products, enabling holistic, pattern-based detection rather than compound-specific identification [19, 20]. When combined with machine learning (ML) algorithms, e-nose platforms offer enhanced discrimination capability and adaptability to complex food matrices, effectively isolating pesticide signatures from the natural background VOCs of the food itself. Overall, these technologies align closely with the requirements of real-time monitoring, decentralized decision-making, and scalable deployment envisioned in modern food quality control and smart packaging systems.

While most existing literature examines either traditional laboratory techniques or isolated electronic sensing mechanisms, the present study offers a deployment-focused synthesis of pesticide measurement technologies tailored for smart supply chains. The evaluation is structured around four interconnected parameters: sensing principles, signal modalities, regulatory relevance, and industrial scalability. In this framework, conventional chromatography is positioned as a confirmatory benchmark rather than a direct alternative to portable sensors. Using this baseline, optical, electrochemical, biosensing, and e-nose systems are

critically assessed regarding their matrix tolerance, calibration requirements, and IoT integrability. Crucially, analytical sensitivity is evaluated directly against statutory MRLs, helping to differentiate preliminary screening platforms from those capable of supporting compliance decisions. By addressing practical constraints such as humidity interference, sensor drift, and calibration transfer, the aim is to bridge the gap between theoretical analytical performance and actual operational feasibility in post-harvest quality control.

This structure also clarifies the position of the present review relative to recent broad surveys on pesticide detection. Rather than cataloguing sensing platforms only by analytical mechanism, the discussion evaluates whether each technology can realistically move from proof-of-concept testing toward continuous use in post-harvest food processing and storage environments.

Pesticides in agriculture

Pesticides play a fundamental role in modern agricultural production by protecting crops from insects, weeds, fungi, and other biological threats that significantly reduce yield and compromise crop quality. Their widespread application has contributed substantially to increased agricultural productivity and global food security, particularly in intensive and large-scale farming systems [21–23]. Conventional chemical pesticides such as organophosphates, carbamates, pyrethroids, neonicotinoids, and triazines remain widely used due to their high efficacy, broad-spectrum activity, and cost-effectiveness [24]. However, the extensive and repeated use of these compounds inevitably leads to the presence of persistent chemical residues on harvested agricultural commodities and processed foods. These residues have raised serious concerns regarding bioaccumulation and chronic human health effects through dietary exposure, leading to increasing regulatory restrictions and rigorous food quality monitoring requirements worldwide [25, 26].

Pesticide classes and residue pathways

Pesticides remain indispensable inputs in modern agriculture for protecting crops against biological threats, ultimately securing the global food supply and maintaining product quality. In practice, pesticide use spans a broad spectrum ranging from conventional synthetic chemicals to naturally derived biopesticides, each characterized by distinct chemical structures, degradation rates, and residue formation pathways on edible crops. Different pesticide classes exhibit distinct stability profiles and toxicological risks during post-harvest storage and food processing [27, 28]. Organophosphates and carbamates, which act primarily by inhibiting acetylcholinesterase, are associated with acute neurotoxicity, necessitating highly sensitive measurement techniques to enforce strict MRLs for consumer safety. Pyrethroids, owing to their lipophilic nature, are highly persistent in the waxy cuticles of fruits and vegetables, making them difficult to remove during standard commercial washing and processing steps. Neonicotinoids are characterized by their systemic action, meaning they are absorbed and distributed throughout the internal plant tissues; this internal accumulation poses significant analytical challenges for surface-level non-destructive testing and requires advanced characterization methods. Furthermore, triazine herbicides are known for their long chemical persistence, frequently leading to trace residues in harvested grains and cereal products. These diverse chemical behaviors highlight the complexity of pesticide risk assessment and the critical need for effective, matrix-specific monitoring across complex food supply chains rather than relying solely on traditional environmental sampling.

Pesticides exhibit heterogeneous physicochemical properties that depend on molecular structure, volatility, solubility, and degradation pathways [29]. Many formulations and their degradation products release VOCs either directly or through interactions with soil, plant tissues, and microbial activity. These VOC emissions constitute the analytical foundation for emerging electronic and sensor-based detection approaches, including e-nose systems and VOC-sensitive gas sensor arrays. In contrast, highly stable and non-volatile pesticide compounds, including many neonicotinoids and pyrethroids, are difficult to detect using direct VOC-based sensing approaches. Their detection typically depends on indirect or laboratory-based analytical approaches.

Beyond volatility, pesticide residues persist across diverse food matrices, including intact peel surfaces, internal fruit tissues, and processed commodities. Their spatial and temporal distribution is heavily influenced by post-harvest variables like storage temperature, humidity fluctuations, and commercial handling practices. These dynamic conditions directly impact sensor response characteristics, baseline stability, and overall detection reliability during real-time quality screening. A comprehensive understanding of pesticide chemical behavior, matrix interactions, and residue dynamics is essential for designing robust, non-destructive detection systems capable of continuous operation within modern food supply chains and smart packaging frameworks [30].

The diversity of pesticide classes used in agriculture results in substantial variability in their physicochemical properties, environmental behavior, and detectability. As summarized in Table 1, pesticide volatility and VOC emission characteristics play a decisive role in determining the suitability of sensor-based detection approaches [31, 32].

Table 1 Classification of major pesticide groups

Pesticide class	Pesticide Types	Volatility	Environmental persistence	Detection Technology
Organophosphates	Chlorpyrifos and Malathion	Moderate–High	Moderate	Suitable for e-nose
Carbamates	Carbaryl and Aldicarb	Low–Moderate	Moderate	Suitable for Biosensors
Pyrethroids	Deltamethrin and Cypermethrin	Low	High	Challenging for VOC-based sensing
Neonicotinoids	Imidacloprid and Thiamethoxam	Very low	High	Mainly lab-based detection
Triazines	Atrazine and Simazine	Low–Moderate	High	Suitable for optical methods
Biopesticides	Neem oil and Trichogramma	High	Low	Ideal for E-nose

Conventional chemical pesticides such as organophosphates exhibit moderate to high VOC emissions either directly or through degradation processes, making them amenable to electronic-nose and gas sensor array-based detection. However, highly stable and non-volatile compounds such as neonicotinoids and certain pyrethroids present significant challenges for VOC-based sensing and often require indirect or laboratory-intensive analytical methods.

Biopesticides, particularly those derived from plant-based sources, often have rich VOC profiles that are suitable for e-nose systems and other VOC-sensitive sensing approaches [33, 34]. By contrast, many conventional chemical pesticides, including carbamates, pyrethroids, neonicotinoids, and triazines, exhibit lower volatility and higher chemical stability, limiting their direct detectability through headspace sensing. These compounds frequently require indirect optical signatures, contact-based electrochemical or biosensor measurements, or confirmatory laboratory analysis. This contrast highlights the need for complementary sensing strategies rather than a universal detection mechanism for all pesticide classes.

Physicochemical properties affecting detection

Detectability of pesticide residues is fundamentally governed by physicochemical properties, including volatility, solubility, molecular stability, adsorption behavior, and degradation pathways. Volatility is particularly critical for VOC-based sensing approaches because it determines whether parent compounds or degradation products can partition into the gas phase and produce measurable headspace signatures [35]. Pesticide formulations may emit VOCs directly or indirectly, for example through interactions with the food matrix, surface microbiomes, and post-harvest storage conditions that promote decomposition. Organophosphates often exhibit moderate to high volatility and can generate VOC patterns either as parent compounds or as breakdown products, which makes them more amenable to e-nose systems and gas sensor arrays. However, stable pesticides like neonicotinoids and pyrethroids are not very volatile. Since they release minimal vapor, detecting them directly with gas sensors is difficult [36]. For such classes, detection frequently relies on contact-based sensing, molecular recognition elements, or optical/spectroscopic strategies that target surface signatures rather than gas-phase emissions.

Solubility and polarity also shape detection feasibility and dictate suitable sensing principles. Highly polar pesticides may be more compatible with liquid-phase electrochemical sensing or biosensor platforms, whereas non-polar and persistent compounds may require sample pretreatment or indirect feature extraction. Chemical stability and post-harvest persistence further complicate detection because residues may remain for extended periods on agricultural commodities or within processed foods, but without producing strong VOC emissions [37]. Additionally, pesticide–matrix interactions influence whether residues remain on the surface, migrate into tissues, or bind strongly to soil organic matter, all of which affect signal strength and sampling strategy. Therefore, sensor selection and system design must be guided by the expected chemical behavior of the target pesticide class under real-world food supply chain and storage conditions, rather than assuming a universal detection mechanism.

Food matrices and post-harvest variability

Pesticide residues occur across diverse food matrices, including external peel surfaces and internal fruit tissues. Their spatial distributions heavily depend on post-harvest handling, washing, and processing practices. Surface residues are particularly relevant for quality control monitoring because they directly impact consumer exposure and compliance with maximum residue limits [38]. However, the detectability of these surface residues changes based on fruit morphology and the efficacy of commercial washing prior to packaging. Matrix-specific processes create heterogeneous residue patterns. These patterns complicate both non-destructive sampling and accurate detection.

Storage and supply chain conditions introduce additional challenges for electronic pesticide detection systems. Temperature and humidity fluctuations in cold storage facilities or packaging lines can alter VOC emission dynamics, shift sensor baselines, and modify adsorption/desorption behavior. This is especially true for MOS and polymer-based gas sensors. Ventilation conditions within warehouses also

affect headspace stability and the dilution of volatile compounds. Complex food matrices emit various interfering compounds, including natural ripening gases, microbial spoilage emissions, and background VOCs from the food itself [39]. These background emissions can reduce sensor selectivity and increase false positives if the algorithms lack robust training. Detection reliability in real-world food industry environments ultimately depends on sensor sensitivity, calibration strategies, humidity drift compensation, and matrix-aware sampling protocols. This highlights the need for criteria-driven evaluation frameworks when comparing pesticide measurement technologies for smart food supply chains.

Review methodology

This review was conducted using a structured methodology to comprehensively analyze recent advances in electronic pesticide detection systems within the framework of Smart Food Supply Chains and Food Industry 4.0. The approach was designed to ensure reproducibility, minimize selection bias, and provide a balanced comparison of laboratory-based and on-site detection technologies reported between 2015 and early 2026. A systematic literature search was performed across major scientific databases, including Web of Science, Scopus, IEEE Xplore, ScienceDirect, and Google Scholar. The search strategy utilized Boolean combinations of keywords such as "pesticide residues", "electronic nose", "biosensors", "hyperspectral imaging", and "non-destructive measurement" to capture high-impact studies relevant to sensor technology and food quality control applications.

The selection process prioritized peer-reviewed journal articles and high-quality conference proceedings focused on rapid and non-destructive electronic detection methods. The review was restricted to studies published between 2015 and 2026 that address food matrices and demonstrate post-harvest deployment or IoT integration potential. Research restricted to off-line analysis using standard chromatographic methods was omitted, as was literature pertaining to strictly environmental or clinical applications. The study selection process followed the PRISMA guidelines for identification, screening, and eligibility assessment, and is summarized in Fig. 1. The selected studies ($n=123$) were categorized based on their detection principle, sensor type, and readiness for industrial deployment. This classification framework allows for a balanced evaluation of sensitivity, selectivity, and suitability for integration into smart food packaging and processing ecosystems. Conventional chromatographic methods are discussed briefly to provide a performance benchmark. However, the primary scope remains focused on emerging electronic sensing technologies that

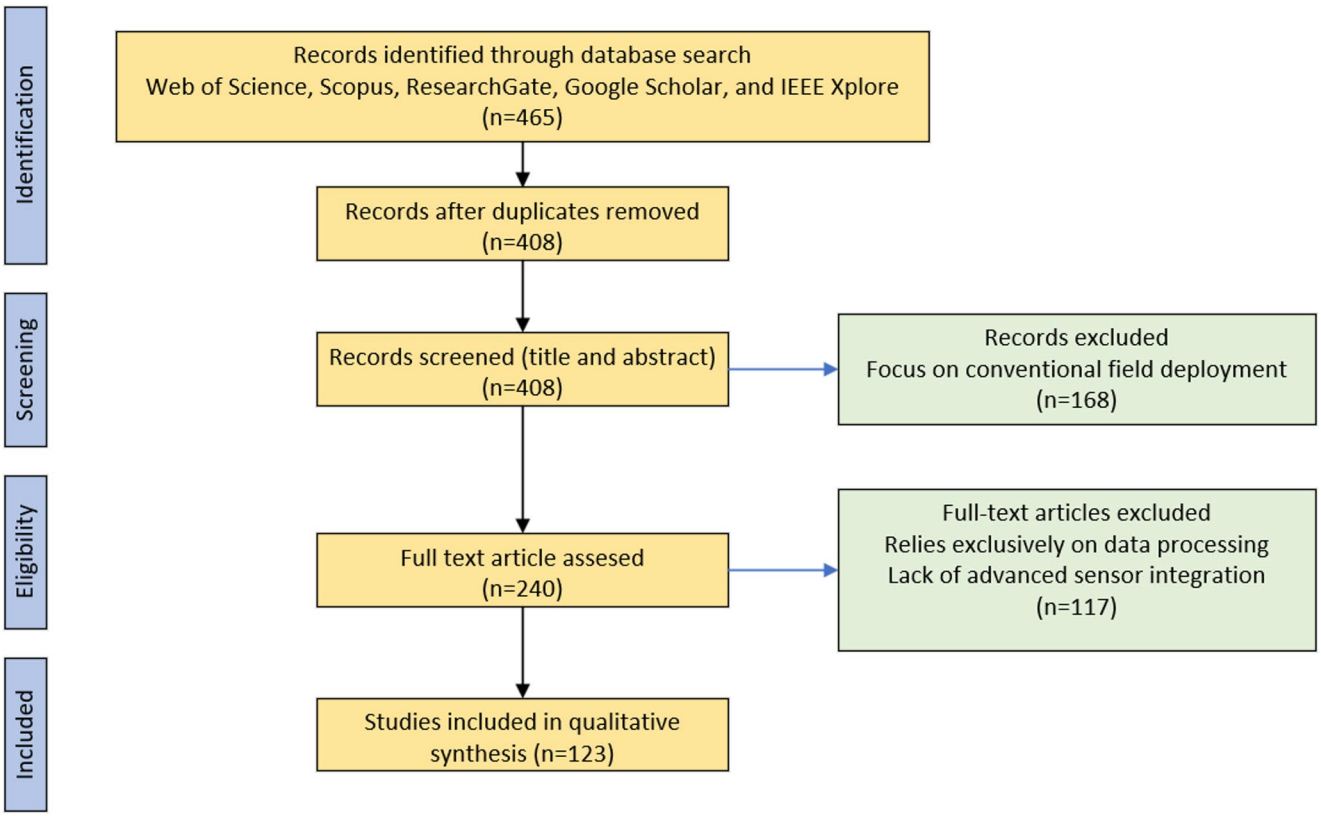

Fig. 1 PRISMA flow diagram of literature review process

offer scalable solutions for real-time pesticide monitoring on production lines.

This comparative analysis seeks to pinpoint critical technological bottlenecks that currently hinder widespread deployment in food processing facilities. By addressing these gaps, the review provides a strategic roadmap for future innovations, including the deeper integration of advanced data analytics and edge computing. Such advancements are vital to accelerate the transition from isolated sensor prototypes to fully autonomous, data-driven monitoring networks that define next-generation food safety.

To avoid a purely descriptive synthesis, the selected studies were interpreted through a common critical framework. Reported analytical performance was assessed together with sample preparation requirements, food-matrix complexity, calibration strategy, validation design, and the extent to which the study demonstrated operation beyond idealized laboratory conditions. The evaluation specifically assessed regulatory-aligned detection limits, external validation protocols, and environmental interferences such as temperature, humidity, and background VOCs. This approach provides a more transparent basis for identifying technologies that are promising for industrial screening but not yet adequate for confirmatory compliance testing.

Conventional pesticide detection techniques

Pesticide residue analysis has traditionally been carried out in laboratories using well-established analytical methods. GC and LC methods, often combined with Mass Spectrometry (MS), have long been the standard techniques. These methods are valued for their precision and sensitivity, and they remain central to monitoring residues and checking compliance with MRLs. MRLs represent the highest concentration of pesticide residues legally permitted in food, as established by international and national regulatory authorities, to ensure consumer safety and facilitate global trade. GC is typically used for volatile and thermally stable compounds, whereas LC is preferred for polar and thermally labile compounds, offering complementary analytical strengths [40, 41]. When combined with MS, these methods enable detailed structural identification and quantification across a wide range of agricultural and environmental matrices. However, despite their analytical reliability and indispensable role in confirmatory testing, these approaches remain constrained by high operational costs, time-intensive sample preparation, and the requirement for specialized laboratory infrastructure and trained personnel. As a result, while conventional techniques continue to serve as a benchmark for pesticide monitoring, they are not readily suited for large-scale, real-time, or field-based applications that have motivated the development of portable, electronic detection systems.

Chromatographic methods

GC is highly effective for detecting volatile and thermally stable pesticide compounds, while LC, particularly High-Performance Liquid Chromatography (HPLC), is more suitable for polar, non-volatile, and thermally labile compounds [42]. The complementary nature of these two approaches ensures a broad coverage of pesticide classes, ranging from organophosphates and pyrethroids to carbamates, neonicotinoids, and triazines. When coupled with Mass Spectrometry, these methods provide enhanced selectivity, structural elucidation, and trace-level quantification, often detecting residues at sub-part-per-billion concentrations [43, 44]. Such performance is critical in meeting regulatory demands, where even minute levels of contamination can have implications for public health and international food trade.

The accuracy, reproducibility, and robustness of GC-MS and LC-MS have established them as core methods in global food safety monitoring programs. Institutions such as the European Food Safety Authority (EFSA) rely extensively on these platforms to conduct large-scale residue screening, publish annual surveillance reports, and enforce compliance with legally defined MRLs. Beyond raw agricultural commodities, these methods are widely applied to processed foods and complex matrices to characterize pesticide degradation and chemical persistence throughout the food supply chain. Recent methodological developments have expanded the analytical scope of conventional mass spectrometry through Mass Spectrometry Imaging. This technique enables the direct spatial mapping of specific molecules, including pesticide residues, across intact food surfaces [45]. By eliminating the need for standard tissue homogenization, MSI delivers detailed microscale chemical data and introduces a crucial spatial dimension to quality control. However, the reliance on expensive instrumentation, complex sample preparation, and specialized personnel severely restricts its deployment outside centralized laboratories. This operational barrier renders the technique unsuitable for continuous, high-throughput screening in active packaging facilities.

Spectroscopic and other laboratory-based pesticide detection methods

Beyond chromatography, several spectroscopic methods have been applied for pesticide residue analysis. Techniques such as Ultraviolet–Visible spectroscopy, Fourier Transform Infrared (FTIR) spectroscopy, and fluorescence spectroscopy provide relatively fast and non-destructive detection,

while Raman and Surface-Enhanced Raman Spectroscopy (SERS) offer molecular fingerprinting with enhanced sensitivity through nanostructured substrates [46–48]. These approaches reduce the need for complex sample preparation and can be combined with chemometric tools for classification and quantification. However, their sensitivity and robustness are generally lower than GC–MS or LC–MS, and they remain vulnerable to matrix interferences in complex food and environmental samples.

Other laboratory-based approaches include immunoassay techniques, such as Enzyme-Linked Immunosorbent Assay (ELISA), which offer high-throughput and cost-effective preliminary screening. Capillary Electrophoresis (CE) and enzyme inhibition assays provide targeted detection for specific pesticide classes [49, 50]. These rapid and affordable alternatives frequently face limitations regarding cross-reactivity, lower quantitative accuracy, and reduced sensitivity. Enzyme inhibition-based assays specifically target organophosphate and carbamate pesticides by exploiting their acetylcholinesterase inhibition activity. These methods are simple, low-cost, and easily adaptable to portable colorimetric or paper-based kits. Their limited selectivity, however, often leads to false positives triggered by naturally occurring interfering substances within complex food matrices. Spectroscopic and immunoassay-based systems serve as valuable preliminary screening tools, yet they remain poorly suited for large-scale, real-time monitoring on active food processing lines. This operational gap highlights the urgent need for portable, non-destructive electronic detection systems capable of continuous quality control within smart food supply chains.

Limitations of conventional methods

Chromatographic, spectroscopic, and immunoassay-based methods deliver exceptional analytical precision and remain indispensable for regulatory compliance. Nevertheless, significant operational limitations restrict their integration into modern, smart food supply chains. These techniques are inherently laboratory-bound, relying on expensive instrumentation, specialized facilities, and trained personnel. This dependency makes them highly impractical for high-throughput food processing and packaging environments, where rapid quality control decisions are critical. Most conventional workflows also require time-consuming sample preparation steps, including chemical extraction, purification, and derivatization, which severely delay detection times and hinder large-scale industrial deployment [51]. Crucially, these laboratory techniques are largely destructive. This fundamental drawback prevents continuous, real-time monitoring of intact agricultural commodities or packaged food batches. Table 2 summarizes representative studies employing conventional methods such as LC–MS/MS, GC–MS/MS, FTIR, SERS, and ELISA across various food matrices. The table outlines their primary applications, analytical advantages, and practical limitations. Despite demonstrating high sensitivity and analytical robustness, these methods consistently face constraints such as high operational costs, labor-intensive processes, complex food matrix interferences, and a distinct lack of on-site applicability for real-time production line screening.

While conventional laboratory methods excel at confirmatory analysis and regulatory compliance testing, they fall short of the operational demands for real-time, continuous monitoring across the food supply chain. The increasing industry demand for rapid, cost-effective, and scalable quality control solutions has accelerated the development of electronic pesticide detection systems. These emerging technologies aim to complement traditional techniques by offering non-destructive, automated, and high-throughput screening capabilities directly on processing lines. Throughout this review, established laboratory techniques such as GC–MS/MS and LC–MS/MS serve as critical performance benchmarks. They provide a necessary analytical context for evaluating the accuracy, detection limits, and reliability of novel electronic sensors. Ultimately, overcoming the constraints of complex sample preparation and centralized laboratory reliance is essential for developing decentralized, real-time sensing platforms tailored for smart food packaging and Food Industry 4.0 applications.

Taxonomy of electronic pesticide detection systems

Diverse sensing mechanisms and practical deployment constraints create significant disparities among electronic pesticide detection technologies, often obscuring direct performance comparisons. To resolve this ambiguity, a structured framework is developed to systematically associate sensing principles with their corresponding roles in modern food quality control and smart supply chains. This approach incorporates industrial readiness metrics and analytical benchmarking criteria to ensure a transparent evaluation. Ultimately, this taxonomy aims to guide the deployment of optimized, non-destructive sensing solutions tailored for high-throughput food processing environments.

Taxonomy overview and classification criteria

Throughout this review, electronic sensing refers to any analytical system converting chemical residues, matrix alterations, or volatile emissions into measurable signals.

Table 2 Conventional pesticide detection studies

Application	Method	Advantage	Limitation	Reference
Eggplant	LC-MS/MS	High analytical sensitivity and accuracy	Single crop and pesticide studied	[52]
Extra Virgin Olive Oil	LC-MS/MS	Quick analysis and consumer risk assessment	Limited number of pesticides analyzed	[53]
Tomato	LC–MS/MS	349 different pesticide analysis and multi-residue method	Requires highly skilled lab professionals and instrument	[54]
Citrus Fruits	LC–MS/MS	Multi-residue analysis, wide panel	Need for ion suppression management in multiple classes	[55]
Fruits and vegetables	LC-MS/MS	Simultaneous determination in rapid/single injection	Optimization needed for polar pesticides	[56]
Fruits and vegetables	GC-MS/MS	High speed and wide panel detection	CODEX recovery range is limited for some compounds	[57]
Fruits and vegetables	LC–MS/MS and GC–MS/MS	High precision, sensitivity and throughput	Requires two devices and high cost & labor	[58]
Cucumber	GC-MS	Good sensitivity and accuracy	Single crop detection and requires advanced equipment	[59]
Fruits and vegetables	SERS	Non-destructive and fast analysis	Reliability and reproducibility	[60]
Milk, Celery, and Leek	ELISA	High specificity and field deployable detection	Antibody preparation complexity	[61]
Vegetables	ELISA	Low-cost and rapid detection	Quantitative accuracy less than chromatography-based methods	[62]
Citrus fruits	GC-MS/MS	Detects various types of pesticides	Detection part selectivity and time dependency	[63]
Vegetables	CE	High sensitivity and simultaneous multi-residue determination	Laboratory-based and Complex ECL setup	[64]

Under this definition, e-nose platforms function specifically as a headspace-oriented subclass. The subsequent taxonomy organizes these measurement tools according to their fundamental transduction mechanism. This primary classification is further defined by five operational variables: detection strategy, sensor interaction, deployment mode, target sample phase, and screening capacity. Organizing diverse platforms along these practical dimensions provides a reliable basis for evaluating optical, electrochemical, biological, and e-nose systems. Consequently, it translates laboratory-scale analytical metrics into actionable parameters for post-harvest food quality control.

The primary classification is defined by the dominant transduction mechanism. Optical methods analyze molecular absorbance, reflectance, fluorescence, or scattering responses, whereas electrochemical platforms quantify redox or interfacial charge-transfer processes. Biological platforms utilize affinity elements including enzymes or aptamers for targeted recognition. Providing a holistic counterpart to these specific methods, e-nose platforms map volatile headspace patterns using arrays of semi-selective gas sensors. The selected transduction mechanism then determines the practical operating mode of the system. Electrochemical and biosensing techniques usually require physical contact, liquid extraction, or a controlled sample-sensor interface to achieve targeted quantification. Optical methods and e-nose platforms more readily support non-destructive, non-contact screening on the sample surface or in the headspace. These non-contact platforms may capture direct pesticide signatures as well as indirect secondary indicators, such as matrix oxidation, surface changes, or natural VOC shifts. Integrating these classification axes clarifies why each technology is suited to different points in the food monitoring workflow, from high-throughput preliminary screening to more specific localized quantification.

Sensing principles and signal modalities

Distinct from the sensing principle, the physical modality of measurement and the format of raw data represent critical axes of variation. This subsection defines a standardized schema for each detection class, encompassing signal modality, sample-sensor interface, representative raw data form, and the processing implications of each data structure.

Chromatographic reference methods such as GC–MS and LC–MS provide compound-resolved quantification and typically rely on extraction and sample preparation protocols, which makes them suitable as validation benchmarks. Optical sensing modalities, including Near-Infrared (NIR), Fourier Transform Infrared (FTIR), Raman spectroscopy, Multispectral Imaging (MSI), and Hyperspectral Imaging (HSI) generate high-dimensional spectral data that can be used for direct chemical identification or proxy-based screening through multivariate analysis. Electrochemical

platforms convert interfacial reaction kinetics into electrical signals, such as voltammograms, impedance spectra, or time-dependent current responses under controlled bias conditions. Biosensors combine biorecognition elements, including enzymes or antibodies, with optical or electrochemical transducers to produce concentration-dependent signals or real-time kinetic responses. VOC-based systems, particularly electronic noses, record multi-channel temporal responses from sensor arrays and transform these signals into characteristic fingerprint patterns for chemometric classification of headspace volatiles. Together, these modality-specific descriptors provide a consistent basis for organizing and comparing detection approaches across different agricultural matrices and deployment scenarios.

As shown in Table 3, the variability in data formats among different sensing technologies means that signal processing and ML approaches cannot be universal. Instead, algorithms must be adapted to the structure of the raw signal, such as spectra, image cubes, voltammograms, kinetic curves, or multivariate sensor-array time series, to ensure accurate classification and quantification in agricultural applications.

Signal analysis and processing strategies

Signal processing is a decisive component of electronic pesticide detection because most rapid sensing platforms do not generate direct concentration values without calibration and feature extraction. Optical spectroscopy and imaging systems typically require noise filtering, baseline correction, scatter correction, normalization, derivative transformation, and wavelength or band selection before multivariate modelling. ML models such as principal component analysis (PCA), partial least squares regression (PLSR), support vector machines (SVM), random forests, and convolutional neural networks can then be used for classification, residue-level prediction, or spatial mapping. For hyperspectral and multispectral imaging, the computational burden is higher because the raw data are image cubes rather than single spectra, making dimensionality reduction and robust external validation essential [65].

Electrochemical sensors and biosensors require different processing strategies because their raw outputs are usually voltammograms, amperometric traces, impedance spectra, or kinetic response curves [66]. Relevant procedures include baseline subtraction, peak current extraction, charge-transfer resistance fitting, calibration-curve construction, limit-of-detection estimation, response-time analysis, and drift correction. In biosensors, kinetic modelling and matrix-effect compensation are particularly important because enzyme activity, antibody binding, and aptamer affinity may vary with pH, ionic strength, temperature, and crude food extract composition. These platforms therefore require both analytical calibration and stability assessment before being considered suitable for repeated on-site screening.

E-nose systems rely most strongly on multivariate signal processing because individual gas sensors are usually only partially selective [67]. Typical preprocessing steps include baseline normalization, fractional response calculation, extraction of maximum response, response and recovery slopes, area-under-curve features, humidity and temperature compensation, and sensor-drift correction. Pattern-recognition methods such as PCA, linear discriminant analysis (LDA), SVM, artificial neural networks (ANNs), and ensemble models are then used to separate pesticide-related VOC fingerprints from natural food volatiles. Across all modalities, model reliability should be evaluated using cross-validation together with independent or blind test samples, and reported with metrics such as accuracy, sensitivity, specificity, prediction error, false-positive rate, and false-negative rate. These reporting practices are necessary for translating sensor prototypes into robust industrial screening tools.

Table 3 Sensing modalities, interfaces, and data structures of pesticide detection systems

Detection type	Primary measured signal	Sampling configuration	Representative raw data form
Chromatography–MS	Retention time + resolved mass spectral intensity	Extracted sample and chromatographic separation	Retention time × mass-to-charge intensity map
Optical Spectroscopy	Wavelength-dependent optical surface response	Proximal spectroscopy	One-dimensional spectrum vector
Optical Imaging	Spatially resolved optical response for multiple spectral bands	Multispectral or hyperspectral camera	Spectral image cube (height × width × bands)
Electrochemical Sensing	Electrical response driven by charge transfer	Electrode-based measurement cell with sample contact	Voltammetric/amperometric curves
Biosensors	Bio-recognition transduction signal vs. time	Chip, strip, and electrode assay	Kinetic response trace and calibration curve
E-nose	Multi-sensor response pattern to headspace volatile mixture	Headspace chamber with controlled flow	Multivariate time-series matrix
E-tongue	Multi-sensor liquid-phase response pattern	Liquid sample or extracted food matrix	Multivariate liquid-response matrix

Electronic pesticide detection systems

The operational limitations of conventional laboratory-based methods have driven significant interest in electronic pesticide detection systems, which are designed to provide rapid, cost-effective, and on-site screening alternatives. These systems take advantage of recent progress in sensor technologies, nanomaterials, and advanced data analytics to deliver real-time, non-destructive monitoring of pesticide residues directly across food matrices and harvested commodities [68, 69]. As summarized in Fig. 2, current electronic detection approaches can be broadly grouped into optical spectroscopy (NIR, FTIR, Raman), optical imaging (fluorescence imaging, HSI, MSI), electrochemical sensing (potentiometry, voltammetry, amperometry), biosensors (enzyme-inhibition, immunosensors, aptamer-based, MIP, microbial), and e-nose platforms (MOS, CP, QCM, SAW, and CM based systems). Unlike traditional techniques, electronic platforms can be miniaturized, integrated with portable devices, and seamlessly connected to IoT and smart agriculture infrastructures. Their adaptability allows detection not only in controlled laboratory environments but also directly under real farming conditions, where timely decisions are critical. By combining portability, automation, and data-driven analysis, electronic pesticide detection technologies represent a transformative approach that bridges the gap between laboratory precision and agricultural practicality.

This classification highlights the diversity of sensing principles and system architectures currently employed for electronic pesticide detection. In the following sections, these technologies are discussed in further detail, with emphasis on their working principles.

Optical methods for pesticide detection

Optical methods, particularly HSI and MSI have gained increasing attention in pesticide residue detection due to their ability to combine spectral and spatial information [70–73]. By measuring reflectance or absorbance across a wide range of wavelengths, these systems can capture subtle chemical differences on crop surfaces that are often invisible to the naked eye. Spectral signatures linked to pesticide contamination can be examined with chemometric and ML methods, such as PCA or SVM. By analyzing these patterns, researchers can correlate spectral data with pesticide residues, allowing for rapid, non-destructive, and non-invasive detection. A major advantage of HSI and MSI is their exceptional scalability for high-throughput screening. They transition seamlessly from laboratory environments to active food sorting and packaging lines, allowing for the real-time, continuous monitoring of bulk samples without the need for any destructive sample preparation.

Beyond HSI and MSI methods, other optical approaches have also been explored. Fluorescence imaging has been used to exploit the natural fluorescence of certain pesticides or their metabolites, offering a simple and low-cost detection strategy [74]. RGB camera systems and thermal infrared imaging are also increasingly utilized to capture indirect signs of chemical exposure. Although these imaging tools

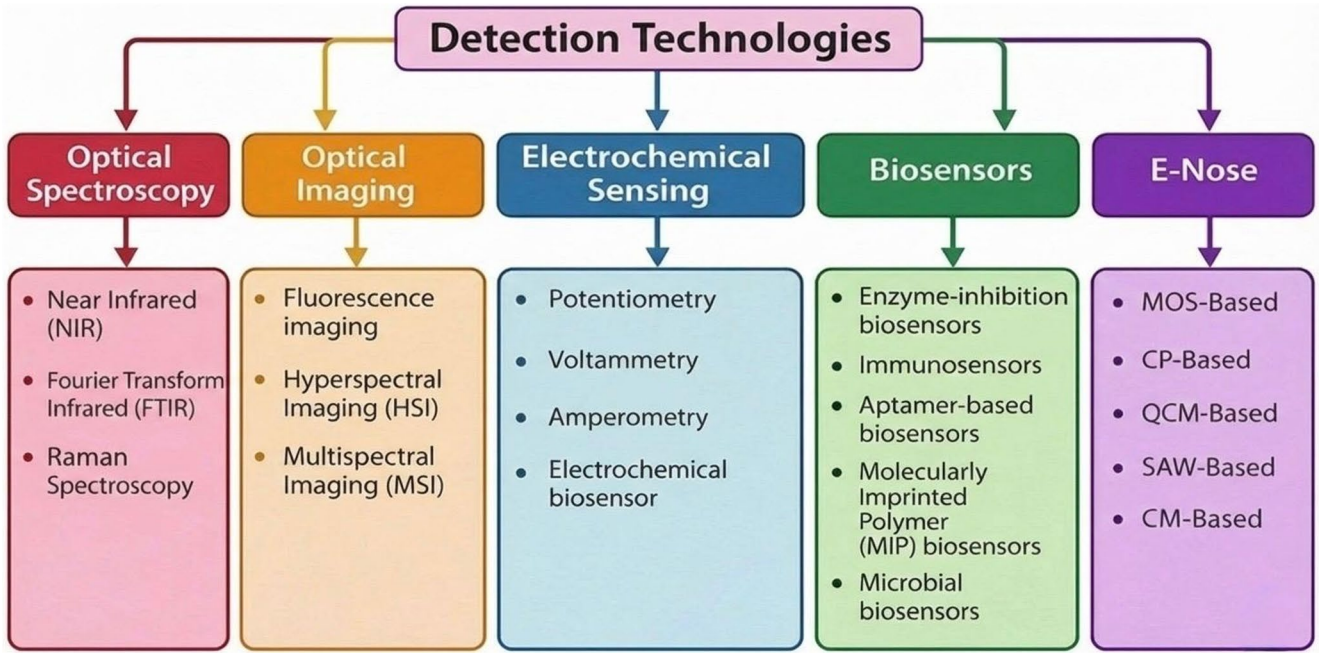

Fig. 2 Classification of electronic pesticide detection technologies

may not directly quantify trace residues, they effectively detect secondary matrix alterations like localized moisture loss, accelerated surface senescence, or oxidative tissue stress. These alterations serve as rapid indirect indicators of chemical application. While the fundamental principles of these large-scale imaging techniques have been extensively demonstrated in pre-harvest applications using remote sensing platforms [75, 76]. In these high-throughput post-harvest environments, optical platforms enable the rapid evaluation of coating uniformity, the mapping of localized chemical diffusion across bulk food batches, and the continuous screening of moving conveyor belts. Although indirect optical methods can be sensitive to ambient lighting or packaging interferences, their unmatched processing speed, wide spatial coverage, and seamless integration with modern data analytics make them invaluable. Therefore, advanced optical sensing become an essential pillar of modern quality control [77]. These methods bridge the gap between precise localized residue analysis and large-scale, continuous monitoring across global food supply chains.

Electrochemical sensors for pesticide detection

Electrochemical sensors are among the most widely studied electronic tools for pesticide detection. Their principle is based on converting chemical interactions between pesticide molecules and the electrode surface into measurable electrical responses, using techniques such as amperometry, voltammetry, potentiometry, or electrochemical impedance. Considerable progress has been achieved using functional nanomaterials, including carbon nanotubes, graphene derivatives, conductive polymers, and metal nanoparticles [78]. These materials improve electrode performance by increasing the active surface area, enhancing catalytic activity, and facilitating electron transfer. More recent advances include the development of label-free sensors and nanocomposite-modified electrodes, which extend applicability to a broader range of pesticide classes and enable direct residue quantification. A major operational advantage of electrochemical sensors is their inherent compatibility with miniaturization and portable platforms. Their seamless integration with smartphone interfaces, wireless modules, and IoT-enabled devices makes them highly attractive for decentralized, real-time pesticide monitoring across modern food supply chains and active processing facilities.

Despite these advantages, several limitations restrict the widespread deployment of electrochemical sensors in smart agriculture [79]. Selectivity remains a major issue because structurally similar pesticides and interfering food-matrix components can generate overlapping signals. Enzyme-based electrodes offer high sensitivity but often suffer from poor stability, limited storage lifetime, and susceptibility to temperature fluctuations. Reproducibility across batches and long-term signal drift further complicate standardization. Current mitigation strategies include signal amplification, molecularly imprinted polymers (MIPs), nanostructured electrode surfaces, anti-fouling interfaces, and ML-assisted signal interpretation [80]. These developments improve robustness, but reliable industrial use still requires matrix-specific calibration and long-term stability validation.

Biosensors for pesticide detection

Biosensors are among the most widely investigated electronic systems for pesticide monitoring [81]. These systems operate by coupling a biological recognition element with a suitable transducer to convert selective target interactions into measurable signals. Depending on the transduction mechanism, biosensors are generally classified as electrochemical, optical, piezoelectric, or thermal platforms. Electrochemical biosensors dominate current applications due to their exceptional sensitivity, inherent portability, and ease of integration into miniaturized diagnostic devices. Enzyme-based platforms heavily rely on acetylcholinesterase inhibition to detect organophosphate and carbamate residues [82]. The measured extent of enzyme inhibition correlates directly with pesticide concentration, enabling ultra-sensitive detection that frequently reaches the nanomolar range. Severe operational challenges remain regarding inherent enzyme instability and signal interference originating from complex food matrices during post-harvest screening. Researchers mitigate these limitations by engineering biosensor interfaces with advanced nanomaterials like mesoporous carbon, functionalized graphene, and bimetallic nanostructures. Rather than merely increasing surface area, these tailored nanomaterials provide a highly biocompatible microenvironment that preserves enzyme activity while amplifying signal transduction. Immunosensors and aptamer-based recognition elements offer a robust alternative to traditional enzymatic designs. These affinity-based systems deliver superior target specificity and enhance structural stability. Their resilience makes them highly suitable for continuous, real-time quality control applications across demanding food processing environments.

Immunosensors and aptamer-based biosensors provide alternatives to enzyme-inhibition platforms by using affinity-based recognition. Antibodies enable selective binding of target pesticide residues, whereas aptamers offer advantages such as chemical stability, programmable synthesis, and lower production cost [83]. These recognition elements can improve specificity in complex food matrices and support compact diagnostic formats integrated with wireless or smartphone-based readout. However, their practical performance still depends on matrix tolerance, regeneration

capability, and validation under realistic storage and packaging conditions.

Electronic nose (e-nose) systems for pesticide detection

The E-nose is a biomimetic device modeled after the human olfactory system, designed to detect and discriminate a broad spectrum of VOCs [84]. Figure 3 illustrates the human olfactory mechanism alongside the working principles of the e-nose device. The human olfactory process begins when volatile compounds enter the nasal cavity and interact with specific receptors. This interaction generates neural signals that travel to the olfactory bulb for organization and refinement. The brain then processes this information to interpret distinct odor patterns. This biological framework directly inspires the operational architecture of e-nose systems. These electronic platforms combine a chemical sensing array with a data processing module, enabling the identification of complex volatile mixtures. The overall sensing performance relies heavily on the selected gas sensors, which determine the system's selectivity toward specific chemical groups. When integrated with advanced signal processing and pattern recognition algorithms, these sensor arrays deliver rapid, non-destructive, and continuous chemical analyses directly on food processing lines. Owing to these capabilities, e-noses have attracted significant interest for applications in food safety and post-harvest quality control [85–88].

E-nose systems typically utilize sensor arrays based on technologies such as metal oxide semiconductors (MOS), conducting polymers (CP), quartz crystal microbalances (QCM), colorimetric (CM) assays, surface acoustic wave (SAW) devices, and nanomaterial-based composites. These arrays exhibit varying sensitivities to VOCs, capturing emissions released directly from pesticide residues or generated during matrix degradation. The combined partial selectivity of each individual sensor creates a unique, characteristic "fingerprint" of the complex volatile mixture. Selecting the optimal type and quantity of sensors is critical for maximizing array performance [89]. In practical field deployments, the selection of specific gas sensors significantly impacts the overall array performance. Achieving reproducible headspace signatures with these semiconductor devices demands rigorous hardware-level protocols. A major operational bottleneck for MOS-based arrays is the requirement for an optimized pre-heating procedure. These sensors depend on high operating temperatures (typically between 200 °C and 400 °C) to facilitate the continuous oxidation and reduction of target gases on their sensing surface. Any

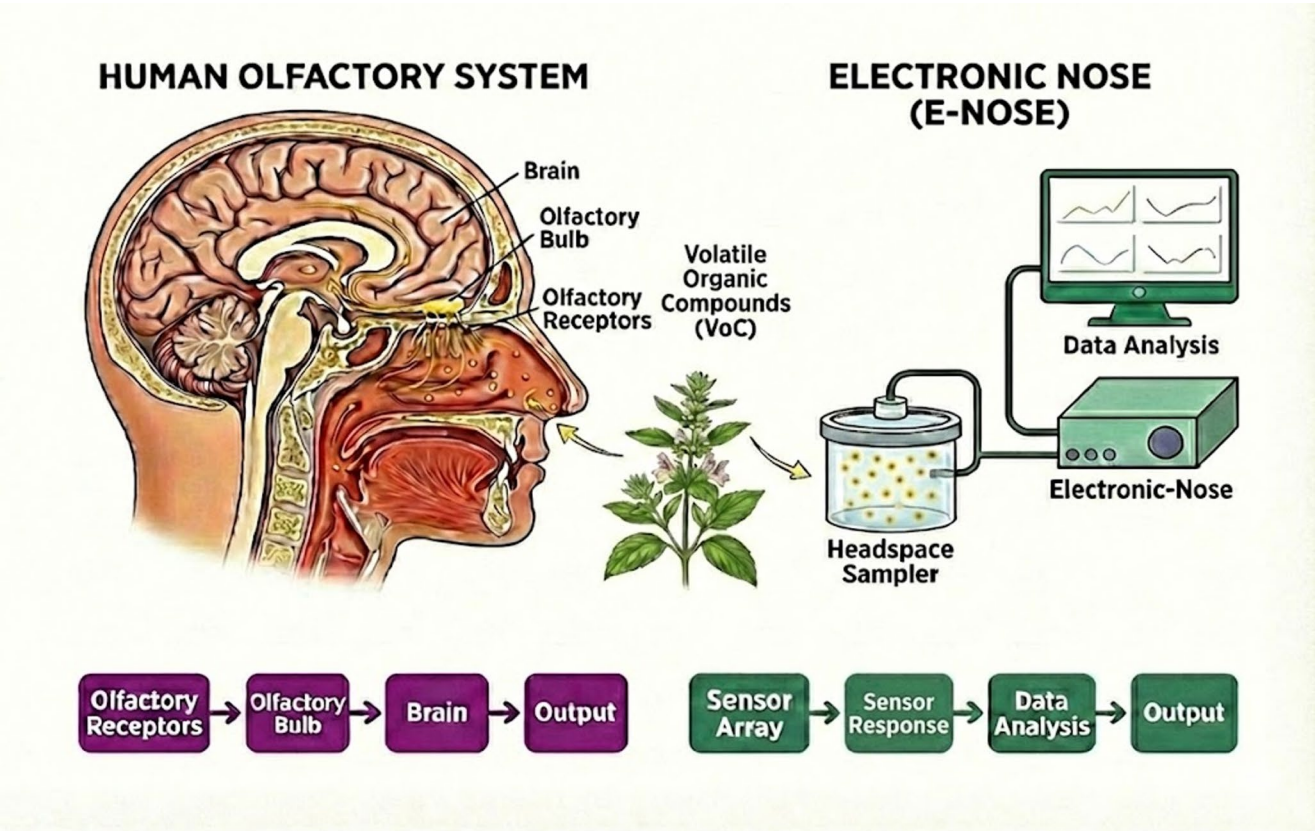

Fig. 3 Representation of the e-nose and the human olfactory system

inconsistency during this thermal activation phase inevitably causes severe baseline drift and signal instability. Future e-nose architectures must incorporate automated thermal stabilization routines, ensuring the sensor baseline is fully equilibrated before continuous headspace sampling begins. Statistical and ML algorithms, including PCA, LDA, SVM, and ANNs, are then deployed to decode these complex multivariate response patterns [90, 91]. Together, these elements allow for the rapid and non-destructive detection of pesticide contamination across a wide range of food matrices and post-harvest commodities.

E-nose systems offer several operational advantages for high-throughput pesticide screening within smart food supply chains. They are portable, non-destructive, and suitable for repeated measurements on intact commodities or packaged batches, while avoiding complex sample preparation. Their relatively low cost and compatibility with wireless communication, mobile applications, and IoT platforms make them attractive for continuous residue monitoring and Quality 4.0 traceability systems [92]. However, their role is best understood as rapid VOC-based screening rather than direct compound-specific quantification. Reliable use in regulatory contexts requires standardized headspace sampling, drift compensation, humidity correction, and confirmatory analysis when predicted residue levels approach MRL thresholds.

Table 4 shows the types of sensors utilized in e-nose systems for pesticide detection, along with their detection type, advantages, and limitations. According to recent studies, MOS sensors are the most utilized sensing elements in E-nose systems, mainly due to their low cost, high sensitivity to VOCs, and operational simplicity.

While these gas-phase sensors drive e-nose platforms, their pattern-recognition principles are closely mirrored by their liquid-phase counterparts. Electronic tongue (e-tongue) systems are also part of the broader family of electronic sensing technologies. Unlike e-nose platforms, which analyze gas-phase or headspace VOC patterns, e-tongue systems use arrays of cross-sensitive electrochemical, potentiometric, voltammetric, or impedimetric sensors to characterize liquid samples or extracts. Their output is usually a multivariate liquid-phase response pattern that requires chemometric interpretation, similar in concept to the pattern-recognition workflow used in e-nose analysis but based on dissolved analytes rather than volatile compounds [66, 90]. Although highly effective for analyzing fruit juices, beverages, or post-harvest wash water, their general reliance on liquid extraction inherently limits their application for the continuous, non-destructive, and on-line surface screening emphasized in this review.

Comparative overview of electronic pesticide detection systems

This section provides a comparative synthesis of the primary electronic pesticide detection platforms developed over the past decade. Optical methods, such as HSI and MSI devices, enable high-throughput, non-destructive screening across bulk food batches and active conveyor systems. They remain constrained by high instrumentation costs and signal sensitivity to ambient testing facility lighting [93, 94]. Electrochemical sensors deliver exceptional analytical sensitivity and inherent portability for on-site quality control. Their continuous industrial deployment is frequently hindered by signal instability and the necessity for frequent calibration under fluctuating storage and processing temperatures. Biosensors achieve unmatched target specificity through molecular recognition elements like enzymes or aptamers. These biological platforms face distinct commercialization challenges regarding the long-term storage stability of their active components and the complexities of large-scale manufacturing standardization. E-nose systems offer a highly cost-effective and continuous approach for capturing complex VOC fingerprints. Their reliable operation within complex food matrices strictly depends on robust computational algorithms to compensate for inherent baseline drift and environmental cross-sensitivity. Because no single sensing architecture currently satisfies all analytical and operational demands of the modern food supply chain, Table 5 outlines

Table 4 Comparison of gas sensors in e-nose systems

Sensor Type	Detection	Advantages	Limitations	Selectivity
MOS	Resistance changes due to gas absorption	Small size, high sensitivity	High power consumption, sensitive to humidity	High
CP	Conductivity changes in polymer layer	Room-temperature operation, wide range of polymers	Sensor drift, humidity sensitivity, limited lifetime	Moderate
QCM	Frequency shift due to mass loading	High sensitivity, diverse coating materials	Complex circuitry, poor reproducibility	High
SAW	Acoustic wave velocity shift	Multi-residue analysis, wide panel	Noise-sensitive, complex fabrication, limited robustness	High
CM	Color change of indicator dyes	Simple, visual readout, robust in hazardous environments	Short lifetime, low reusability, limited to certain gases	Moderate

a comprehensive technical comparison of their key performance metrics [26, 42, 70, 76].

The performance metrics summarized in Table 5 illustrate the inherent technical boundaries and operational trade-offs across different electronic sensing modalities. To facilitate a clear analytical comparison, the Limit of Detection (LOD) values are expressed using both molar concentrations and mass-based ratios, reflecting standard reporting practices in chemical and biological sensing. Metrics such as fM (femtomolar) and nM (nanomolar) define the absolute molar sensitivity of electrochemical and affinity-based platforms. Parallel to this, ppb (parts per billion) and ppm (parts per million) provide practical mass-concentration assessments. These mass-based units are strictly required for evaluating regulatory compliance with legally defined MRLs across complex food matrices and post-harvest commodities.

For regulatory interpretation, LOD and limit of quantification (LOQ) values should not be considered in isolation. A more useful screening metric is the ratio between the method detection capability and the commodity-specific MRL for the target pesticide [95]. Operationally, an LOD/MRL or LOQ/MRL ratio below 0.1 provides a reliable margin for early-warning screening. Ratios between 0.1 and 1.0 can support risk-based triage if strictly validated for the target matrix, while values exceeding 1.0 lack the sensitivity required to enforce legal thresholds. For example, a sensor response equivalent to 10 micrograms kg-1 for a pesticide-commodity combination with an MRL of 100 micrograms kg-1 corresponds to an LOD/MRL ratio of 0.10. This type of normalization is essential because electronic sensing studies often report sensitivity in different units such as molarity, ppb, ppm, or mg kg-1, which complicates direct comparison across food matrices.

A comparative analysis of these metrics reveals that electrochemical and biosensor-based platforms deliver superior analytical sensitivity, frequently reaching the fM range. This extreme precision, however, inherently necessitates a longer Response Time to accommodate complex biological recognition and binding kinetics. The industrial readiness of these highly sensitive systems is intricately linked to their vulnerability to ambient interferences within active processing facilities [96]. Although advanced optical scanning provides the highest spatial coverage for continuous bulk monitoring, its sensitivity is generally limited to the ppm (mg/kg) level. This fundamental limitation arises because non-contact optical systems often rely on indirect spectral markers of localized matrix degradation rather than the direct chemical quantification of trace residues. Ultimately, selecting an optimal sensing architecture requires balancing the strict necessity for ultra-trace-level detection against the demand for rapid, continuous operational robustness across demanding Food Industry 4.0 environments [97].

This regulatory benchmarking also shows why high analytical sensitivity alone does not guarantee industrial readiness. A biosensor may achieve extremely low LODs under buffered laboratory conditions, yet still require destructive extraction, enzyme stabilization, and frequent recalibration before it can be applied to a heterogeneous food matrix. Conversely, optical and e-nose systems may offer high throughput and non-destructive operation but often provide indirect or pattern-based signals that require confirmatory testing when results approach the MRL. Therefore, the most realistic near-term role of many electronic sensing platforms is rapid screening and batch prioritization, followed by confirmatory GC-MS or LC-MS analysis for samples flagged as non-compliant or borderline.

To move beyond theoretical performance benchmarks, it is necessary to examine how these technologies operate within complex food matrices. To ensure a criteria-driven evaluation, representative studies published between 2015 and 2026 were systematically analyzed based on their specific detection limits, targeted chemical residues, and validation status under simulated or actual industrial processing conditions. This empirical evidence highlights the practical trade-offs between analytical precision and continuous online applicability across diverse post-harvest commodities and dynamic food supply chains. A comprehensive summary of these selected studies, categorized by their primary sensing modality (electrochemical, optical, biosensors and e-nose), is presented in Table 6.

Building on the evidence summarized in Table 6, the following subsections establishes a comprehensive evaluation framework to critically examine the inherent trade-offs among analytical sensitivity, target selectivity, and industrial scalability within complex food matrices.

Evaluation framework and comparison criteria

The analysis of complex food matrices for pesticide residues demands both high analytical precision and robust sensor stability. Biosensors address this analytical requirement by providing exceptional sensitivity for trace-level detection.

Table 5 Technical performance benchmarks and operational specifications of electronic pesticide detection technologies

Detection Technology	Detection Principle	Limit of Detection	Response Time	On-site Deployability
Optical	Light-matter interaction	0.1 ppb to 100 ppb	1 s to 2 min	Intermediate
Electrochemical	Redox reaction kinetics at electrode interface	fM to µM	10 s to 1 min	High
Biosensors	Biorecognition affinity (enzymes/aptamers)	fM to nM	5 min to 30 min	Low-Moderate
E-nose	VOC pattern recognition	ppb to ppm	30 s to 90 s	High

Table 6 Electronic pesticide detection studies

Application	Method	Advantage	Limitation	Reference
Vegetable oil	Electrochemical	High sensitivity via enzyme inhibition	Enzyme instability and matrix interference	[98]
Fruits and vegetables	Electrochemical	Portable and miniaturized electrochemical system design	Instability of biological components	[99]
Vegetables	Electrochemical biosensor	High sensitivity and portable	Enzyme stability and environmental condition variability	[100]
Fruits	Electrochemical biosensors	Portable and rapid analysis	Environmental conditions affect multi-pesticide selectivity	[101]
Fruits and vegetables	Electrochemical aptasensor	Strong selectivity from aptasensors	Batch variability	[102]
Tomato leaves	Optical (HSI)	Rapid and non-destructive detection	Environmental variability affects performance and high-cost equipment	[103]
Fruit cuticles	FTIR, FTIR-PAS (Spectroscopy)	Non-destructive and fast analysis	Lower sensitivity than LC/GC–MS	[104]
Tomato	Optical (ATR-FTIR)	Rapid and non-destructive	Calibration needed and limited sensitivity	[105]
Vegetables	Optical (Colorimetric Paper Chip)	Quick analysis and cheap equipments	Low resolution and illumination sensitivity	[106]
Vegetable leaves	Optical (NIR, Spectroscopy)	High selectivity and portable	Matrix interference and photobleaching	[107]
Melon	Optical (Short Wave Infrared, HSI)	Multiple pesticide detection and non-destructive	Sensitive to spectral noise and illumination variability	[108]
Vegetables	Optical (FTIR HSI)	Portable device and rapid detection	Requires calibration on different types of pesticides	[109]
Apple	Optical (HSI)	Non-destructive and rapid detection	Single product detection	[110]
Fruits and Vegetables	Optical (Spectroscopic)	Combines spectroscopic images with AI	Require large datasets	[111]
Black vegetables	Optical (HSI and MSI)	High accuracy on dark-surface crops	Requires heavy computation	[112]
Rice	Optical (Multi Spectral NIR)	Accurate detection of chlorpyrifos-methyl	Limited to single type of pesticide	[113]
Tomato	Optical (NIR)	Non-destructive and high accuracy detection	Preprocessing and ML model dependent	[114]
Food matrices	Optical (THz Frequency Spectroscopy)	High spectral selectivity and accurate quantitative prediction	Sensitivity affected by moisture content and matrix complexity	[115]
Toona sinensis leaves	Optical (THz Time Spectroscopy)	Trace-level identification and spatial visualization of multiple residues	Limited test validation and high instrumentation cost	[116]
Fruits	Wearable Ache-based biosensor	Real time pesticide detection	Enzyme stability and non-reusable sensors	[117]
Apple	E-nose	Non-destructive and high accuracy	Limited to two pesticides and environmental variability	[118]
Food	E-nose	Low-cost and portable detection	Sensor drift and selectivity for specific pesticides	[119]
Tea leaves	E-nose	High accuracy and fast detection	Tea volatiles affect the performance	[120]
Apple	E-nose	Low-cost and high accuracy detection	Single pesticide detection and sensor drift	[121]
Cherry	E-nose	Low-cost and portable detection	Sensor drift and small dataset	[122]
Mint leaves	E-nose	High accuracy and low-cost detection	Accuracy drops significantly on multiple pesticide types	[123]

These devices use specific biorecognition elements to quantify trace pesticide concentrations at levels similar to standard benchtop instrumentation. This analytical sensitivity is often restricted by poor stability in real sample conditions. Enzyme-based systems, such as those relying on acetylcholinesterase (AChE) inhibition, are susceptible to denaturation from the pH variations and compositional fluctuations found in crude food extracts. The diverse biochemical composition of agricultural commodities also introduces interfering compounds that cause overlapping electrochemical signals. This matrix effect limits continuous sensor operation and necessitates extensive sample pretreatment or surface regeneration.

Optical imaging methods provide high sample throughput and spatial evaluation rather than targeted molecular sensitivity. These non-destructive techniques enable the rapid scanning of agricultural product surfaces and bulk food samples, acquiring broader spatial data than localized

point sensors. The reliance on spectral signatures increases susceptibility to physical and optical interferences. Surface irregularities, natural color variations, and textural differences of food items obscure the subtle spectral shifts caused by pesticide residues. Differentiating chemical contamination signals from natural matrix variations necessitates computationally intensive calibration models and advanced chemometric analysis.

E-nose systems analyze the volatile profile of food samples by applying pattern recognition algorithms to headspace gases. These sensor arrays provide a rapid screening method for detecting VOCs associated with pesticide residues. The long-term analytical reliability of e-nose systems is frequently compromised due to continuous sensor drift. MOS sensors, which form the core of many commercial arrays, exhibit strong cross-sensitivity to variations in sample moisture content and ambient temperature. This environmental susceptibility causes significant baseline instability during the characterization of complex food matrices. Accurate classification and quantification depend on regular calibration protocols and the application of robust drift compensation algorithms.

Deployability, scalability, and iot integration

The practical application of these detection technologies in smart agriculture depends on economic factors and data integration capabilities. Continuous monitoring in food supply chains and storage facilities requires scalable sensor networks. Optical systems provide detailed spatial data, but high equipment costs and heavy data processing requirements limit their widespread use. These financial and computational demands restrict their deployment in small-scale operations or dense monitoring networks. E-nose arrays and electrochemical sensors offer a cost-effective alternative. Their lower manufacturing costs and simpler data structures facilitate their integration into extensive wireless sensor networks.

Integrating these detection technologies into food quality monitoring networks necessitates both efficient data transmission and minimal analysis latency. Optical imaging systems produce substantial spectral data cubes; consequently, processing these intricate datasets demands considerable transmission bandwidth and cloud computing resources, thereby extending the overall analysis time. Conversely, e-nose arrays and electrochemical sensors generate low-volume time-series data. This reduced data payload enables the application of edge computing techniques, such as TinyML. These localized processing architectures analyze sensor data directly on microcontrollers, thereby facilitating real-time pesticide detection with minimal power consumption.

Implementing scalable sensor networks in large food storage and supply chain facilities require reliable communication and efficient energy management. However, conventional high-bandwidth communication technologies such as Wi-Fi and cellular networks often suffer from limited coverage and high operational costs when deployed in large warehouse environments. Low-Power Wide-Area Network (LPWAN) protocols, including LoRaWAN and Narrowband-IoT (NB-IoT), offer suitable communication architecture for these applications. These protocols transmit low-volume, edge-processed data from E-nose and electrochemical sensors over extended distances with minimal power consumption. Continuous operation of dense monitoring networks also necessitates sustainable energy sources. Integrating energy harvesting technologies enhances the longevity of sensor nodes and minimizes the need for manual upkeep in extended food storage scenarios. A decision matrix, as shown in Table 7, aids in the selection of suitable detection technologies, contingent upon the specific food matrix and operational demands. Optical techniques offer swift, non-invasive screening capabilities for bulk agricultural commodities. Electrochemical sensors can quantify trace levels within intricate food extracts. Furthermore, e-nose systems facilitate continuous surveillance of volatile pesticide residues within post-harvest storage environments.

Table 7 outlines the analytical and operational capabilities of the discussed detection technologies for food matrix analysis. Optical methods facilitate rapid, non-contact screening of bulk samples but are heavily restricted by matrix interferences and complex calibration requirements. Electrochemical and biosensor platforms provide superior selectivity and support localized edge processing, yet their application in crude food extracts is limited by surface fouling, bioreceptor degradation, and the need

Table 7 Decision matrix for electronic pesticide detection technologies

Criteria	Optical	Electrochemical	Biosensors	E-nose
Sensitivity	High	High	Very High	High
Selectivity	Moderate-High	High	Very High	Moderate
Environmental robustness	Weak	Moderate	Weak	Moderate
Calibration	Weak	Moderate	Weak	Weak
Spatial coverage	High	Moderate	Weak	Moderate
Multi-residue capability	High	Moderate	Moderate	Moderate
IoT/edge compatibility	Moderate	High	Moderate	High

for controlled sample–sensor contact. E-nose arrays offer a cost-effective solution for continuous volatile monitoring, if baseline drift is adequately compensated. From an implementation perspective, technology selection should therefore consider not only sensitivity and response time, but also sample throughput, calibration transferability, cleaning or regeneration requirements, operator skills, false positive rates, maintenance burden, and compatibility with routine production-line workflows. Consequently, comprehensive pesticide residue monitoring in food supply chains necessitates integrated analytical workflows. Combining high-throughput initial screening via optical or e-nose systems with highly selective electrochemical or biosensor-based quantification provides a robust strategy for complex sample characterization.

Challenges and future research directions

Translating pesticide detection technologies from laboratory prototypes to continuous food monitoring systems requires addressing severe operational stability issues under authentic processing and storage conditions. High analytical sensitivity must be coupled with reproducible sampling, reliable baseline behavior, and validation across multiple commodities rather than only standard solutions or small spiked datasets. The biochemical complexity of crude food extracts, intact food surfaces, and dynamic post-harvest conditions introduces significant measurement variability. Temperature fluctuations, humidity changes, surface texture, cultivar differences, and background food volatiles can alter optical responses, electrode fouling, bioreceptor activity, and VOC partitioning. These factors may increase false positives or reduce sensitivity when models are transferred from controlled experiments to real production environments. Therefore, real-world applicability should be assessed through external or blind validation, matrix-diverse datasets, calibration-transfer studies, false-positive and false-negative reporting, and stability tests under extended operation. Overcoming these limitations necessitates multimodal sensor fusion within food supply chains. For example, high-throughput optical screening can rapidly evaluate bulk agricultural products on processing lines. These non-destructive primary scans can identify suspect batches, guiding localized electrochemical or e-nose arrays to perform more specific quantification. Long-term measurement accuracy in these distributed networks is further degraded by continuous sensor drift and component aging. Implementing decentralized algorithms, such as federated learning, provides a dynamic calibration strategy. Local processing nodes can update drift-compensation models independently and share only the refined parameter weights across the network. This architecture allows the monitoring system to adapt to local storage environment changes while minimizing bandwidth usage and power consumption.

Future advancements in this field depend on shifting the research focus from isolated sensitivity metrics to the practical challenges of complex food matrices. Reliable post-harvest monitoring relies heavily on intelligent signal processing, specifically integrating sensor fusion, drift compensation, and edge-compatible ML. To bridge the gap between laboratory success and industrial application, extensive field testing within active food processing environments is essential. This transition also necessitates standardized benchmarking using real-world commodity datasets to ensure technological reproducibility. In the longer term, emerging computational frameworks, including quantum-assisted analytics, may support the processing of high-dimensional multimodal sensor data, but their value will depend on first establishing reliable datasets, transparent validation procedures, and practical deployment protocols.

Conclusion

Electronic pesticide detection systems provide the essential analytical infrastructure for rapid and decentralized food safety screening. These platforms address the critical need for continuous residue monitoring across dynamic agricultural supply chains. This review evaluates these sensor-based technologies, specifically focusing on their application within complex food matrices and post-harvest environments. Conventional chromatographic and spectroscopic methods establish the analytical standard for regulatory compliance and precise reference analysis. The high instrumentation costs, extensive sample preparation, and lack of portability associated with these standard techniques restrict their integration into continuous food quality screening networks. Electronic detection platforms, including optical imaging, electrochemical sensors, biosensors, and e-nose arrays, provide rapid and non-destructive analysis capabilities suitable for high-throughput food characterization.

E-nose provides a scalable approach for continuous monitoring by analyzing the VOC profiles of pesticide residues in food headspace. Integrating these sensor networks with advanced chemometrics and edge computing facilitates real-time quality assessment in post-harvest storage facilities. The analytical reliability of these systems is currently restricted by baseline drift, cross-sensitivity to food matrix moisture, and the degradation of sensor materials over time. Validating these platforms requires shifting from idealized laboratory settings to authentic supply chain environments using complex food extracts. Overcoming these analytical

limitations necessitates the development of multimodal sensor fusion architectures and the adoption of robust drift-compensation algorithms.

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Declarations

Conflict of interest The authors declare no conflicts of interest.

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