

REVIEW ARTICLE

Advancements in Intelligent Sensing Technologies for Food Safety Detection

Wenhui Jiang¹, Changhong Liu^{1*}, Wei Liu², and Lei Zheng^{1*}

¹Engineering Research Center of Bio-Process, Ministry of Education, School of Food and Biological Engineering, Hefei University of Technology, Hefei 230009, China. ²Intelligent Control and Compute Vision Lab, Hefei University, Hefei 230601, China.

*Address correspondence to: changhong22@hfut.edu.cn (C.L.); lzheng@hfut.edu.cn (L.Z.)

As a critical global public health concern, food safety has prompted substantial strategic advancements in detection technologies to safeguard human health. Integrated intelligent sensing systems, incorporating advanced information perception and computational intelligence, have emerged as rapid, user-friendly, and cost-effective solutions through the synergy of multisource sensors and smart computing. This review systematically examines the fundamental principles of intelligent sensing technologies, including optical, electrochemical, machine olfaction, and machine gustatory systems, along with their practical applications in detecting microbial, chemical, and physical hazards in food products. The review analyzes the current state and future development trends of intelligent perception from 3 core aspects: sensing technology, signal processing, and modeling algorithms. Driven by technologies such as machine learning and blockchain, intelligent sensing technology can ensure food safety throughout all stages of food processing, storage, and transportation, and provide support for the traceability and authenticity identification of food. It also presents current challenges and development trends associated with intelligent sensing technologies in food safety, including novel sensing materials, edge-cloud computing frameworks, and the co-design of energy-efficient algorithms with hardware architectures. Overall, by addressing current limitations and harnessing emerging innovations, intelligent sensing technologies are poised to establish a more resilient, transparent, and proactive framework for safeguarding food safety across global supply chains.

Introduction

In the global food industry, safeguarding food safety is of paramount importance as it has direct implications for public health and corporate reputation. Recently, there has been a notable increase in the frequency of food safety incidents globally. These incidents are primarily caused by various contaminants, such as pesticides, veterinary drugs, heavy metals, mycotoxins, pathogens, and the misuse of food additives. To ensure food remains safe for consumption, researchers are committed to developing sensitive and rapid analytical methods for efficient contamination detection. This ongoing research is crucial for preempting potential health risks and upholding the integrity of global food safety standards.

Traditionally, the acquisition of food safety information has largely relied on specific analytical detection techniques. High-performance liquid chromatography (HPLC) and liquid chromatography–mass spectrometry (LC-MS) are employed for the separation and quantitative analysis of compounds, while gas chromatography (GC) and gas chromatography–mass spectrometry (GC-MS) are utilized for the analysis of volatile substances. Additionally, bioanalytical methods such as enzyme-linked immunosorbent assay, which measures antigen–antibody interactions, and polymerase chain reaction, which amplifies DNA sequences, are also employed. These methods are widely

used in food safety detection due to their high sensitivity and accuracy. However, they typically require complex sample preparation and skilled technicians, making them unsuitable for rapid analysis, particularly for real-time quality monitoring in the food industry [1]. Moreover, these methods are often limited to sampling or retrospective third-party testing and fail to meet consumer and processor demands for high-quality food.

Intelligent perception technology is the ability to be aware of and learn from experiences, which was originally defined by Keith M. Kendrick in 1998 as the adaptive learning responses animals exhibit to their environment or themselves [2]. As for human intelligent technology, intelligent perception refers to the process in which various advanced sensors, intelligent algorithms, and data processing technologies are utilized to enable devices or systems to automatically acquire, analyze, and understand the information from the surrounding environment, so as to make intelligent decisions and responses [3]. In the context of the food industry, intelligent perception technology can be understood as the integration of traditional sensing techniques with artificial intelligence to simulate certain human perceptual and computational functions in specific scenarios. This enables technology to provide optimal decision-making information for human production and life. Compared to conventional detection methods, intelligent perception technology offers several advantages, including nondestructiveness, high precision, real-time

Citation: Jiang W, Liu C, Liu W, Zheng L. Advancements in Intelligent Sensing Technologies for Food Safety Detection. *Research* 2025;8:Article 0713. <https://doi.org/10.34133/research.0713>

Submitted 13 January 2025

Revised 11 April 2025

Accepted 30 April 2025

Published 2 June 2025

Copyright © 2025 Wenhui Jiang et al. Exclusive licensee Science and Technology Review Publishing House. No claim to original U.S. Government Works. Distributed under a Creative Commons Attribution License (CC BY 4.0).

processing, and comprehension ability. It can meet the requirements for online processing in terms of recognition speed and provide comprehensive knowledge of detection targets. The common intelligent sensing technologies include optical, electrical, acoustic, magnetic, machine olfactory, and machine gustatory detection. These technologies are not only highly versatile but also user-friendly, allowing nonprofessionals to operate them and thus reaching a wider audience than traditional methods. This accessibility further enhances the practicality and applicability of intelligent perception technology in various fields. It can be integrated with other technologies such as storage systems, production processes, and blockchain to address a wide range of issues across the food industry. This multifunctional capability highlights its potential as a versatile tool for modern food production and management.

This review investigates the development and application of common intelligent sensing technologies in food safety fields. In addition, it delves into the challenges these technologies encounter throughout the food supply chain and proposes potential solutions to address these issues. Moreover, this review explores future trends in intelligent sensing technologies, emphasizing their growing role in advancing food safety standards and operational efficiency within the industry. This analysis not only underscores the current capabilities and limitations of these technologies but also projects their potential for future impact on global food safety practices.

Overview of Intelligent Sensing Technology

Detection technologies in intelligent sensing

Optical detection technology

Optical detection technologies, which have the characteristics of being noninvasive, rapid, and accurate, are extensively applied in food manufacturing and product testing processes. They utilize light properties such as absorption, scattering, emission, and refraction. In addition, they use models trained using algorithms such as artificial neural networks (ANNs) to analyze food freshness, purity, and safety. Common optical detection technologies include machine vision (MV), near-infrared spectroscopy (NIRS), hyperspectral imaging (HSI), surface-enhanced Raman spectroscopy (SERS), terahertz spectroscopy (THz), and laser-induced breakdown spectroscopy (LIBS). Figure 1 illustrates these techniques schematically.

MV has gained considerable attention in the food industry since its inception in the 1960s [4]. Fueled by enhancements in computational capabilities and algorithmic innovations, MV has undergone remarkable development and has been widely applied in automated inspection tasks. MV systems employ cameras and computers to replace human eyes for recognizing, tracking, and measuring objects, followed by further image processing (Fig. 1A). Through image segmentation, feature extraction, content analysis, and object recognition, raw images are transformed into meaningful datasets from which key assessment indicators are derived. As the MV system foundation, image acquisition typically employs RGB color cameras. These cameras capture images using 3 filters centered on red (R), green (G), and blue (B) wavelengths. Precise measurements require high-resolution cameras and quality lenses. Preprocessing steps, such as noise removal, contrast enhancement, and grayscale conversion, enhance image quality. Effective image segmentation, based on different features, is crucial for feature expression and content analysis. These features feed machine learning algorithms for target recognition [5].

The application of MV in food safety inspection is extremely extensive, covering the entire process of quality control from raw material selection to finished product packaging. Rong et al. [6] captured 1,264 images of juglans using a high-resolution camera and employed a 2-stage convolutional network method to achieve image segmentation and impurity detection, with an accuracy rate of 96.5% and a processing time of less than 60 ms, markedly enhancing both efficiency and accuracy. Moreover, the combination of MV with machine learning algorithms has been instrumental in detecting package completion, thereby reducing associated production costs [7]. Nevertheless, practical MV applications face limitations. Environmental factors, especially fluctuations in lighting and changes in background, can notably reduce detection accuracy. Moreover, the complex shapes, diverse colors, and varying surface textures of food products also make image segmentation and feature extraction more challenging. Often, the integration of high-quality hardware and advanced deep learning algorithms, which can be expensive and intricate, is necessary to overcome these obstacles [8]. It is possible to enhance the adaptability of MV to environmental conditions by utilizing adaptive algorithms and integrating advanced lighting systems [9]. MV integration with complementary sensing technologies may enable more comprehensive, accurate detection [1].

NIRS analyzes molecular vibrations through characteristic absorption spectra (Fig. 1B). When near-infrared (NIR) light interacts with a substance, hydrogen-containing functional groups in organic molecules (e.g., C-H, N-H, and O-H) experience vibrational transitions. These transitions alter the molecular dipole moments, resulting in the absorption of NIR light at specific frequencies and producing absorption spectra within the NIR region of 780 to 2,500 nm (wavenumbers 12,500 to 4,000 cm^{-1}) [10]. NIRS is widely adopted in food safety due to its rapid, nondestructive, accurate, cost-effective nature and operational simplicity. For instance, the combination of NIRS and partial least squares discriminant analysis (PLS-DA) has effectively distinguished between different brands of liquor with identical flavor profiles and alcohol content, achieving a high predictive performance with a recognition rate of 98.7% [11]. Carbas et al. [12] formulated partial least squares (PLS) and ANN prediction models using NIRS combined with machine learning algorithms for the quantitative detection of fumonisins. This enhanced fumonisin detection efficiency/accuracy, improving corn supply chain safety monitoring. Unlike traditional methods, NIRS eliminates the need for chemical reagents, thus cutting costs related to waste disposal [13]. In operational settings, the implementation of real-time monitoring through NIRS facilitates the quality and safety assessment of the food supply chain [14]. Despite its advantages, NIRS faces challenges. For trace hazardous substances outside the detection capabilities of NIRS, signal enhancement may be achieved by extending the optical path length or by increasing the number of scans [15]. Concurrently, enriching target analytes during sample preparation can enhance detection sensitivity. Typically, the performance of NIRS is compromised by matrix effects, such as moisture, necessitating the application of spectral preprocessing or wavelength selection techniques to enhance analytical precision [16]. The NIR spectral region is characterized by broad molecular vibration bands and overlapping signals, complicating direct component analysis. Consequently, chemometric methods are employed to develop calibration models, using statistical correlations to assist in peak identification

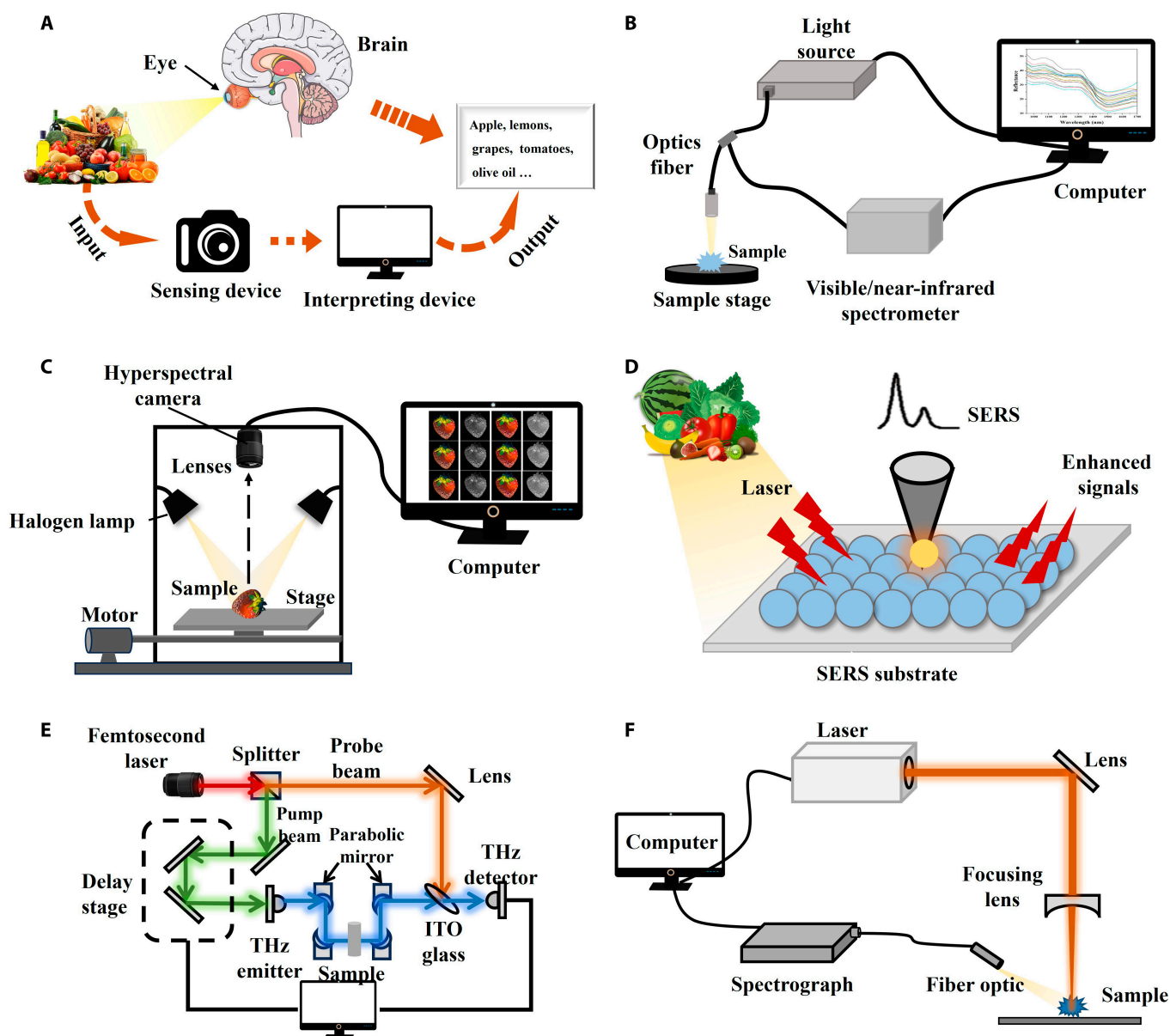


Fig. 1. Common optical detection technologies. (A) Machine vision (MV): A camera captures the image and provides it to the computer, which automatically performs tasks that could be done by the human visual system. (B) Near-infrared spectroscopy (NIRS): The technique detects characteristic absorption of 780 to 2,500 nm near-infrared light by C-H, O-H, and N-H groups in molecular structures, combined with chemometric modeling. (C) Hyperspectral imaging (HSI): The technique that simultaneously captures spatial and spectral information, forming a 3D data cube (x, y, λ) for analysis. (D) Surface-enhanced Raman spectroscopy (SERS): A spectroscopic technique that enhances the Raman signal of molecules through metallic nanostructures, achieving single-molecule level sensitivity. (E) Terahertz spectroscopy (THz): A nondestructive technique for characterizing low-frequency vibrational modes of materials by detecting absorption, reflection, or emission of electromagnetic waves across the microwave to infrared range. (F) Laser-induced breakdown spectroscopy (LIBS): A technique for rapid multielement detection by analyzing the emission spectrum of laser-induced plasma generated on the sample surface using pulsed lasers.

[17]. These methods can be integrated with other spectroscopic technologies to better interpret NIR spectra, thereby enhancing the interpretability of the results [18–20]. On the hardware front, advancements are directed toward miniaturization and integration, which lowers costs and boosts portability, thus enabling immediate on-site detection [21,22].

HSI combines spectroscopy and imaging to provide simultaneous spectral and spatial data. Unlike NIRS, which primarily captures spectral data, HSI additionally analyzes spatial surface characteristics. Moreover, HSI covers a broad spectral range, from ultraviolet to terahertz wavelengths, primarily utilizing

the visible (Vis) and NIR bands. This dual capability enables precise physicochemical characterization with high reliability. An HSI system includes essential components such as an array camera, spectroscopic equipment, light sources, transmission mechanisms, and computer hardware and software (Fig. 1C). HSI can be categorized into point, line, or area scanning, depending on the image acquisition and formation methods [23]. Hyperspectral data acquisition involves reflection, transmission, and diffuse transmission methods, each characterizing a unique interaction between light and the target object. These interactions modify light properties, embedding them with a

wealth of internal and external information of the object. By analyzing these encoded spectral data, HSI achieves a rapid and nondestructive assessment of critical parameters related to food safety [24]. Employing interactions with materials to gather information, HSI offers a nondestructive approach to sample analysis that eliminates the need for complex preprocessing or the addition of chemical reagents, thus avoiding the complications associated with hazardous waste disposal [25]. Capable of performing a single test to assess multiple parameters, HSI is ideally suited for comprehensive evaluations of food safety [26]. Additionally, HSI boasts robust spatial distribution and localization capabilities, which are instrumental in precisely identifying and segregating problematic areas in food products [27]. Area scanning is common in multispectral imaging (MSI), using fewer wavelengths than HSI. As an HSI derivative, MSI acquires narrow-band images at discrete wavelengths. Its primary function is to determine unique wavelength characteristics for each pixel of the observed object, making MSI especially important in the food industry [28].

Raman spectroscopy, as a complementary tool to infrared spectroscopy, has been widely used for food safety detection [29]. However, some samples exhibit strong fluorescence interference that obscures the Raman signals [30]. The limited sensitivity of this technique restricts its practical applications [31]. To overcome these limitations, researchers have made modifications to Raman spectroscopy, leading to the development of SERS [32]. SERS notably boosts molecular Raman signals through electromagnetic fields and chemical effects from metal nanostructures (Fig. 1D). The mechanism involves electromagnetic enhancement, achieved via localized surface plasmon resonance. This occurs when the frequency of incident light approaches the oscillation frequency of free electrons on the metal surface, creating strong localized electromagnetic fields that greatly enhance the Raman scattering intensity of molecules within. Another mechanism is chemical enhancement, occurring when charge transfer effects arise from interactions between the metal substrate and molecules adsorbed on its surface [33]. Studies have shown that SERS can enhance the Raman signals of target molecules by factors of 10^5 to 10^6 , demonstrating its high sensitivity, specificity, nondestructive nature, and rapid response [34]. These characteristics make SERS a promising tool in food safety detection. For foodborne pathogens, the detection limit can be as low as a few to several tens of CFU/ml. Functionalized nanoparticles are used to separate pathogens from samples. By adding nanoparticles with signal probes, a “sandwich” structure is formed, creating a “hot spot” effect that enhances the Raman signals. The pathogen concentration is quantified by detecting the signal intensity of the reporter molecule [35]. Additionally, Raman reporter molecules possess large Raman scattering cross-sections and narrow characteristic peaks, making them suitable for the simultaneous detection of multiple pathogens [36]. SERS offers ultrahigh sensitivity, enabling the quantitative analysis of trace compounds. Xie et al. [37] utilized a novel flexible SERS substrate made of polydimethylsiloxane film and 3D Au nanostructures for on-site detection of pesticide residues on fruits, achieving a detection limit as low as 9.3×10^{-9} M. However, food formulations often contain complex components like proteins, fats, and carbohydrates, which may produce strong Raman signals that interfere with the characteristic peaks of target substances [38]. Machine learning and deep learning algorithms can be employed to automatically calibrate or correct spectral signal

variations across different substrate batches, enhancing signal reproducibility and quantitative accuracy. Hajikhani et al. [39] proposed a novel method combining SERS and the transformer model for the rapid detection of pesticide residues in agricultural products. This method utilizes gold–silver core–shell nanoparticles to enhance SERS signals and employs a machine learning model to achieve high-precision qualitative and quantitative analysis. In addition, due to the high sensitivity and specificity of SERS, other spectroscopic techniques can be used for large-scale preliminary screening. Once the target area is located, SERS can be used to accurately confirm and identify trace components [40].

THz is a technique for analyzing substances using electromagnetic radiation in the frequency range of 0.1 to 10 THz, positioned between microwaves and infrared light (Fig. 1E). It exhibits both electronic and photonic properties. The most prevalent method within THz spectroscopy is terahertz time-domain spectroscopy (THz-TDS), a time-resolved technique utilizing femtosecond laser pulses that generate and detect terahertz electric fields, with spectral information being obtained via Fourier transform. The THz-TDS system is composed of a femtosecond laser, a THz emitter, a THz receiver, a time delay control system, and a data acquisition and signal-processing system. Femtosecond laser pulses, divided by a beam splitter into pump and probe beams, are used to generate and detect THz waves [41]. Most chemical compounds exhibit a highly specific absorption spectrum that is frequency-dependent within the THz region. By leveraging this characteristic, chemicals in food can be identified and quantified based on their unique THz fingerprint [42]. THz-TDS is widely applied owing to its excellent coherence, nondestructive nature, and high resolution, making it an effective method for detecting foreign objects in food [43], microbial contamination [44], and toxic compounds [45]. In practical applications, the utility of THz spectroscopy in the food industry is largely limited by strong water absorption, which severely attenuates THz radiation [46]. To overcome this challenge, spectral preprocessing techniques and specialized sample preparation methods may offer viable solutions to enhance measurement accuracy and reliability [47]. THz serves as a powerful tool for detecting moisture content in dry food products, where maintaining low water levels is critical for food safety. However, a key limitation of this method is sample thickness, as measurements become unreliable for samples exceeding 1 mm in thickness. To address this issue, low-frequency terahertz measurements can be employed as an alternative. Additionally, samples may be dried or frozen to reduce interference from liquid water, thereby improving measurement accuracy [45]. Although THz has been demonstrated to facilitate rapid detection of harmful chemical substances in food, its limit of detection (LOD) and accuracy remain relatively lower compared to methods such as immunoassays [48]. Further research is required to enhance the LOD and accuracy of predictive models for food contaminants.

LIBS is an elemental analysis technique based on atomic emission spectroscopy (Fig. 1F). When a high-energy-density pulsed laser is focused on the surface of a sample, the intense power density of the laser rapidly heats a localized area of the sample to extremely high temperatures (over 30,000°C), causing rapid vaporization, melting, and partial ionization to form a transient plasma. As the plasma cools, excited electrons and ions return to lower energy states, emitting characteristic photons that constitute the emission spectrum of the plasma. This

spectrum is analyzed to identify the types and concentrations of elements in the sample [49]. LIBS, which requires no sample preparation, offers noncontact measurements, minimal sample damage, and rapid analysis. It is effective not only for detecting heavy metals [50] and pesticide residues [51], but also for identifying food components and assessing authenticity [52], as well as enabling simultaneous multielement detection in complex samples [53], thus providing robust technical support for ensuring food safety. However, detecting trace elements with LIBS is challenging due to its relatively low spectral sensitivity. Common methods to enhance LIBS sensitivity include utilizing dual-pulse laser excitation and employing additional energy sources or tunable lasers to amplify plasma emission, which lowers the detection limits for trace elements [54]. To further enhance the quantitative and elemental mapping capabilities of LIBS, Nanou et al. [55] proposed a LIBS method combined with machine learning (such as principal component analysis [PCA], linear discriminant analysis [LDA], and support vector machine [SVM]) for real-time detection of extra virgin olive oil (EVOO) adulteration with lower-quality oils (pomace, soybean, sunflower, and corn oils). Results demonstrated high efficiency and accuracy, achieving nearly 100% classification and prediction accuracy in distinguishing pure EVOOs from adulterated samples and identifying specific adulterant types. Wen et al. [56] achieved ultrasensitive detection of lead in water by integrating resin enrichment technology with LIBS assisted by laser-induced fluorescence. This approach yielded a remarkable LOD of 88 ng/l, representing a full order of magnitude improvement compared to conventional resin-enriched LIBS alone. In addition, the integration of LIBS with liquid-to-solid phase conversion techniques has been demonstrated to notably enhance spectral signals while effectively reducing detection limits [57].

Electrochemical detection technology

Electrochemical detection technology operates based on electrochemical reactions for substance analysis. In a typical setup, a conventional 3-electrode system (working electrode, reference electrode, and counter electrode) is immersed in an electrolyte solution containing the analyte. This configuration facilitates redox reactions that generate measurable current signals. According to the laws of electrolysis established by Faraday, the reaction current exhibits a linear relationship with analyte concentration, enabling quantitative analysis through current measurement. Electrochemical sensors are widely adopted in food analysis due to their inherent advantages, including miniaturization potential, cost-effectiveness, high sensitivity and selectivity, and rapid response. Notably, they achieve high analytical accuracy even in complex food matrices with minimal sample volumes, making them ideal for on-site applications [58]. Recent advancements in this field have diversified detection methodologies to address varying environmental and analytical requirements. Based on differences in analyte physicochemical properties and detection mechanisms, electrochemical detection techniques can be categorized into direct and indirect approaches.

Direct electrochemical detection relies on redox reactions involving inherent electroactive functional groups within the molecular structure of the analyte. However, when using bare electrodes, the detected signals are often considerably weakened due to the poor electrochemical activity of many target molecules. This limitation has led to widespread adoption of electrode surface modifications employing various nanomaterials

(e.g., metallic nanoparticles and graphene oxides) [59,60] or biomaterials (e.g., proteins and polymers) [61]. Such modifications primarily function to substantially increase the active surface area of electrode while simultaneously enhancing electron transfer kinetics and introducing additional catalytically active sites, which together can boost detection sensitivity by several orders of magnitude.

For analytes exhibiting inherently low electrochemical activity, the incorporation of redox mediators (e.g., potassium ferrioxalate and methylene blue) serves to amplify detectable signals through enhanced electron transfer processes [62]. An alternative approach involves indirect detection methodologies utilizing immobilized biorecognition elements, including enzymes, antibodies, and DNAszymes, on electrode surfaces. In these systems, specific target binding events induce quantifiable modifications in the electrochemical behavior of reporter molecules. This principle has been implemented through various sensor architectures, notably electrochemical enzymatic biosensors employing glucose oxidase for detection [63], functional nucleic acid-based sensors incorporating aptamer recognition systems [64], and molecularly imprinted polymer sensors that mimic antibody–antigen interactions [65].

Electrochemical enzyme sensors employ enzymes as recognition elements to catalyze substrate-specific reactions, generating electroactive species that modulate the electrochemical response. As illustrated in Fig. 2A, Zhang et al. [66] developed an acetylcholinesterase-based biosensor using a Ti_3C_2 MXene/ MoS_2 @AuNPs nanocomposite for organophosphorus pesticide detection in fruits. This sensor demonstrated remarkable sensitivity, enhanced conductivity, and operational stability, proving its efficacy in complex food matrices. Functional nucleic acids (e.g., aptamers and DNAszymes) enable target recognition through high-affinity binding or catalytic activity. In electrochemical aptamer sensors, immobilized aptamers undergo conformational changes upon target binding, perturbing the interfacial electron transfer. For instance, Dou et al. [67] designed a miniaturized tetracycline biosensor by functionalizing a graphene field-effect transistor with aptamers (Fig. 2B). The sensor utilized 2 complementary detection methods: transfer characteristic curve analysis and chronoamperometric measurement, achieving respective detection limits of 2.073 and 100 pM in validated skim milk samples. The biosensor proved effective for skim milk analysis. Similarly, Zhao et al. [68] engineered a Pb^{2+} biosensor using a solution-gated graphene transistor (SGGT) modified with a Pb^{2+} -specific DNAszyme. Unlike conventional DNAszyme probes, this design leveraged a noncleavable binding mode, achieving an ultralow detection limit (0.39 $\mu\text{g/l}$) in milk samples, underscoring its potential for on-site monitoring. Molecular imprinting technology facilitates the creation of polymer matrices containing 3-dimensional recognition cavities with tailored molecular geometry and functional group alignment, achieving high specificity for target molecule binding. The extensive utilization of tetrabromobisphenol A (TBBPA) in industrial manufacturing has led to its persistent accumulation in aquatic environments, raising notable concerns due to its endocrine-disrupting effects and ecological toxicity. As illustrated in Fig. 2C, Shao et al. [69] addressed this analytical challenge by developing an electrochemical sensor through sequential modification of a glassy carbon electrode with MXene nanosheets and gold nanoparticles, followed by drop-coating of molecularly imprinted polymers. This architecture demonstrated exceptional selectivity for TBBPA detection in aqueous systems, with validation studies

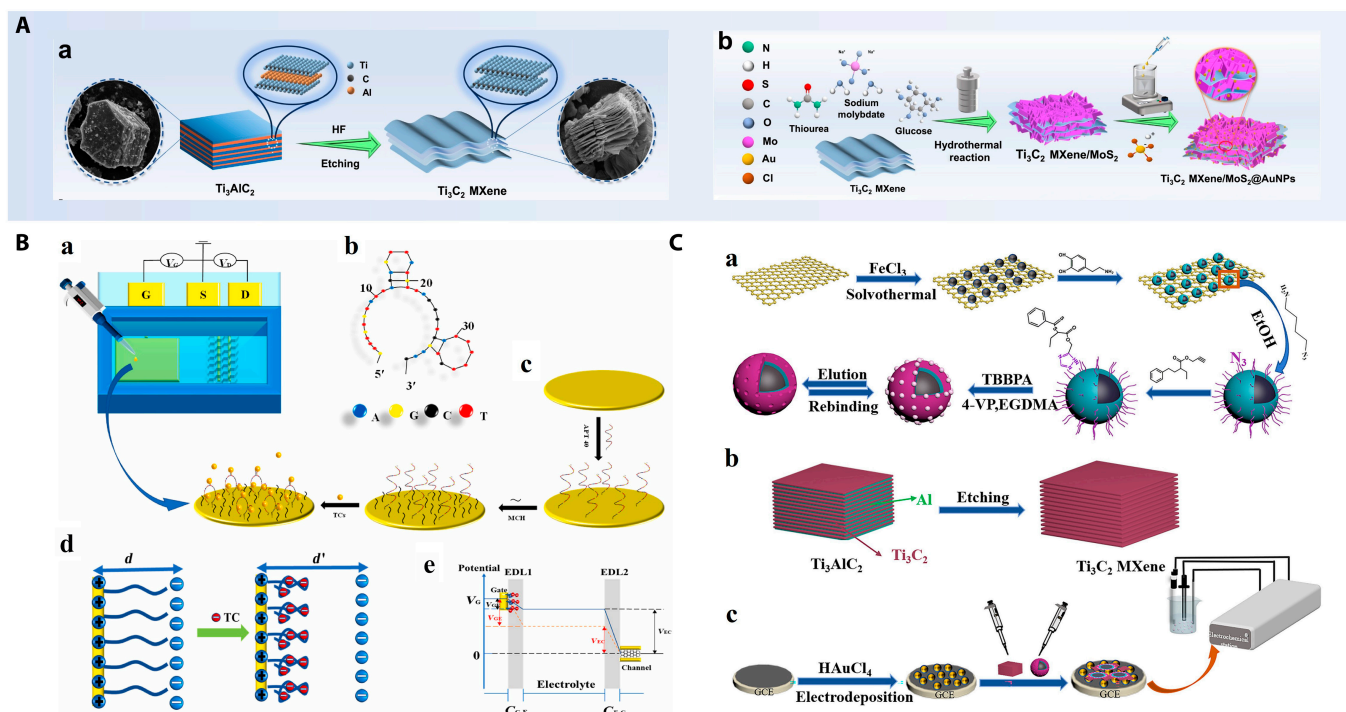


Fig. 2. (A) (a) Preparation process of Ti_3C_2 MXene nanosheets and synthesis of Ti_3C_2 MXene/ MoS_2 and (b) Ti_3C_2 MXene/ MoS_2 @AuNPs nanocomposites. Reproduced with permission [66]. Copyright 2025, Elsevier. (B) Schematic diagrams illustrate (a) the miniaturized Apt-SGGT biosensor structure, (b) the 2D structure of APT40, (c) the modification process using APT40 and the detection of TC by immobilized APT40 probes, (d) alterations in the bilayer before and after the addition of TC, and (e) charge recombination at the electrode surface triggers potential fluctuations in the double electric layer. Reproduced with permission [67]. Copyright 2024, Elsevier. (C) (a) Preparation procedure of $GO@Fe_3O_4@MIP$, (b) MXene, and (c) TBBPA-imprinted electrochemical sensor. Reproduced with permission [69]. Copyright 2022, Springer Nature.

reporting recovery rates of 97.1%–106% during real-water sample analysis.

Machine olfaction technology

Machine olfaction technology, also referred to as artificial olfactory system or electronic nose (E-nose), simulates human olfaction (Fig. 3A). It detects and identifies volatile compounds using sensors and utilizes data processing algorithms to analyze their chemical composition and concentration. In the 1980s, Persaud and Dodd [70] integrated array sensors with pattern recognition algorithms to develop a device capable of identifying 21 distinct odors, marking the inception of the E-nose. The key advantages of E-nose technology include reduced sample volume needs and high-speed analysis capabilities. However, they face challenges in identifying or quantifying individual compounds present in food [71].

E-nose primarily comprises 3 components: a gas sensor array, a signal-processing unit, and pattern recognition algorithms. The gas sensor array, as the core of the system, detects volatile organic compounds (VOCs) and converts chemical signals into electrical signals, directly determining the performance of the system. Common gas sensors include metal oxide semiconductor (MOS) sensors, quartz crystal microbalance sensors, conductive polymer sensors, and surface acoustic wave sensors [72]. The signal-processing unit amplifies, filters, and digitizes analog signals, while pattern recognition algorithms, such as ANN, SVM, and fuzzy logic, classify the processed data to achieve odor identification [73]. E-nose has emerged as an effective technology for detecting VOCs, offering a rapid method for identifying food contamination, adulteration, and origin authentication, which is crucial for consumer safety and cost-effective solutions.

However, E-nose generates high-dimensional time-series raw signals for target gases, which can be noisy, redundant, and difficult to interpret. To address this challenge, advanced E-nose systems are integrated with machine learning algorithms to enable accurate identification of gas molecules [74]. Makarichian et al. [75] integrated E-nose technology with SVM, LDA, and backpropagation neural network (BPNN) methods to rapidly and accurately predict fungal contamination in garlic samples. Employing a 9-sensor MOS array and selecting the decay severity index as an auxiliary parameter, their study demonstrated that the classification accuracy of BPNN improved progressively with increasing infection duration. By the eighth day of infection, the BPNN algorithm successfully discriminated between samples at different contamination levels. Leggieri et al. [76] developed a combined E-nose and ANN system for rapid detection of aflatoxin B_1 (AFB_1) and fumonisins in corn samples. Analyzing multiple production batches using a portable E-nose with 10 MOS sensors, the integrated ANN model demonstrated 78% accuracy for AFB_1 detection and 77% for fumonisins, confirming the effectiveness of this system in identifying mycotoxins within regulatory limits.

Machine gustatory technology

Machine gustatory technology is a technique that utilizes sensor technology and advanced algorithms to emulate the taste perception abilities of humans or animals, with the electronic tongue (E-tongue) system representing the most typical machine taste system (Fig. 3B). E-tongue technology, which leverages biomimetic principles to mimic the taste functions of the human tongue, operates by initiating interactions (such as charge transfer, molecular adsorption, or desorption) between the molecules

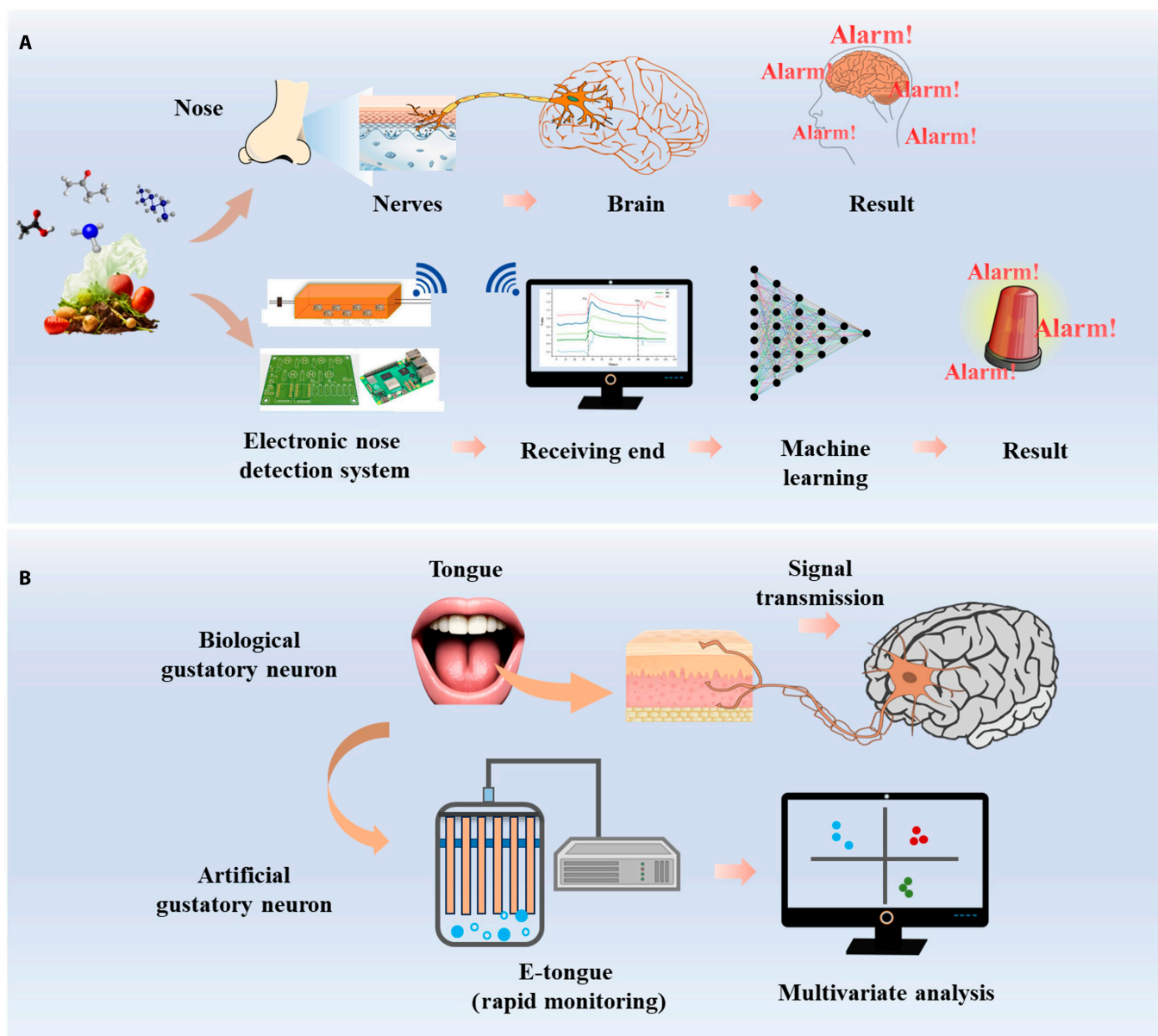


Fig. 3. (A) E-nose: mimics human smell using sensors to detect odors, processed by machine learning for alert-based results. (B) E-tongue: imitates human taste, capturing flavor signals analyzed by computers for rapid response.

in a test sample and the sensors of E-tongue, producing a series of electrical signals. These signals are captured and converted into mathematical signals for data processing and analysis, thereby identifying and differentiating various taste types and quantitatively assessing their intensity and complexity [73]. Taste sensors serve as the core components of the E-tongue system. These sensors differ in type and principle, such as potentiometric, voltammetric, and optical taste sensors. Through their different mechanisms, these sensors detect gustatory components in food and generate corresponding signals. These signals are then analyzed to conduct both qualitative and quantitative assessments, with common multivariate analysis methods such as PCA utilized to process the multidimensional data from the E-tongue. The simplicity of operation and low cost render E-tongue particularly suitable for real-world applications [77]. Cheng et al. [78] introduced a voltammetric E-tongue technology based on the “reference sample comparison method” to

evaluate the shelf life of fresh milk. By introducing reference samples, the method quantifies the quality difference between fresh milk samples with varying shelf lives and the reference samples. This approach, combined with a first-order kinetic model and the Arrhenius equation, successfully established a shelf life prediction model for fresh milk stored at 4 °C. The results demonstrated that this method exhibited superior predictive performance in assessing the shelf life of overall quality, microbial safety, and sensory quality, markedly outperforming the traditional “many-to-one” model. Specifically, it improved prediction accuracy by 11.14% to 17.17% for overall quality shelf life evaluation and by 14.86% to 44.47% for other metrics. In addition to the voltammetric E-tongue, another prevalent type is the potentiometric E-tongue. The potentiometric E-tongue relies on polymer membrane ion-selective electrodes and ion-selective field-effect transistors, detecting analytes by measuring potential differences under zero-current conditions [79]. Gil

et al. [80] designed a custom-made E-tongue consisting of 6 electrodes (Au, Ag, Cu, Pb, Zn, and C) and a reference electrode. This device was used to assess changes in physicochemical, microbial, and biochemical parameters in refrigerated pork loin during storage. The responses from the E-tongue showed relatively good correlations with certain degradation indices, such as pH, microbial counts, and nucleotide concentrations.

Others

In addition to the aforementioned detection technologies, acoustic and magnetic methods have been considered in preliminary application research for food safety detection. Ultrasonic waves, with frequencies above 20 kHz, demonstrate excellent propagation characteristics owing to their high frequency and experience minimal loss when traveling through solids and liquids [81]. Ultrasonic testing typically employs the pulse-echo method, where pulses of ultrasonic waves are emitted and then reflected from the surface of an object, are captured by a receiver, and are converted into electrical signals for analysis [82]. In food testing, ultrasonic devices usually immerse the probe in the liquid food or attach it to the container walls, operating at a certain distance on both sides of the food. Depending on the measurement mode, 2 probes can transmit and receive ultrasonic waves either once or multiple times, recording the interval between transmission and reception and other related data to assess whether the food quality level meets the standard requirements, and further determine the potential degree of spoilage [83].

Nuclear magnetic resonance (NMR) technology is an analytical method based on the spinning behavior of atomic nuclei in a magnetic field. Its core mechanism is the resonance of magnetically active nuclei under an applied external magnetic field and radiofrequency radiation, enabling detection through spin-state transitions. By measuring the NMR signals in a sample, information about molecular structure, composition, and interactions can be obtained [84]. In practical applications, NMR technology can induce nuclear spin oscillations at the Larmor frequency by applying appropriate radiofrequency pulses to generate energy-absorption signals. Subsequently, the nuclei undergo 2 different relaxation processes: longitudinal relaxation (T_1), which results in energy transfer from the excited state to the surrounding spinning nuclei, and transverse relaxation (T_2), which involves energy transfer between nuclei, leading to a loss of coherence [85]. The intensity of the NMR signal is proportional to the number of excited nuclei. Time-domain data are transformed into frequency-domain data through Fourier transform, producing a typical NMR spectrum. Each signal in the spectrum exhibits a specific chemical shift value that reflects the chemical environment of the surrounding nuclei [86]. NMR technology boasts several advantages due to its nondestructive, high-resolution, multidimensional, and nonspecific nature, making it highly effective in the detection of additives, contaminants, residues, and authenticity issues in food.

Signal-processing technologies in intelligent sensing

Intelligent sensing technology accurately captures physical and chemical information from food samples with high precision, providing strong data support for food safety detection. The signal-processing technologies upon which these systems rely are crucial for interpreting and utilizing this information; their complexity and importance cannot be overlooked. Effective signal processing not only dramatically enhances the quality

of the detection data but also prepares it for subsequent analysis by removing noise, correcting baselines, normalizing, and executing other optimization steps.

Preprocessing steps are a critical component in enhancing the accuracy of food safety detection, with different technologies adopting various methods tailored to their specific needs. In spectroscopic techniques, common preprocessing steps include noise removal, baseline correction, and signal normalization, which improve the accuracy and comparability of subsequent data analyses [87]. Common NIRS often requires multiple mathematical transformations, such as logarithmic transformations [88], to enhance small absorption differences, whereas HSI may need spatial filtering to remove background noise [89]. For E-nose and E-tongue systems, preprocessing steps such as signal smoothing, baseline drift correction, compression, and response normalization are typically required to reduce response differences between sensors [90]. For acoustic signals, certain techniques such as sound amplification and high-pass filtering are commonly used to eliminate low-frequency environmental noise and accurately capture the required acoustic signals [91].

Feature extraction is a crucial step in data analysis because it improves data quality, reduces dimensionality, and enhances interpretability. For spectral data, feature extraction tools are commonly used to select optimal feature wavelengths from spectral datasets, thereby removing redundant information. Popular techniques are sequential projection algorithm (SPA), competitive adaptive reweighting sampling (CARS), uninformative variable elimination (UVE), and interval partial least squares (iPLS) [92]. Feature extraction techniques for E-nose and E-tongue can be categorized into 3 types: the first involves fitting functions, the second extracts features directly from the raw response functions of sensors, and the third involves transformations using mathematical functions [73]. In addition, widely used dimensionality reduction techniques such as PCA and independent component analysis are key tools for reducing dimensions. For univariate data, certain techniques such as wavelet transform, kernel PCA, and LDA are often employed for dimension reduction and feature extraction [93]. In electrochemical detection, it is common to extract the peak features that identify the redox properties and concentrations of chemicals. In electrochemical impedance spectroscopy, resistance and impedance changes can reveal the electrochemical characteristics of samples [94]. When using acoustic and magnetic technologies for detection, attention is typically given to changes in the frequency, amplitude, and phase of sound or magnetic waves [95,96]. Overall, these feature extraction techniques not only accurately capture the key attributes of food but also provide robust data support for subsequent safety monitoring.

Modeling technologies in intelligent sensing

Machine learning

The selection of algorithms and models is pivotal for achieving efficient intelligent sensing, requiring alignment with data characteristics and specific objectives. Linear regression models, known for their simplicity and effectiveness in linear scenarios, have been widely adopted in rapid food safety detection to calculate safety parameters. Their results are consistent with traditional methods while offering superior efficiency. However, real-world data often involve complex nonlinear relationships, prompting the use of traditional machine learning models such as SVM, decision trees (DT), and random forest (RF) for low-dimensional data analysis (Fig. 4A to C) [97]. For instance,

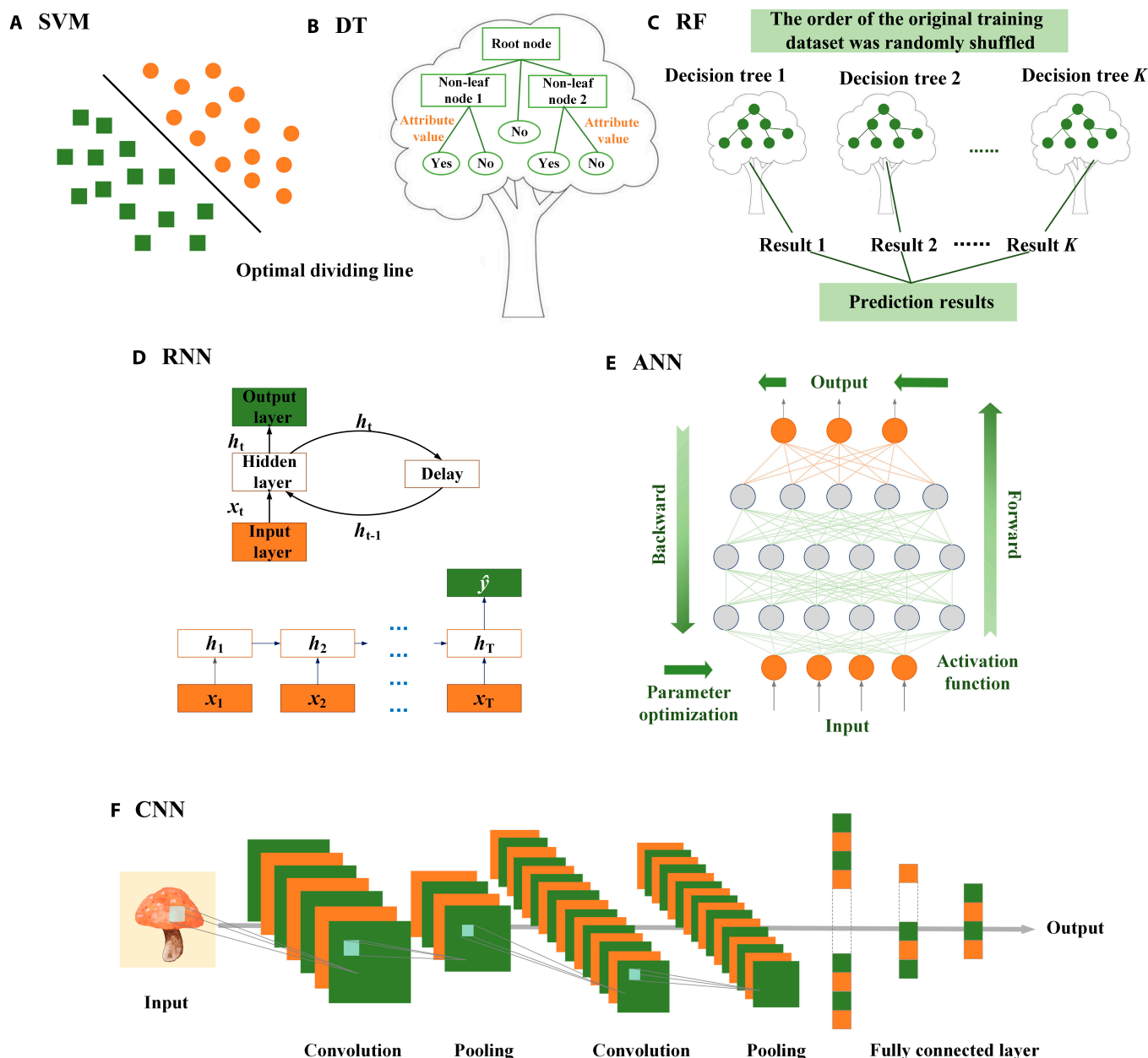


Fig. 4. Machine learning algorithm models: (A) Support vector machine (SVM): finds the optimal dividing line or hyperplane that best separates different classes of data. (B) Decision tree (DT): uses a tree-like model of decisions and their possible consequences to classify data. (C) Random forest (RF): constructs a multitude of decision trees at training time and outputs the class that is the mode of the classes of the individual trees. (D) Recurrent neural network (RNN): processes sequences by maintaining a state that represents information calculated from previous inputs. (E) Artificial neural network (ANN): consists of layers of interconnected nodes or neurons that process input data through weighted connections for various types of classification and prediction tasks. (F) Convolutional neural network (CNN): employs a hierarchy of layer-wise convolutions specifically designed to process pixel data, ideal for image recognition tasks.

Xie et al. [98] integrated NIRS with RF and SVM to predict carcinogen levels in coffee, where RF outperformed SVM with calibration ($R^2 = 0.98$) and prediction ($R^2 = 0.92$) accuracies. Similarly, Wu et al. [99] leveraged DT models on agricultural data for early disease detection in crops. Despite their success in low-dimensional contexts, these models face limitations in processing high-dimensional data (e.g., images or audio). Such challenges necessitated a fundamental shift toward deep learning, which leverages automated feature extraction to handle complex sensing tasks.

Deep learning

The deep learning revolution originated from the seminal work of Hinton et al. [100], who, in 2006, proposed deep belief networks (DBNs) alongside efficient training algorithms. This breakthrough demonstrated the potential of hierarchical feature learning, paving the way for architectures tailored to high-dimensional data. Among these, convolutional neural networks (CNNs, Fig. 4F) and recurrent neural networks (RNNs, Fig. 4D) emerged as dominant paradigms, addressing the limitations of traditional models in image and sequence processing, respectively [101].

CNNs are composed of distinct layers. The input layer serves as the initial layer, receiving data such as images of food. The output layer produces the final prediction, such as the freshness of the food. The hidden layers, positioned between the input and output layers, comprise convolutional layers, pooling layers, and fully connected layers. These layers often incorporate rectified linear unit (ReLU) activation functions to enhance the expressive capacity of the model [102]. Wang et al. [103] applied the CNN algorithm to a colorimetric microneedle sensor (CMS) for visual monitoring of meat freshness. The CMS changes color in response to pH variations caused by meat spoilage. A total of 2,921 images of CMS affixed to meat with different freshness were imported into the CNN model as the training source. Through convolutional processing of the CMS color features, the model classified meat freshness into 3 categories: “fresh”, “less fresh”, and “spoiled”, achieving an accuracy of approximately 95.3%. The application of CNN enabled rapid and precise identification of meat freshness, substantially improving the efficiency and accuracy of meat quality assessment compared to traditional manual inspection methods.

While CNNs excel at extracting spatial features for static image classification tasks like meat freshness detection, they are less suited for analyzing data with temporal dependencies or dynamic changes over time. For such scenarios, researchers often turn to RNNs. However, traditional RNNs face limitations such as vanishing or exploding gradients, which hinder their ability to learn long-term dependencies in sequences. To address these challenges, enhanced architectures like long short-term memory network (LSTM) [104] and gated recurrent unit [105] were introduced. These variants employ gating mechanisms to selectively retain or discard information over time, enabling RNNs to capture critical temporal patterns while mitigating gradient-related issues. This capability makes them particularly suited for tasks like continuous food safety monitoring, production process analysis, or risk prediction, where understanding temporal trends is critical [106]. RNN is very important in identifying the authenticity of food products and is mainly used to analyze spectral data. Wu et al. [107] synthesized a highly sensitive star-shaped SERS substrate to rapidly detect adulteration of EVOO with 2 phthalate esters. By leveraging LSTM networks to process spectral data in the 1,000 to 1,800 cm^{-1} range, they achieved exceptional performance: After optimizing the data using t-distributed stochastic neighbor embedding (t-SNE) for dimensionality reduction, the LSTM model demonstrated 98.15% accuracy in identifying adulterated olive oil, notably outperforming conventional full-spectrum analysis methods. Beyond this, LSTM has also been applied to assess foodborne hazards such as aflatoxins, leveraging spectral reconstruction and model parameter compression techniques to address data imbalance and reduce computational complexity [108].

Semi-supervised learning and unsupervised learning

While supervised learning frameworks have demonstrated remarkable success in food safety tasks, their reliance on large annotated datasets poses challenges in real-world scenarios where labeled data may be scarce or costly to acquire. To address these limitations, researchers are increasingly adopting semi-supervised learning and unsupervised learning paradigms. The core idea of semi-supervised learning is to improve the model's generalization ability by utilizing the underlying structural information in unlabeled data. In contrast to food safety assessments, which is often time-consuming and expensive, semi-supervised learning offers substantial advantages,

as it requires experts to evaluate and label the data. Common semi-supervised learning approaches are self-training, co-training, graph-based semi-supervised learning, and generative adversarial networks (GANs). Recent studies have introduced semi-supervised learning models for pseudo-label monitoring [109] and multilabel food recognition [110], which further improve the performance of semi-supervised learning in food detection.

In unsupervised learning, the training data are unlabeled. Clustering and dimensionality reduction are 2 typical applications of unsupervised learning. PCA is a key technique for reducing data dimensionality, achieved by projecting high-dimensional data onto orthogonal directions (principal components) with the maximum variance, thereby preserving critical information while reducing dimensions [111]. PCA can rapidly distinguish EVOO from other edible oils based on triglyceride profiles. Similarly, K-Means clustering has demonstrated excellent performance in automated quality and safety grading. Green et al. [112] employed clustering methods to standardize the freshness assessment of 7 fish species, comparing K-Means, K-Means++, AHC-S, AHC-W, DBSCAN, and spectral clustering, with K-Means and K-Means++ showing superior performance. These cases illustrate that unsupervised learning can uncover actionable patterns from unlabeled food data by optimizing intra-class compactness and inter-class separability, making it particularly valuable for exploratory research in dynamic food safety studies where prior knowledge is limited.

Model evaluation

Model evaluation metrics are essential tools for assessing the performance of predictive models. Different types of tasks (e.g., classification and regression) generally require distinct evaluation metrics. For classification problems, metrics such as accuracy, precision, recall, and the F_1 score are commonly used to assess model performance. In contrast, for regression tasks, metrics like mean squared error (MSE), root mean squared error (RMSE), mean absolute error (MAE), and the coefficient of determination (R^2) are typically employed to evaluate the effectiveness of model. Lower values of MSE, RMSE, and MAE indicate better model fit, while an R^2 value closer to 1 signifies a stronger explanatory power [113]. Detailed formulas for these metrics are available in the referenced literature [114,115].

$$\text{Accuracy} = \frac{\text{TP} + \text{TN}}{\text{TP} + \text{TN} + \text{FP} + \text{FN}} \quad (1)$$

$$\text{Precision} = \frac{\text{TP}}{\text{TP} + \text{FP}} \quad (2)$$

$$\text{Recall} = \frac{\text{TP}}{\text{TP} + \text{FN}} \quad (3)$$

$$F1 \text{ core} = 2 \cdot \frac{\text{Precision} \cdot \text{Recall}}{\text{Precision} + \text{Recall}} \quad (4)$$

$$\text{MSE} = \frac{1}{n} \sum_{i=1}^n (y_i - \hat{y}_i)^2 \quad (5)$$

$$\text{RMSE} = \sqrt{\frac{1}{n} \sum_{i=1}^n (y_i - \hat{y}_i)^2} \quad (6)$$

$$\text{MAE} = \frac{1}{n} \sum |y_i - \hat{y}_i| \quad (7)$$

$$R^2 = 1 - \frac{\sum_{i=1}^n (y_i - \hat{y}_i)^2}{\sum_{i=1}^n (y_i - \bar{y})^2} \quad (8)$$

TP (true positive): the number of samples that the model correctly predicts as positive classes.

TN (true negative): the number of samples correctly predicted by the model to be in the negative category.

FP (false positive): the number of samples that the model incorrectly predicts as positive.

FN (false negative): the number of samples that the model incorrectly predicts as negative.

y_i : actual value of sample i ; \hat{y}_i : predicted value for sample i ;
 \bar{y} : average of actual values.

n : total sample size.

The Application of Intelligent Sensing Technology in Food Safety Detection

Microbial hazard detection

Foodborne diseases have emerged as a major public health concern, with pathogenic bacteria and molds being the primary culprits [116]. Pathogens such as *Salmonella* and *Shigella* can cause food poisoning and illness, whereas certain serotypes of *Escherichia coli* are highly pathogenic, leading to diarrhea and other extraintestinal infections. Toxins produced by molds, such as aflatoxin, can cause cancer if ingested over a long period. Given these potential threats, selecting more efficient and accurate detection methods to ensure food safety is crucial. Intelligent sensing technologies provide unique advantages in the detection of microbial hazards. They offer rapid, efficient, accurate, reliable, and fully automatic monitoring in real time, making them essential tools for ensuring food safety. Table 1 presents specific examples of intelligent sensing technology applications in the detection of food microbial hazards.

Chemical hazard detection

Chemical hazards, such as pesticide residues, veterinary drug residues, misuse of food additives, heavy metal contamination, and mycotoxins, can enter the food chain either directly during production and processing or indirectly through environmental pathways. Pesticides are among the primary sources of chemical hazards, comprising insecticides, herbicides, fungicides, and rodenticides [117]. These are widely used in agricultural production to protect crops from pests and other threats. However, pesticides often spread to nontarget species, the air, and water bodies, causing environmental pollution and entering the human body through the food chain. Food additives are substances added to food to enhance its quality, color, aroma, and taste or use for preservation and processing purposes. These additives can be either synthetically produced or derived from natural sources [118]. Although approved food additives are

generally considered safe, regulatory limits vary by country, and some manufacturers illegally add harmful substances to increase profits, violating laws and potentially posing serious health risks to consumers. Heavy metal contamination in food is a global safety concern, originating from natural and anthropogenic sources, such as industrial wastewater, emissions, and waste. Heavy metals, which are not easily degraded in the environment, enter the human body via the food chain, leading to chronic poisoning and severe health risks [119]. Moreover, mycotoxins are metabolic products produced by fungi growing in food or feed, which consist of highly toxic and carcinogenic substances (e.g., aflatoxins, ochratoxin A, vomitoxin, and zearalenone), all of which pose serious threats to human and animal health [120]. Table 2 lists the applications of intelligent sensing technology in food chemical hazard detection.

Physical hazard detection

Physical hazards are the unintentional presence of foreign objects in food that can pose risks to consumers. The common physical hazards comprise insects, dust, glass fragments, metal shavings, wood splinters, plastic particles, and bones. These contaminants can cause mechanical injuries, such as cuts and punctures, and may also lead to choking or more severe health issues. Such contamination can occur at any stage of the food supply chain. Therefore, to prevent these incidents, manual screening methods can be used; however, they are time-consuming, labor-intensive, and often ineffective for detecting small foreign objects that are difficult to see with the naked eye.

To address these challenges, researchers have explored various technological methods to detect physical contaminants in food. For instance, grains stored for long periods in granaries, if not properly managed, may be subject to pest infestations. Pests can breach physical barriers and leave behind harmful foreign objects, such as excrement, carcasses, and other secretions, rendering the grains unfit for consumption. To address this issue, Biancolillo et al. [121] used combining NIRS with chemometric methods to develop PLS-DA and soft independent modeling of class analogy models, achieving over 90% accuracy in distinguishing between edible rice and insect-infested rice in test sets. In addition, Srivastava and Mishra [122] utilized Vis light and NIR hyperspectral technology to detect and differentiate *Sitophilus oryzae*, a common rice pest, from healthy rice. Applications of technologies such as NIR, HSI, THz, and NMR for detecting foreign objects in food are quite extensive [123,124]. For instance, spectroscopic detection technologies can identify contaminants by analyzing the unique spectral features of different materials at specific wavelengths. NMR works by exciting protons in food materials, and as these protons return to their ground state, they release energy that is converted into image data. The differences in the image data can then be used to identify foreign objects [125].

Challenges and Solutions

Accuracy and stability requirements

Intelligent sensing technology has substantial potential in food safety detection, although it faces several challenges. The complexity of food matrices hinders the accurate identification and quantification of target substances. Achieving a balance between detection sensitivity and specificity requires optimizing factors such as detection limits, chemical fingerprint recognition,

Table 1. Detection of intelligent sensing techniques in food microbiological hazards

Type	Food product	Safety attribute	Method	Methodological application	Performance	Reference
Viruses	Cauliflower	Bacterial soft rot	MV	A modified YOLOv8 model called Cauli-Det	Classification accuracy 93.2%, recall 82.6%, mean average precision 91.1%	[150]
	<i>Salmo salar</i>	Bacterial numbers	NIR (800–2,500 nm)	PLS	Calibration equation: $R^2 = 0.95$ and $RMSE = 0.12 \log CFU/g$ Validation curve: $R^2 = 0.64$ and $RMSE = 0.32 \log CFU/g$	[151]
	Kombucha	Bacterial concentration	Vis-NIR	BP-ANN, ELM-ANN, RBF-ANN	RBF-ANN best (RPD = 6.7878), BP-ANN with a max error of 0.0169 Au	[152]
	<i>Longissimus dorsi</i> muscle of beef	Microbial load	HSI	PLS-R and data fusion	4 °C: $RMSE_p = 0.58 \log CFU/g$, $RPD_p = 4.13$, $R^2_p = 0.96$ 10 °C: $RMSE_p = 0.97 \log CFU/g$, $RPD_p = 3.28$, $R^2_p = 0.94$	[153]
	Pork and milk	<i>Salmonella typhimurium</i>	Electrochemical sensor	A novel molecularly imprinted polymer sensor based on screen-printed electrodes	Detection limit: approximately of $10^1 CFU/ml$ and a detection time of only 4 min	[154]
	Pork	<i>Salmonella typhimurium</i>	E-nose	SVMR, GA, PSO, and GS	Predictive accuracy: GA-SVMR > PSO-SVMR > SVMR > GS-SVMR ($R^2_p = 0.989$; $RMSE_p = 0.137$; RPD = 14.93)	[155]
	Milk	<i>Escherichia coli</i> , <i>Klebsiella pneumoniae</i> , and <i>Salmonella enterica</i>	E-tongue	Data processing: PCA and LDA Data classification: SVM and k-NN	Classification accuracy 92.5%, the E-tongue with gold electrodes accurately distinguished decreasing <i>E. coli</i> concentrations (1×10^6 to $1 \times 10^{-2} CFU/ml$) with 98.7% success.	[156]

(Continued)

Table 1. (Continued)

Type	Food product	Safety attribute	Method	Methodological application	Performance	Reference
Mold	Unhulled paddy	<i>Aspergillus nidulans</i> , <i>Aspergillus niger</i> , <i>Penicillium citrinum</i> , <i>Aspergillus oryzae</i> , and <i>Aspergillus versicolor</i>	MV	SVM, BPNN, CNN, and DBN	The DBN model excels in mold species identification, while the CNN model is fast and accurate for mold colony region detection.	[157]
	Peanut	<i>Aspergillus</i> spp.	NIR and E-nose	Classification: LDA Quantification: PLSR	Classification accuracy: NIR 92.11%, E-nose 86.84% Quantification: NIR ($R_p^2 = 0.886$, RPD = 3.0, LOD = 0.578 log CFU/g), E-nose ($R_p^2 = 0.785$, RPD = 2.1, LOD = 0.808 log CFU/g)	[158]
	Green tea	Total mold colony count	HSI (431–962 nm)	CARS, SVR, GA, PSO	CARS-GA-PSO-SVR achieved accuracy with an R_p^2 of 0.9577 and an RMSE of prediction set of 0.1140 lg (CFU/g)	[159]
	Pumpkin seeds	Degree of mold	THz-TDS	SVM, RF, CNN	Classification accuracy: CNN best 96%	[160]
	Spanish-style green olives	Spoilage mold species	E-nose	PCA and PLS-DA	PC ₁ and PC ₂ explained 70.23% and 23.27% of the total variance, classification accuracy 95.5%	[161]
	Corn kernels	Mildew-damaged kernels	Impact acoustics	Pretreatment: EEMD Classification: PSO-SVM	Classification accuracy 99.3%	[162]

MV, machine vision; NIR, near-infrared; PLS, partial least squares; RMSE, root mean squared error; BP-ANN, backpropagation ANN; ELM-ANN, extreme learning machine ANN; RBF-ANN, radial basis function ANN; RPD, relative predictive deviation; HSI, hyperspectral imaging; SVMR, support vector machine regression; GA, genetic algorithm; PSO, particle swarm optimization; GS, grid searching; PCA, principal component analysis; LDA, linear discriminant analysis; k-NN, k-nearest neighbors; BPNN, backpropagation neural network; CNN, convolutional neural network; DBN, deep belief networks; PLSR, partial least squares regression; CARS, competitive adaptive reweighting sampling; SVR, support vector regression; THz-TDS, terahertz time-domain spectroscopy; SVM, support vector machine; RF, random forest; PLS-DA, partial least squares discriminant analysis; EEMD, ensemble empirical mode decomposition

Table 2. Detection of intelligent sensing techniques in food chemical hazards

Type	Food product	Safety attribute	Method	Methodological application	Performance	Reference
Pesticide	Jujube	Chlorpyrifos and imidacloprid	HSI (900–1,700 nm), GC-MS	PLS-DA and LWPLSR	E _s -AWLS-GSD-RC-LWPLSR model yielded R _{Cv} of 0.757 and 0.898 for chlorpyrifos and imidacloprid	[163]
	Bean, apple, and vegetable	Triazole pesticides	SERS	Au decahedral substrate with high E-field intensity	Low LOD and wide detection range for in situ and simultaneous detection of triazoles in fruit and vegetable samples	[164]
Food additive	Cabbage	Acetamiprid (AD) and malathion (ML)	Electrochemical aptasensor	Substrates: PR and NFs/HP-U1066-NH ₂ Signal amplification: redox molecule/MOF composites	Linear range: 10 pM to 0.1 μM Detection limits: AD (4.8 pM), ML (0.51 pM)	[165]
	Apple	Cypermethrin and chlorpyrifos	E-nose	Build signal labels: FcCysAu/CeMOF (III, IV) and MB/MOF235 PCA, LDA, SVM	Higher accuracy than HPLC-MS for cabbage samples PCA shows the best classification and differentiation ability	[166]
	Sausages	Sodium nitrite	NIR-HSI	PLSR, PLS-DA	PLSR: R _p 0.92, RMSEP 15.603 mg/kg Classification accuracy: PLS-DA 91.3%	[167]
Food additive	Beverage	Lycopene	SERS	A 2D composite semiconductor, formed by growing ZIF-67 film on BP nanosheets, shows enhanced performance due to efficient charge transfer in the BP/ZIF-67 system	Recovery rates: 86.9% to 93.3%	[168]
	Infant formula	Vanillin	THz-TDS	Enhanced detection sensitivity using quasi-bound states in the continuum, quasi-BIC property	Vanillin has an absorption peak at 1.83 THz	[169]
Food additive	Fruit juice	Benzoic acid and chitosan	E-nose	RF, ELM, SVM, PLSR	ELM and RF have higher R _s ² and lower RMSEs	[170]
	Dessert	Vanillin	Electrochemical sensor	Co ₂ NiO ₄ @PtCu-MIG as an artificial antibody to construct electrochemical sensors for the selective detection of vanillin	Wide linear range: 0.05–500 μM LOD 3.45 nM	[171]
Food additive	Bread and bakery products	Propionic acid and sorbic acid	¹ H NMR	Short time extraction of sorbic and propionic acid from bread by automatic steam distillation	NMR is fast and reproducible in the quantitative analysis of 2 substances	[172]

(Continued)

Table 2. (Continued)

Type	Food product	Safety attribute	Method	Methodological application	Performance	Reference
Veterinary	Mutton	Pefloxacin	HSI and Vis-NIR	PLSR and data fusion	Low-level fusion: $R_p^2 = 0.907$ and $RMSEP = 0.462$ Intermediate-level fusion: $R_p^2 = 0.940$ and $RMSEP = 0.375$	[134]
	Milk and fish	Quantitative, accurate and multiple	SERS	SERS activity of plasmonic gold nanobipyramid@Silver nanorod (Au NBP@Ag NR)-CsPbX ₃ thin films	Enhancement of Au NBPs@Ag NRS films is 3.6	[173]
	Water and fish	Malachite green	Electrochemical sensor	A dual-mode colorimetric and electrochemical method based on P-CeO ₂ NR@Mxene and m-TDN was developed.	Colorimetric mode: 95.4 pM Electrochemical mode: 83.6 fM Colorimetric recovery: 97%–104%, RSD 1.74%–3.62%	[174]
Heavy metal	Mussel	Zn, Pb, Cd, and Cu	NIRS (900–1,700 nm)	CDELM	Electrochemical recovery: 95%–103.7%, RSD 2.03%–4.13%	[175]
	Water	Cu and Fe	HSI	Feature recognition: RF	Classification accuracy: Zn 97.53%, Pb 95.67%, Cd 99.00%, Cu 98.8%	[176]
	Tea	Hg	SERS	Predictive model: GA-PLSR Novel dual-mode paper sensor constructed	Cu: R^2 0.75, RMSE 0.004, MRE 0.382 Fe: R^2 0.73, RMSE 0.036, MRE 0.464 LOD 0.48 pM	[177]
	Water	Pb and Ni	THz	AuNPs as colorimetric signal molecules and SERS substrates Microalgae as a medium	Increased sensitivity: 200-fold for colorimetry, 500-fold for SERS Optimal time for testing: Pb ²⁺ 6 h, Ni ²⁺ 18 h	[178]
	Tea infusion	Cr and Cu	LIBS combined with electrostatic spinning	PLS and PCA Modification of electrostatically spun nanofibrous membranes by AuNPs and AgNPs	Accuracy: Pb ²⁺ 100%, Ni ²⁺ 93.2% Detection accuracy: increase from 10 to 1 ng/ml	[179]
	Water	Pb	E-tongue	Evaluation of ternary nanocomposites based on electrospun nanofibers, cellulose nanowhiskers, and silver nanoparticles as a sensing layer for the electrical detection of heavy metals	LOD: Cr 5 µg/l and Cu 10 µg/l Recovery rate: Cr 99%–106%, Cu 99%–108%	[180]
	Milk	Cd, Pb, Cu, and Hg	Electrochemical sensor	Heavy metal ions mixed with Fe ₃ O ₄ @SiO ₂ after alkali treatment	Effectively differentiates between pure water and aqueous solutions contaminated with Pb ²⁺ at concentrations as low as 10 nmol l ⁻¹ . LOD: Cd 56.1 nM, Pb 16.5 nM, Cu 79.4 nM, Hg 56.7 nM Recovery rate: 96.0%–104.3%	[181]

(Continued)

Table 2. (Continued)

Type	Food product	Safety attribute	Method	Methodological application	Performance	Reference
Mycotoxin	Peanut	AFB ₁	Portable NIR spectroscopy	IVSO initial screening, BWO optimization of feature variables SVM	RMSE 24.6322 µg·kg ⁻¹ , correlation coefficient 0.9761, relative percent deviation 4.6999	[182]
	Peanut	AFB ₁ and total aflatoxin	Short-wave infrared hyperspectral imaging (SWIR-HSI)	IVISSA-SPA-PLSR	Accurate prediction of AFB ₁ and total aflatoxin content Residual prediction deviation: 2.7959 and 2.7274 Limits of detection: 29.3722 and 45.7429 µg/kg	[183]
	Oat	Deoxynivalenol (DON)	NIR-HSI	PLS	RMSEP 403.18 µg/kg, R ² 0.75 The most contributing wavelengths are 1,203 and 1,388 nm	[184]
	Maize	Zearalenone (ZEN)	MSI	GA-BPNN	The accuracy of ZEN pollution levels is 93.33%	[185]
	Maize and wheat	DON	SERS	Designed a probe consisting of an AuNR@Ag core, an ultra-thin SiO ₂ layer and an AuNPs satellite with high surface coverage	R _p 0.95, RMSEP 3.66 µg/kg, RPD 5.39, bias 1.55 µg/kg LOD 0.053 fg/ml Wide linear range: 0.1 fg/ml to 1 µg/ml	[186]
	Soybean oil	AFB ₁	THz	Signal pretreatment: t SNE	BPNN combined with t-SNE predicted the best results	[187]
	Maize	ZEN	Electrochemical sensor	LS-SVM, BPNN, RF, and PLS ECL immunosensor was established using SnO ₂ QDs and Pd-GO	R _p 0.9948, RMSEP 0.7124 µg/kg Wide linear range: 0.0005–500 ng/ml LOD 0.16 pg/ml	[188]
	Maize	AFB ₁	E-nose	SVM and k-NN	Recovery rate: 82.5%–96.3%, RSD < 12.8% Accuracy: 68%–94%	[189]

HSI, hyperspectral imaging; GC-MS, gas chromatography–mass spectrometry; PLS-DA, partial least squares discriminant analysis; LWPLSR, locally weighted partial least square regression; AWLS-GSD, automatic weighted least squares and gap segment derivative; RC, regression coefficient; SERS, surface-enhanced Raman spectroscopy; LOD, limit of detection; PCA, principal component analysis; LDA, linear discriminant analysis; SVM, support vector machine; NIR, near-infrared; PLSR, partial least squares regression; RMSEP, root mean square error of prediction; THz-TDS, terahertz time-domain spectroscopy; BIC, bound states in the continuum; RF, random forest; ELM, extreme learning machine; NMR, nuclear magnetic resonance; NIRS, near-infrared spectroscopy; CDELM, constrained difference extreme learning machine; RMSE, root mean squared error; MRE, mean relative error; PLS, partial least squares; AFB₁, aflatoxin B₁; IVSO, iteratively variable subset optimization; BWO, beluga whale optimization; IVISSA, interval variable iterative space shrinkage approach; SPA, sequential projection algorithm; MSI, multispectral imaging; LS-SVM, least squares support vector machine; BPNN, backpropagation neural network; QDs, quantum dots; k-NN, k-nearest neighbors

complex food matrix handling, and operation in harsh environments, where the stability and adaptability of current technologies often fall short.

To address these challenges and enhance the role played by intelligent sensing technology in food safety monitoring, several strategies can be implemented. First, advancing research and development to improve the precision and reliability of sensing technologies is essential. As sensors are the core components of intelligent sensing systems, their performance directly impacts detection accuracy. Employing high-precision sensors combined with digital filtering techniques, such as moving average, median, and Kalman filtering [126–128], effectively reduces noise and interference, thereby boosting the signal-to-noise ratio and enhancing detection precision. Additionally, using compressed sensing techniques, as demonstrated by Fessler in NMR image reconstruction, enhances imaging velocity and image clarity while minimizing artifacts [129]. Moreover, these methods facilitate clinical applications by decreasing the number of detection operations, increasing efficiency, and reducing costs, yet maintaining high accuracy [130]. Integrating artificial intelligence and real-time big data mining into data analysis enhances the collection and integration of multisource heterogeneous data. The use of machine learning and deep learning algorithms greatly boosts the accuracy and efficiency of detection systems. Commonly employed machine learning techniques in food safety detection are Bayesian networks, neural networks, RF, and SVM [97]. Building on these advancements, the integration of multimodal feature technologies represents a further evolution in intelligent sensing, merging inputs from diverse sensory modalities like vision, olfaction, and taste to enhance the efficacy and accuracy of food safety detection systems.

Multimodal feature integration technology is expected to see further advancement by leveraging information from multiple sensory modalities, such as vision, olfaction, and taste, thereby providing a more comprehensive approach to food safety detection. Key fusion strategies include data-level, feature-level, and decision-level fusion [80]. Multimodal fusion, by offering more complete and accurate information than single-data analysis, enhances decision-making intelligence, automation, and model robustness [131–133]. For instance, Li et al. [134] applied Vis-NIR and NIR-HSI systems along with data fusion technology to predict enrofloxacin residue levels in lamb, demonstrating that data fusion markedly outperformed single-source data, particularly at the feature-level fusion ($R_p^2 = 0.940$, RMSEP = 0.375). Similarly, Shen et al. [135] integrated Vis-HSI with MV technologies for real-time detection of *Aspergillus* spp. and *Fusarium* spp. in stored corn. Through LDA-based data fusion, the combined approach achieved a 5.5% accuracy improvement in fungal strain differentiation and contamination level classification compared to unimodal methods. Through the integration of various sensor types and data sources, multimodal fusion technology greatly enhances the accuracy, efficiency, and scope of food safety detection. Further advancements in sensor technology are crucial, as they build on how multimodal fusion technology enhances food safety detection via comprehensive data analysis. These innovations focus not only on integrating multiple sensing modalities but also on refining the capabilities of individual sensors to resist interference and improve overall system reliability.

Developing new sensor technologies to enhance anti-interference capabilities is essential for advancing food safety detection. This development hinges on selecting advanced sensing

materials and applying cutting-edge techniques, such as bio- and electrochemical methods. These approaches enhance the sensitivity, specificity, stability, and anti-interference performance of sensors. Metal-organic frameworks, noted for their orderly structure, high surface area, and permanent porosity, are widely used for detecting mycotoxins [136], heavy metals [137], and pathogens [138]. Advances in aptamer screening technologies have notably enhanced the specificity and applicability of detecting heavy metal ions in complex grain matrices, overcoming the challenge of obtaining heavy metal antibodies in grains [139]. Furthermore, microfluidic electrokinetic effects facilitate efficient target enrichment of heavy metals in food, with nucleic acid aptamers and other probes providing selective recognition [140]. Nanocolorimetric sensing technology is especially effective in detecting mold in food and grain crops, overcoming the limitations faced by traditional volatile substance detection sensors, such as MOS-type gas sensors, which suffer from poor stability and environmental sensitivity [141].

Industrial integration and digital transformation

In the complex landscape of global food safety regulation, the integration of intelligent sensing technology is driving innovation in the food industry. By mimicking human sensory organs, intelligent sensors can capture various sensory attributes of food samples. When combined with intelligent recognition algorithms for signal processing, these sensors allow a comprehensive, human-like assessment of food quality. As Kwon [142] has noted, intelligent sensing technology can transform sensory data into big data that support personalized dietary decisions, catering to the growing consumer demand for customized food. This advancement represents a crucial direction for the food industry during the Fourth Industrial Revolution.

Leveraging digital technology to integrate food information with advanced technologies has led to the creation of precise digital food products. The food industry is evolving into a new industrial model through the integration of digital technology and physical enterprises, promoting sustainable development. To achieve end-to-end quality control, digital technology enables full traceability of food from production to distribution, sale, and consumption. However, traditional traceability systems often face challenges such as fragmented data storage and vulnerability to tampering. This is where decentralized technologies like blockchain become critical: As an immutable digital ledger, blockchain enhances transaction transparency and food safety by providing a unified platform for recording and verifying every step of the supply chain [143]. Consumers can access comprehensive information about a product's origin, processing journey, and the path it took to reach store shelves. This helps build trust and serves as a safeguard against fraudulent activities.

Artificial intelligence (AI) and Internet of Things (IoT) technologies synergize with blockchain to enhance analytical accuracy and real-time oversight. Liu et al. [144] proposed an integrated AI-IoT-blockchain framework that leverages spectroscopy, mass spectrometry, visual imaging, and sensor networks combined with machine/deep learning algorithms. This integration facilitates rapid adulteration detection, predictive quality management, and automated fraud identification. For example, IoT sensors deployed on beverage production lines can monitor parameters such as mixing consistency, bottle-filling precision, and packaging integrity, while blockchain immutably logs these data to ensure accountability across manufacturing stages [145]. Zhang et al.

[146] developed flexible paper-based sensors capable of tracking critical variables like moisture, humidity, and fruit weight during storage and transportation. These sensors transmit real-time data to smartphones, enabling proactive interventions to mitigate spoilage risks. Environmental factors, such as temperature, humidity, and oxygen levels, are continuously monitored through blockchain-linked smart sensors, generating tamper-evident records of storage and transport conditions. This dual-layer architecture, combining IoT for real-time data acquisition and blockchain for secure verification, not only safeguards food safety but also reduces operational costs. Additionally, blockchain-powered smart contracts automate compliance checks and transaction processes. For instance, a beverage manufacturer can encode quality assurance protocols into self-executing contracts, which automatically validate batch-specific data across distributed nodes. This automation streamlines supply chain operations while providing consumers with cryptographically verifiable product information, thereby reinforcing trust [147].

Energy efficiency requirements

Digitalization is driving the transition to green development by accelerating the integration of digital and environmental technologies. Intelligent sensing technology reduces resource consumption and environmental pollution during detection while enhancing production efficiency and product quality through intelligent manufacturing. In addition, it contributes to lower energy consumption and carbon emissions. Utilizing sensors, artificial intelligence, and big data analysis, intelligent sensing technology can rapidly and accurately detect harmful substances in food, thereby safeguarding consumer health [144]. Moreover, it promotes resource recycling, improves energy efficiency, strengthens environmental impact assessments, and supports the development of green supply chains. The integration of blockchain technology further enhances transparency and efficiency within the food supply chain, addressing issues such as information sharing and procedural irregularities [145]. Collectively, the application of these technologies not only ensures food safety and quality but also promotes resource conservation and environmental protection, providing strong support for the greening and sustainable development of the food industry.

To further enhance energy efficiency, intelligent sensing technology should prioritize low-power sensor designs and optimized AI algorithms that minimize computational overhead, ensuring sustainable operation over long periods. This principle has been successfully demonstrated in recent innovations. Researchers at Koç University in Istanbul, Turkey have developed a miniature sensor that can monitor food freshness in real time wirelessly and battery-free, while transmitting results to smartphones. The sensor is created by layering an easily synthesized polymer onto electrodes, utilizing capacitive sensing technology to detect biogenic amines produced by protein-rich foods. Weighing approximately 2 g with dimensions of 0.3 inches (2 cm²), the sensor employs near-field communication (NFC) technology. Its chip connects to smartphones through an antenna, enabling real-time wireless data transmission. When an NFC-enabled smartphone is brought near the sensor, the chip harvests sufficient energy through proximity-based power transfer [148]. While energy-efficient hardware design addresses data acquisition challenges, intelligent data processing in food safety systems requires complementary algorithmic optimization. These demands become particularly

acute when processing complex image data, which necessitates substantial hardware investments and incurs considerable energy consumption. To mitigate these dual challenges, researchers are adopting a threefold approach: long-term strategic investments amortize upfront costs across extended operational cycles, while cloud-edge computing integration allocates computationally intensive model training to centralized cloud infrastructure and delegates latency-sensitive inference tasks to decentralized edge devices. Furthermore, advanced model compression techniques, such as quantization and pruning, dramatically lower memory footprints and energy requirements without compromising detection accuracy. This synergistic framework not only enhances computational sustainability but also enables real-time, energy-conscious food safety monitoring at scale [149].

Conclusion

This review analyzes the application of intelligent sensing technologies in food safety fields, particularly their remarkable progress in identifying microbial, chemical, and physical hazards in food. It delves into the fundamental principles of technologies such as optical detection, electrochemical detection, machine olfaction, and machine gustation. Through the synergy of multisource sensors and smart computing, the improvements made by these technologies to traditional detection methods are not limited to the enhancement of detection accuracy and efficiency. Moreover, the detection accuracy and limitation of relevant indicators must meet food safety standards while ensuring stability and speed. The applications of intelligent sensing technologies can be applied across various sectors of the modern food industry. Integrating with machine learning and blockchain, it can optimize processing technology, assist decision-making, and minimize losses throughout all food industry chain. Despite the remarkable advancements in intelligent sensing technologies, several challenges remain, such as interference from complex food matrices, the demand for real-time detection, and the integration of large-scale data processing.

With the continuous advancement of sensor resolution and algorithmic robustness, emerging intelligent sensing systems will bring more transformative changes to the food industry especially for food safety. Overall, these innovations are crucial for enhancing global food security and sustainability, ensuring a safer, more transparent, and resilient food supply chain that meets the evolving demands of consumers and regulatory bodies.

Acknowledgments

Funding: This study is supported by the National Natural Science Foundation of China (U23A2081 and U23A20265), the Key R&D Program of Anhui Province (2023n06020052 and 2023n06020010), Major Special Projects of Suzhou Science and Technology Program (SZKJXM202310), and the Fundamental Research Funds for the Central Universities Special Funding Project (JZ2024HGTG0286).

Author contributions: W.J.: Writing—original draft, validation, investigation, and formal analysis. C.L.: Writing—review and editing and supervision. W.L.: original draft, methodology, investigation, and formal analysis. L.Z.: Writing—review and editing, supervision, funding acquisition, and conceptualization.

Competing interests: The authors declare that they have no competing interests.

References

1. Guo MQ, Wang KQ, Lin H, Wang L, Cao LM, Sui JX. Spectral data fusion in nondestructive detection of food products: Strategies, recent applications, and future perspectives. *Compr Rev Food Sci Food Saf*. 2024;23(1):Article e13301.
2. Kendrick KM. Intelligent perception. *Appl Anim Behav Sci*. 1998;57(3–4):213–231.
3. Niu HS, Yin FF, Kim ES, Wang WX, Yoon D, Wang C, Liang JE, Li Y, Kim NY. Advances in flexible sensors for intelligent perception system enhanced by artificial intelligence. *InfoMat*. 2023;5(5):Article e12412.
4. Kumar PK, Kar A, Jha NS, Khan AM. Machine vision system: A tool for quality inspection of food and agricultural products. *J Food Sci Technol*. 2012;49(2):123–141.
5. Zhao ZY, Wang R, Liu MH, Bai L, Sun Y. Application of machine vision in food computing: A review. *Food Chem*. 2025;463(Pt 4):Article 141238.
6. Rong D, Wang HY, Xie LJ, Ying YB, Zhang YS. Impurity detection of juglans using deep learning and machine vision. *Comput Electron Agric*. 2020;178:Article 105764.
7. Kerr D, Shi F, Brown N, Jackson M, Parkin R. Quality inspection of food packaging seals using machine vision with texture analysis. *Proc Inst Mech Eng B J Eng Manuf*. 2004;218(11):1591–1599.
8. Shen C, Wang R, Nawazish H, Wang B, Cai KZ, Xu BC. Machine vision combined with deep learning-based approaches for food authentication: An integrative review and new insights. *Compr Rev Food Sci Food Saf*. 2024;23(6): Article e70054.
9. Zhuang JJ, Luo SM, Hou CJ, Tang Y, He Y, Xue XY. Detection of orchard citrus fruits using a monocular machine vision-based method for automatic fruit picking applications. *Comput Electron Agric*. 2018;152:64–73.
10. Biswas A, Chaudhari SR. Exploring the role of NIR spectroscopy in quantifying and verifying honey authenticity: A review. *Food Chem*. 2024;445(1):Article 138712.
11. Yang B, Yao LJ, Pan T. Near-infrared spectroscopy combined with partial least squares discriminant analysis applied to identification of liquor brands. *Engineering*. 2017;9(2): 181–189.
12. Carbas B, Sampaio P, Barros SC, Freitas A, Silva AS, Brites C. Rapid screening of fumonisins in maize using near-infrared spectroscopy (NIRS) and machine learning algorithms. *Food Chem X*. 2025;27:Article 102351.
13. Li X, Zhang LX, Zhang Y, Wang D, Wang XF, Yu L, Zhang W, Li PW. Review of NIR spectroscopy methods for nondestructive quality analysis of oilseeds and edible oils. *Trends Food Sci Technol*. 2020;101:172–181.
14. Torres I, Sánchez MT, Entrenas JA, Garrido-Varo A, Pérez-Marín D. Monitoring quality and safety assessment of summer squashes along the food supply chain using near infrared sensors. *Postharvest Biol Technol*. 2019;154:21–30.
15. Fan S, Xu ZP, Cheng WM, Wang Q, Yang Y, Guo JY, Zhang PF, Wu YJ. Establishment of non-destructive methods for the detection of amylose and fat content in single rice kernels using near-infrared spectroscopy. *Agriculture*. 2022;12(8):1258.
16. Peng W, Beggio G, Pivato A, Zhang H, Lü F, He P. Applications of near infrared spectroscopy and hyperspectral imaging techniques in anaerobic digestion of bio-wastes: A review. *Renew Sustain Energy Rev*. 2022;165:Article 112608.
17. Wang SP, Altaner C, Feng L, Liu PP, Song ZY, Li LQ, Gui AH, Wang XP, Ning JM, Zheng PC. A review: Integration of NIRS and chemometric methods for tea quality control—principles, spectral preprocessing methods, machine learning algorithms, research progress, and future directions. *Food Res Int*. 2025;205:Article 115870.
18. Moro MK, de Castro EV, Romão W, Filgueiras PR. Data fusion applied in near and mid infrared spectroscopy for crude oil classification. *Fuel*. 2023;340(15):Article 127580.
19. Yu HD, Qing LW, Yan DT, Xia GH, Zhang CH, Yun YH, Zhang WM. Hyperspectral imaging in combination with data fusion for rapid evaluation of tilapia fillet freshness. *Food Chem*. 2021;348(30):Article 129129.
20. Ping JC, Hao N, Guo XT, Miao PQ, Guan ZQ, Chen HY, Liu CQ, Bai G, Li WL. Rapid and accurate identification of *Panax ginseng* origins based on data fusion of near-infrared and laser-induced breakdown spectroscopy. *Food Res Int*. 2025;204:Article 115925.
21. Fulgêncio ACC, Resende GAP, Teixeira MCF, Botelho BG, Sena MM. Screening method for the rapid detection of diethylene glycol in beer based on chemometrics and portable near-infrared spectroscopy. *Food Chem*. 2022;391:Article 133258.
22. McGrath TF, Haughey SA, Islam M, Elliott CT, Kelly SD, Suman M, Rindy T, Taous F, García-González DL, Singh D, et al. The potential of handheld near infrared spectroscopy to detect food adulteration: Results of a global, multi-instrument inter-laboratory study. *Food Chem*. 2021;353:Article 128718.
23. Feng YZ, Sun DW. Application of hyperspectral imaging in food safety inspection and control: A review. *Crit Rev Food Sci Nutr*. 2012;52(11):1039–1058.
24. Soni A, Dixit Y, Reis MM, Brightwell G. Hyperspectral imaging and machine learning in food microbiology: Developments and challenges in detection of bacterial, fungal, and viral contaminants. *Compr Rev Food Sci Food Saf*. 2022;21(4):3717–3745.
25. Liu YW, Pu HB, Sun DW. Hyperspectral imaging technique for evaluating food quality and safety during various processes: A review of recent applications. *Trends Food Sci Technol*. 2017;69:25–35.
26. Akter T, Faqeerzada MA, Kim Y, Pahlawan MFR, Aline U, Kim H, Kim H, Cho BK. Hyperspectral imaging with multivariate analysis for detection of exterior flaws for quality evaluation of apples and pears. *Postharvest Biol Technol*. 2025;223:Article 113453.
27. Patel D, Bhise S, Kapdi S, Bhatt T. Non-destructive hyperspectral imaging technology to assess the quality and safety of food: A review. *Food Prod Processing Nutr*. 2024;6(1):69.
28. Gomes WPC, Gonçalves L, da Silva CB, Melchert WR. Application of multispectral imaging combined with machine learning models to discriminate special and traditional green coffee. *Comput Electron Agric*. 2022;198:Article 107097.
29. Wu L, Tang XM, Wu T, Zeng W, Zhu XW, Hu B, Zhang SH. A review on current progress of Raman-based techniques in food safety: From normal Raman spectroscopy to SESORS. *Food Res Int*. 2023;169:Article 112944.
30. Park M, Somborn A, Schlehuber D, Keuter V, Deerberg G. Raman spectroscopy in crop quality assessment: Focusing on sensing secondary metabolites: A review. *Hort Res*. 2023;10(5):uhad074.

31. Guo LM, Zhang J, Bao Y, Zhang Y, Zhang DX, Ma XY, Zhang JD. Label-free and highly sensitive detection of aflatoxin B₁ by ag IANPs via surface-enhanced Raman spectroscopy. *Food Chem.* 2024;458:Article 140231.
32. Wang JJ, Chen QS, Belwal T, Lin XY, Luo ZS. Insights into chemometric algorithms for quality attributes and hazards detection in foodstuffs using Raman/surface enhanced Raman spectroscopy. *Compr Rev Food Sci Food Saf.* 2021;20(3):2476–2507.
33. Dong YL, Hu JY, Jin JL, Zhou HB, Jin SY, Yang DT. Advances in machine learning-assisted SERS sensing towards food safety and biomedical analysis. *TrAC Trends Anal Chem.* 2024;180:Article 117974.
34. Li BZ, Liu SJ, Huang LJ, Jin MJ, Wang JL. Nanohybrid SERS substrates intended for food supply chain safety. *Coord Chem Rev.* 2023;494:Article 215349.
35. Zhu AF, Ali S, Jiao TH, Wang Z, Ouyang Q, Chen QS. Advances in surface-enhanced Raman spectroscopy technology for detection of foodborne pathogens. *Compr Rev Food Sci Food Saf.* 2023;22(3):1466–1494.
36. Su Y, Yuan BZ, Jiang YW, Wu P, Huang XL, Zhu JJ, Jiang LP. A bioinspired hollow g-C₃N₄-CuPc heterostructure with remarkable SERS enhancement and photosynthesis-mimicking properties for theranostic applications. *Chem Sci.* 2022;13(22):6573–6582.
37. Xie TH, Cao ZJ, Li YJ, Li ZY, Zhang FL, Gu YQ, Han CQ, Yang GH, Qu LL. Highly sensitive SERS substrates with multi-hot spots for on-site detection of pesticide residues. *Food Chem.* 2022;381:Article 132208.
38. Nilghaz A, Mousavi SM, Amiri A, Tian JF, Cao R, Wang XA. Surface-enhanced Raman spectroscopy substrates for food safety and quality analysis. *J Agric Food Chem.* 2022;70(18):5463–5476.
39. Hajikhani M, Hegde A, Snyder J, Cheng JL, Lin MS. Integrating transformer-based machine learning with SERS technology for the analysis of hazardous pesticides in spinach. *J Hazard Mater.* 2024;470:Article 134208.
40. Ma LX, Yang XN, Xue SS, Zhou RY, Wang C, Guo ZM, Wang YS, Cai JR. “Raman plus X” dual-modal spectroscopy technology for food analysis: A review. *Compr Rev Food Sci Food Saf.* 2025;24(1):Article e70102.
41. Fu Y, Ren YQ, Sun DW. Novel analysis of food processes by terahertz spectral imaging: A review of recent research findings. *Trends Food Sci Technol.* 2024;147:Article 104463.
42. Feng CH, Otani C. Terahertz spectroscopy technology as an innovative technique for food: Current state-of-the-art research advances. *Crit Rev Food Sci Nutr.* 2021;61(15):2523–2543.
43. Hu J, Zhan CH, Shi HY, Qiao P, He Y, Liu YD. Rapid non-destructive detection of foreign bodies in fish based on terahertz imaging and spectroscopy. *Infrared Phys Technol.* 2023;131:Article 104448.
44. Wang KQ, Pu HB, Sun DW. Emerging spectroscopic and spectral imaging techniques for the rapid detection of microorganisms: An overview. *Compr Rev Food Sci Food Saf.* 2018;17(2):256–273.
45. Afsah-Hejri L, Hajeb P, Ara P, Ehsani RJ. A comprehensive review on food applications of terahertz spectroscopy and imaging. *Compr Rev Food Sci Food Saf.* 2019;18(5):1563–1621.
46. Wang KQ, Sun DW, Pu HB. Emerging non-destructive terahertz spectroscopic imaging technique: Principle and applications in the Agri-food industry. *Trends Food Sci Technol.* 2017;67:93–105.
47. Yu M, Yan J, Chu JW, Qi H, Xu P, Liu SQ, Zhou L, Gao JL. Accurate prediction of wood moisture content using terahertz time-domain spectroscopy combined with machine learning algorithms. *Ind Crop Prod.* 2025;227:Article 120771.
48. Ge HY, Jiang YY, Lian FY, Zhang Y. Terahertz spectroscopy investigation of preservative molecules. *Optik.* 2016;127(12):4954–4958.
49. Yao SC, Yu ZY, Hou ZY, Guo LB, Zhang L, Ding HB, Lu Y, Wang QQ, Wang Z. Development of laser-induced breakdown spectroscopy based spectral tandem technology: A topical review. *TrAC Trends Anal Chem.* 2024;177:Article 117795.
50. Su LJ, Shi W, Chen XJ, Meng LW, Yuan LM, Chen X, Huang GZ. Simultaneously and quantitatively analyze the heavy metals in *Sargassum fusiforme* by laser-induced breakdown spectroscopy. *Food Chem.* 2021;338:Article 127797.
51. Multari RA, Cremers DA, Scott T, Kendrick P. Detection of pesticides and dioxins in tissue fats and rendering oils using laser-induced breakdown spectroscopy (LIBS). *J Agric Food Chem.* 2013;61(10):2348–2357.
52. Zhong J, Jiang XM, Lin M, Dai HL, Zhu FL, Qiao X, Zhao ZF, Peng JY. Fast quantification of matcha adulterants with laser-induced breakdown spectroscopy spectrum and image. *Comput Electron Agric.* 2023;209:Article 107813.
53. Peng JY, Liu YF, Ye LF, Jiang JD, Zhou F, Liu F, Huang J. Fast detection of minerals in rice leaves under chromium stress based on laser-induced breakdown spectroscopy. *Sci Total Environ.* 2023;860:Article 160545.
54. Khan ZH, Ullah MH, Rahman B, Talukder AI, Wahadoszamen M, Abedin KM, Haider A. Laser-induced breakdown spectroscopy (LIBS) for trace element detection: A review. *J Spectrosc.* 2022;2022(1):3887038.
55. Nanou E, Pliatsika N, Couris S. Rapid authentication and detection of olive oil adulteration using laser-induced breakdown spectroscopy. *Molecules.* 2023;28(24):7960.
56. Wen XL, Hu ZL, Nie JF, Gao Z, Zhang D, Guo LB, Ma SX, Dong DM. Detection of lead in water at ppt levels using resin-enrichment combined with LIBS-LIF. *J Anal At Spectrom.* 2023;38(5):1108–1115.
57. Ma SX, Tang Y, Ma YY, Dong DM, Guo LB, Zhu HH, Liu JG, Lu YF. The pH effect on the detection of heavy metals in wastewater by laser-induced breakdown spectroscopy coupled with a phase transformation method. *J Anal At Spectrom.* 2020;35(7):1499.
58. Ghaani M, Azimzadeh M, Büyüktaş D, Carullo D, Farris S. Electrochemical sensors in the food sector: A review. *J Agric Food Chem.* 2024;72(44):24170–24190.
59. Kumar H, Kumari R, Singh D, Mangla B. Advances in nanomaterials based electrochemical sensors for rapid detection of food additives: A comprehensive review. *TrAC Trends Anal Chem.* 2024;181:Article 118011.
60. Xu YX, Li Q, Xue HG, Pang H. Metal-organic frameworks for direct electrochemical applications. *Coord Chem Rev.* 2018;376:292–318.
61. Diculescu VC, Chiorcea-Paquim AM, Oliveira-Brett AM. Applications of a DNA-electrochemical biosensor. *TrAC Trends Anal Chem.* 2016;79:23–36.
62. Shang CL, Li YS, Zhang Q, Tang S, Tang XQ, Ren HL, Hu P, Lu SY, Li PW, Zhou Y. Alkaline phosphatase-triggered

- dual-signal immunoassay for colorimetric and electrochemical detection of zearalenone in cornmeal. *Sensors Actuators B Chem.* 2022;358:Article 131525.
63. Liu PP, Huo XH, Tang YF, Xu J, Liu XQ, Wong DKY. A TiO₂ nanosheet-g-C₃N₄ composite photoelectrochemical enzyme biosensor excitable by visible irradiation. *Anal Chim Acta.* 2017;984:86–95.
 64. Hu MJ, Yue FL, Dong JW, Tao C, Bai MY, Liu MY, Zhai SX, Chen SH, Liu WZ, Qi GY, et al. Screening of broad-spectrum aptamer and development of electrochemical aptasensor for simultaneous detection of penicillin antibiotics in milk. *Talanta.* 2024;269:Article 125508.
 65. Motia S, Bouchikhi B, El Bari N. An electrochemical molecularly imprinted sensor based on chitosan capped with gold nanoparticles and its application for highly sensitive butylated hydroxyanisole analysis in foodstuff products. *Talanta.* 2021;223:Article 121689.
 66. Zhang JN, Guo XH, Zhang J, Guo XB, Xu YY, Chen LJ. Ti₃C₂ MXene/MoS₂@AuNPs ternary nanocomposite for highly sensitive electrochemical detection of phoxim residues in fruits. *Food Chem.* 2025;462:Article 140939.
 67. Dou XZ, Wu QL, Luo SJ, Yang J, Dong BL, Wang L, Qu H, Zheng L. A miniaturized biosensor for rapid detection of tetracycline based on a graphene field-effect transistor with an aptamer modified gate. *Talanta.* 2024;271:Article 125702.
 68. Zhao S, Yang J, Wang L, Dong B, Mao Y, Qu H, Zheng L. Selective detection of Pb²⁺ ions based on a graphene field-effect transistor gated by DNazymes in binding mode. *Biosens Bioelectron.* 2023;237(1):Article 115549.
 69. Shao Y, Zhu Y, Zheng R, Wang P, Zhao Z, An J. Highly sensitive and selective surface molecularly imprinted polymer electrochemical sensor prepared by au and MXene modified glassy carbon electrode for efficient detection of tetrabromobisphenol A in water. *Adv Compos Hybrid Mater.* 2022;5(4):3104–3116.
 70. Persaud K, Dodd G. Analysis of discrimination mechanisms in the mammalian olfactory system using a model nose. *Nature.* 1982;299(5881):352–355.
 71. Wei GZ, Dan ML, Zhao GH, Wang DM. Recent advances in chromatography-mass spectrometry and electronic nose technology in food flavor analysis and detection. *Food Chem.* 2023;405:Article 134814.
 72. Li YC, Wang ZK, Zhao TN, Li H, Jiang JK, Ye JH. Electronic nose for the detection and discrimination of volatile organic compounds: Application, challenges, and perspectives. *TrAC Trends Anal Chem.* 2024;180:Article 117958.
 73. Mahanti NK, Shivashankar S, Chhetri KB, Kumar A, Rao BB, Aravind J, Swami DV. Enhancing food authentication through E-nose and E-tongue technologies: Current trends and future directions. *Trends Food Sci Technol.* 2024;150:Article 104574.
 74. Girmatsion M, Tang X, Zhang Q, Li P. Progress in machine learning-supported electronic nose and hyperspectral imaging technologies for food safety assessment: A review. *Food Res Int.* 2025;209:Article 116285.
 75. Makarichian A, Chayjan RA, Ahmadi E, Zafari D. Early detection and classification of fungal infection in garlic (*A. sativum*) using electronic nose. *Comput Electron Agric.* 2022;192:Article 106575.
 76. Leggieri MC, Mazzoni M, Fodil S, Moschini M, Bertuzzi T, Prandini A, Battilani P. An electronic nose supported by an artificial neural network for the rapid detection of aflatoxin B₁ and fumonisins in maize. *Food Control.* 2021;123:Article 107722.
 77. da Silva TA, Juncá MAC, Braunger ML, Riul A Jr, Barbin DF. Application of a microfluidic electronic tongue based on impedance spectroscopy for coconut water analysis. *Food Res Int.* 2024;187:Article 114353.
 78. Cheng SW, Qin YM, Mao YZ, Cao YY, Zheng RH, Han JZ, Tian SY, Qin ZH. “Reference sample comparison method”: A new voltammetric electronic tongue method and its application in assessing the shelf life of fresh milk. *Food Chem.* 2025;463:Article 141064.
 79. Grassi S, Benedetti S, Casiraghi E, Buratti S. E-sensing systems for shelf life evaluation: A review on applications to fresh food of animal origin. *Food Packag Shelf Life.* 2023;40:Article 101221.
 80. Gil L, Barat JM, Baigts D, Martínez-Mañez R, Soto J, Garcia-Breijo E, Aristoy MC, Toldrá F, Llobet E. Monitoring of physical-chemical and microbiological changes in fresh pork meat under cold storage by means of a potentiometric electronic tongue. *Food Chem.* 2011;126(3):1261–1268.
 81. Das K, Zhang M, Bhandari B, Chen HZ, Bai BS, Roy MC. Ultrasound generation and ultrasonic application on fresh food freezing: Effects on freezing parameters, physicochemical properties and final quality of frozen foods. *Food Rev Intl.* 2023;39(7):4465–4495.
 82. Bhargava N, Mor RS, Kumar K, Sharanagat VS. Advances in application of ultrasound in food processing: A review. *Ultrason Sonochem.* 2021;70:Article 105293.
 83. McClements DJ, Gunasekaran S. Ultrasonic characterization of foods and drinks: Principles, methods, and applications. *Crit Rev Food Sci Nutr.* 1997;37(1):1–46.
 84. Huang YJ. Principles of nuclear magnetic resonance and its applications in medication. *Highl Sci Eng Technol.* 2023;46:205–213.
 85. Bloembergen N, Purcell EM, Pound RV. Relaxation effects in nuclear magnetic resonance absorption. *Phys Rev.* 1948;73(7):679.
 86. Cao RG, Liu XR, Liu YQ, Zhai XQ, Cao TY, Wang AL, Qiu J. Applications of nuclear magnetic resonance spectroscopy to the evaluation of complex food constituents. *Food Chem.* 2021;342:Article 128258.
 87. Luka BS, Yunusa BM, Vihikwagh QM, Kuhwa KE, Oluwasegun TH, Ogalagu R, Yuguda TK, Adnoui M. Hyperspectral imaging systems for rapid assessment of moisture and chromaticity of foods undergoing drying: Principles, applications, challenges, and future trends. *Comput Electron Agric.* 2024;224:Article 109101.
 88. Zhao PZ, Fallu DJ, Pears B, Allonsius C, Lembrechts JJ, van de Vondel S, Meysman FJR, Cucchiaro S, Tarolli P, Shi P, et al. Quantifying soil properties relevant to soil organic carbon biogeochemical cycles by infrared spectroscopy: The importance of compositional data analysis. *Soil Tillage Res.* 2023;231:Article 105718.
 89. Sun HZ, Zheng K, Liu M, Li C, Yang D, Li JD. Hyperspectral image mixed noise removal using a subspace projection attention and residual channel attention network. *Remote Sens.* 2022;14(9):2071.
 90. Sanaeifar A, ZakiDizaji H, Jafari A, de la Guardia M. Early detection of contamination and defect in foodstuffs by electronic nose: A review. *TrAC Trends Anal Chem.* 2017;97:257–271.

91. Cuan KX, Zhang TM, Li ZY, Huang JD, Ding YB, Fang C. Automatic Newcastle disease detection using sound technology and deep learning method. *Comput Electron Agric.* 2022;194:Article 106740.
92. Sun D-W, Pu H, Yu J. Applications of hyperspectral imaging technology in the food industry. *Nat Rev Electr Eng.* 2024;1(4):251–263.
93. Li W, Xu JJ, Yang WR, Liu FL, Zhou HY, Yan ZH. Approach and application of extracting matching features from E-nose signals for AI tasks. *Biomedical Signal Process Control.* 2024;90:Article 105869.
94. Lee BE, Kang TY, Jenkins D, Li Y, Wall MM, Jun S. A single-walled carbon nanotubes-based electrochemical impedance immunosensor for on-site detection of *Listeria monocytogenes*. *J Food Sci.* 2022;87(1):280–288.
95. Papadakis G, Murasova P, Hamiot A, Tsougeni K, Kaprou G, Eck M, Rabus D, Bilkova Z, Dupuy B, Jobst G, et al. Micro-nano-bio acoustic system for the detection of foodborne pathogens in real samples. *Biosens Bioelectron.* 2018;111:52–58.
96. Wen ZF, Fahrig R, Williams ST, Pelc NJ. Shimming with permanent magnets for the x-ray detector in a hybrid x-ray/MR system. *Med Phys.* 2008;35(9):3895–3902.
97. Wang XX, Bouzembrak Y, Lansink A, van der Fels-Klerx HJ. Application of machine learning to the monitoring and prediction of food safety: A review. *Compr Rev Food Sci Food Saf.* 2022;21(1):416–434.
98. Xie CQ, Wang CY, Zhao MY, Zhou WD. Detection of the 5-hydroxymethylfurfural content in roasted coffee using machine learning based on near-infrared spectroscopy. *Food Chem.* 2023;422:Article 136199.
99. Wu F, Li NQ, Zhang JJ, Guo SY. The design about early warning of vegetable disease in facility agriculture. *J Phys Conf Ser.* 2019;1168:Article 032052.
100. Hinton GE, Osindero S, Teh YW. A fast learning algorithm for deep belief nets. *Neural Comput.* 2006;18(7):1527–1554.
101. Huang YQ, Kangas LJ, Rasco BA. Applications of artificial neural networks (ANNs) in food science. *Crit Rev Food Sci Nutr.* 2007;47(2):113–126.
102. Liu Y, Pu HB, Sun DW. Efficient extraction of deep image features using convolutional neural network (CNN) for applications in detecting and analysing complex food matrices. *Trends Food Sci Technol.* 2021;113:193–204.
103. Wang J, Xia LL, Liu H, Zhao C, Ming SY, Wu JY. Colorimetric microneedle sensor using deep learning algorithm for meat freshness monitoring. *Chem Eng J.* 2024;481:Article 148474.
104. Hochreiter S, Schmidhuber J. Long short-term memory. *Neural Comput.* 1997;9(8):1735–1780.
105. Mou LC, Ghamisi P, Zhu XX. Deep recurrent neural networks for hyperspectral image classification. *IEEE Trans Geosci Remote Sens.* 2017;55(7):3639–3655.
106. Deng ZW, Wang T, Zheng Y, Zhang WL, Yun YH. Deep learning in food authenticity: Recent advances and future trends. *Trends Food Sci Technol.* 2024;144:Article 104344.
107. Wu XJ, Du ZR, Ma RQ, Zhang X, Yang DL, Liu HL, Zhang YA. Qualitative and quantitative studies of phthalates in extra virgin olive oil (EVOO) by surface-enhanced Raman spectroscopy (SERS) combined with long short term memory (LSTM) neural network. *Food Chem.* 2024;433: Article 137300.
108. Zhu HF, Zhao YF, Zhao LG, Yang RB, Han ZZ. Pixel-level spectral reconstruction and compressed projection based on deep learning in detecting aflatoxin B₁. *Comput Electron Agric.* 2025;232:Article 110071.
109. Menezes GK, Astolfi G, Martins J, Tetila EC, Junior ADSO, Gonçalves D, Junior JM, Silva J, Li J, Gonçalves W, et al. Pseudo-label semi-supervised learning for soybean monitoring. *Smart Agric Technol.* 2023;4:Article 100216.
110. Morales R, Martinez-Arroyo A, Aguilar E. Robust deep neural network for learning in noisy multi-label food images. *Sensors.* 2024;24(7):2034.
111. Ding H, Xie Z, Yu W, Cui X, Wilson DI. Artificial intelligence enhances food testing process: A comprehensive review. *Food Biosci.* 2025;68:Article 106404.
112. Green HS, Li X, De Pra M, Lovejoy KS, Steiner F, Acworth IN, Wang SC. A rapid method for the detection of extra virgin olive oil adulteration using UHPLC-CAD profiling of triacylglycerols and PCA. *Food Control.* 2020;107:Article 106773.
113. Zeng XQ, Cao R, Xi Y, Li XJ, Yu MH, Zhao JL, Cheng JY, Li J. Food flavor analysis 4.0: A cross-domain application of machine learning. *Trends Food Sci Technol.* 2023;138:116–125.
114. Bupi N, Sangaraju VK, Phan LT, Lal A, Vo TTB, Ho PT, Qureshi MA, Tabassum M, Lee S, Manavalan B. An effective integrated machine learning framework for identifying severity of tomato yellow leaf curl virus and their experimental validation. *Research.* 2023;6:0016.
115. Kang Z, Zhao Y, Chen L, Guo Y, Mu Q, Wang S. Advances in machine learning and hyperspectral imaging in the food supply chain. *Food Eng Rev.* 2022;14(4):596–616.
116. Hadi J, Rapp D, Dhawan S, Gupta SK, Gupta TB, Brightwell G. Molecular detection and characterization of foodborne bacteria: Recent progresses and remaining challenges. *Compr Rev Food Sci Food Saf.* 2023;22(3): 2433–2464.
117. Treviño M, Pereira-Coelho M, López AGR, Zarazúa S, Madureira LADS, Majchrzak T, Potka-Wasyłka J. How pesticides affect neonates?—Exposure, health implications and determination of metabolites. *Sci Total Environ.* 2022;856(Pt 1):Article 158859.
118. Sun LC, Xin FJ, Alper HS. Bio-synthesis of food additives and colorants—A growing trend in future food. *Biotechnol Adv.* 2021;47:Article 107694.
119. Zhang Z, Wu HF, Zhang AY, Tan MT, Yan SC, Jiang D. Transfer of heavy metals along the food chain: A review on the pest control performance of insect natural enemies under heavy metal stress. *J Hazard Mater.* 2024;478:Article 135587.
120. Wang J, Sufar EK, Bernhoft A, Seal C, Rempelos L, Hasanaliyeva G, Zhao BQ, Iversen PO, Baranski M, Volakakis N, et al. Mycotoxin contamination in organic and conventional cereal grain and products: A systematic literature review and meta-analysis. *Compr Rev Food Sci Food Saf.* 2024;23(3):Article e13363.
121. Biancolillo A, Firmani P, Bucci R, Magri A, Marini F. Determination of insect infestation on stored rice by near infrared (NIR) spectroscopy. *Microchem J.* 2019;145: 252–258.
122. Srivastava S, Mishra HN. Detection of insect damaged rice grains using visible and near infrared hyperspectral imaging technique. *Chemom Intell Lab Syst.* 2022;221:Article 104489.
123. Wang C, Zhou RY, Huang YX, Xie LJ, Ying YB. Terahertz spectroscopic imaging with discriminant analysis for detecting foreign materials among sausages. *Food Control.* 2019;97:100–104.

124. Song SY, Liu ZF, Huang M, Zhu QB, Qin JW, Kim MS. Detection of fish bones in fillets by Raman hyperspectral imaging technology. *J Food Eng.* 2020;272:Article 109808.
125. Payne K, O'Bryan CA, Marcy JA, Crandall PG. Detection and prevention of foreign material in food: A review. *Heliyon.* 2023;9(9):Article e19574.
126. Zhou YC, Peng JT, Chen CLP. Dimension reduction using spatial and spectral regularized local discriminant embedding for hyperspectral image classification. *IEEE Trans Geosci Remote Sens.* 2015;53(2):1082–1095.
127. Mishra P, Karami A, Nordon A, Rutledge DN, Roger JM. Automatic de-noising of close-range hyperspectral images with a wavelength-specific shearlet-based image noise reduction method. *Sensors Actuators B Chem.* 2019;281:1034–1044.
128. Ren SX, Chen H, Hou J, Zhao P, Dong Q, Feng H. Based on historical weather data to predict summer field-scale maize yield: Assimilation of remote sensing data to WOFOST model by ensemble Kalman filter algorithm. *Comput Electron Agric.* 2024;219:Article 108822.
129. Fessler JA. Optimization methods for magnetic resonance image reconstruction: Key models and optimization algorithms. *IEEE Signal Process Mag.* 2020;37(1):33–40.
130. Yi J, Jiang HL, Wang XY, Tan Y. A comprehensive review on sparse representation and compressed perception in optical image reconstruction. *Archi Comput Methods Eng.* 2024;31(5):3197–3209.
131. Wang FX, Wang CG. Improved model for starch prediction in potato by the fusion of near-infrared spectral and textural data. *Food Secur.* 2022;11(19):3133.
132. Saeed F, Khan MA, Sharif M, Mittal M, Goyal LM, Roy S. Deep neural network features fusion and selection based on PLS regression with an application for crops diseases classification. *Appl Soft Comput.* 2021;103:Article 107164.
133. Ballabio D, Robotti E, Grisoni F, Quasso F, Bobba M, Vercelli S, Gosetti F, Calabrese G, Sangiorgi E, Orlandi M, et al. Chemical profiling and multivariate data fusion methods for the identification of the botanical origin of honey. *Food Chem.* 2018;266:79–89.
134. Li H, Dong FJ, Lv Y, Ma ZY, Chen Y, Chen SC, Xian JH, Feng YJ, Liu SJ, Cui JR, et al. Rapid determination of residual pefloxacin in mutton based on hyperspectral imaging and data fusion. *J Food Compos Anal.* 2024;132:Article 106285.
135. Shen F, Huang Y, Jiang XS, Fang Y, Li P, Liu Q, Hu QH, Liu XQ. On-line prediction of hazardous fungal contamination in stored maize by integrating Vis/NIR spectroscopy and computer vision. *Spectrochim Acta A Mol Biomol Spectrosc.* 2020;229:Article 118012.
136. Sohrabi H, Sani PS, Zolfaghari R, Majidi MR, Yoon Y, Khataee A. MOF-based mycotoxin nanosensors for food quality and safety assessment through electrochemical and optical methods. *Molecules.* 2022;27(21):7511.
137. Cheng WW, Tang XZ, Zhang Y, Wu D, Yang WJ. Applications of metal-organic framework (MOF)-based sensors for food safety: Enhancing mechanisms and recent advances. *Trends Food Sci Technol.* 2021;112:268–282.
138. Marimuthu M, Arumugam SS, Jiao TH, Sabarinathan D, Li HH, Chen QS. Metal organic framework based sensors for the detection of food contaminants. *TrAC Trends Anal Chem.* 2022;154:Article 116642.
139. Guo WF, Zhang CAX, Ma TT, Liu XY, Chen Z, Li S, Deng Y. Advances in aptamer screening and aptasensors' detection of heavy metal ions. *J Nanobiotechnol.* 2021;19(1):166.
140. Chen ZJ, Liu Z, Liu JJ, Xiao XL. Research progress in the detection of common foodborne hazardous substances based on functional nucleic acids biosensors. *Biotechnol Bioeng.* 2023;120(12):3501–3517.
141. Lin H, Kang WC, Han E, Chen QS. Quantitative analysis of colony number in mouldy wheat based on near infrared spectroscopy combined with colorimetric sensor. *Food Chem.* 2021;354:Article 129545.
142. Kwon DY. Personalized diet oriented by artificial intelligence and ethnic foods. *J Ethn Foods.* 2020;7:10.
143. Chen HL, Chen ZY, Lin FT, Zhuang PF. Effective management for blockchain-based agri-food supply chains using deep reinforcement learning. *IEEE Access.* 2021;9:36008–36018.
144. Liu Z, Yu X, Liu N, Liu C, Jiang A, Chen L. Integrating AI with detection methods, IoT, and blockchain to achieve food authenticity and traceability from farm-to-table. *Trends Food Sci Technol.* 2025;158:Article 104925.
145. Schorn-García D, Ezenarro J, Busto O, Aceña L, Boqué R, Mestres M, Giussani B. A new index to detect process deviations using IR spectroscopy and chemometrics process tools. *Food Bioprocess Technol.* 2024;17(9):2782–2792.
146. Zhang Y, Li H, Yao Y, Shen X, Xu C, Fu L, Lin B. Multifunctional flexible Ag-MOFs@CMFP composite paper for fruit preservation and real-time wireless monitoring of fruit quality during storage and transportation. *Food Chem.* 2022;395:Article 133614.
147. Kshetri N. Blockchain's role in enhancing quality and safety and promoting sustainability in the food and beverage industry. *Sustain For.* 2023;15(23):16223.
148. Istif E, Mirzajani H, Dağ C, Mirlou F, Ozuaciksoz EY, Cakir C, Koydemir HC, Yilgor I, Yilgor E, Beker L. Miniaturized wireless sensor enables real-time monitoring of food spoilage. *Nat Food.* 2023;4(5):427–436.
149. Huang JJ, Zhang M, Mujumdar AS, Li CL. AI-based processing of future prepared foods: Progress and prospects. *Food Res Int.* 2025;201:Article 115675.
150. Uddin MS, Mazumder MKA, Prity AJ, Mridha MF, Alfarhood S, Safran M, Che DR. Cauli-Det: Enhancing cauliflower disease detection with modified YOLOv8. *Front Plant Sci.* 2024;15:1373590.
151. Tito NB, Rodernann T, Powell SM. Use of near infrared spectroscopy to predict microbial numbers on Atlantic salmon. *Food Microbiol.* 2012;32(2):431–436.
152. Zhao SG, Jiao TH, Adade SY-S, Wang Z, Wu XX, Li HH, Chen QS. Based on Vis-NIR combined with ANN for on-line detection of bacterial concentration during kombucha fermentation. *Food Biosci.* 2024;60:Article 104346.
153. Achata EM, Oliveira M, Esquerre CA, Tiwari BK, O'Donnell CP. Visible and NIR hyperspectral imaging and chemometrics for prediction of microbial quality of beef *longissimus dorsi* muscle under simulated normal and abuse storage conditions. *LWT.* 2020;128:Article 109463.
154. Wang YM, He X, Wang S, Ma JY, Hu DF, Liang HY, Ma CY, Jin YF, Chen XQ, Xu GR, et al. Rapid detection of *Salmonella typhimurium* in food samples using electrochemical sensor. *LWT.* 2024;206:Article 116567.
155. Bonah E, Huang XY, Yang HY, Aheto JH, Ren Y, Yu SS, Tu HY. Detection of *Salmonella typhimurium* contamination levels in fresh pork samples using electronic nose smellprints in tandem with support vector machine regression and metaheuristic optimization algorithms. *J Food Sci Technol.* 2021;58(10):3861–3870.

156. Carrillo-Gómez JK, Acevedo CMD, García-Rico RO. Detection of the bacteria concentration level in pasteurized milk by using two different artificial multisensory methods. *Sens Bio-Sens Res.* 2021;33:Article 100428.
157. Sun K, Wang ZJ, Tu K, Wang SJ, Pan LQ. Recognition of mould colony on unhulled paddy based on computer vision using conventional machine-learning and deep learning techniques. *Sci Rep.* 2016;6(1):37994.
158. Shen F, Wu QF, Liu P, Jiang XS, Fang Y, Cao CJ. Detection of *Aspergillus* spp. contamination levels in peanuts by near infrared spectroscopy and electronic nose. *Food Control.* 2018;93:1–8.
159. Cao Y, Li HR, Sun J, Zhou X, Yao KS, Nirere A. Nondestructive determination of the total mold colony count in green tea by hyperspectral imaging technology. *J Food Process Eng.* 2020;43(12):Article e13570.
160. Sun ZX, Li B, Yang AK, Liu YD. Detection the quality of pumpkin seeds based on terahertz coupled with convolutional neural network. *J Chemom.* 2024;38(7): Article e3547.
161. Sánchez R, Pérez-Nevado F, Martillanes S, Montero-Fernández I, Lozano J, Martín-Vertedor D. Machine olfaction discrimination of Spanish-style green olives inoculated with spoilage mold species. *Food Control.* 2023;147:Article 109600.
162. Sun XH, Guo M, Ma M, Mankin RW. Identification and classification of damaged corn kernels with impact acoustics multi-domain patterns. *Comput Electron Agric.* 2018;150: 152–161.
163. Su WH, Sun DW, He JG, Zhang LB. Variation analysis in spectral indices of volatile chlorpyrifos and non-volatile imidacloprid in jujube (*Ziziphus jujuba* mill.) using near-infrared hyperspectral imaging (NIR-HSI) and gas chromatograph-mass spectrometry (GC-MS). *Comput Electron Agric.* 2017;139:41–55.
164. Chen ZA, Tan R, Zeng M, Yuan X, Zhuang KY, Feng CS, He Y, Luo XJ. SERS detection of triazole pesticide residues on vegetables and fruits using au decahedral nanoparticles. *Food Chem.* 2024;439:Article 138110.
165. Wu F, Guo H, Wang B, Kang K, Wang L, Wang Y, Ji X. Dual signal amplification strategy-based electrochemical aptasensor utilizing redox molecule/MOF composites for multi-pesticide detection. *Sensors Actuators B Chem.* 2025;423:Article 136757.
166. Tang Y, Xu KL, Zhao B, Zhang MC, Gong CH, Wan HL, Wang YH, Yang ZP. A novel electronic nose for the detection and classification of pesticide residue on apples. *RSC Adv.* 2021;11(34):20874–20883.
167. Tantantrakun A, Thompson AK, Terdwongworakul A, Teerachaichayut S. Assessment of nitrite content in Vienna chicken sausages using near-infrared hyperspectral imaging. *Food Secur.* 2023;12(14):2793.
168. Xue DN, Tang J, Zhang JY, Liu H, Gu CJ, Zhou XF, Jiang T, Shi LL. Construction of composite SERS substrate based on black phosphorus/mesoporous ZIF-67 and its selective monitoring of food additives. *Appl Surf Sci.* 2024;661: Article 160001.
169. Sun MJ, Lin J, Xue Y, Wang WJ, Shi SN, Zhang S, Shi YP. A terahertz metasurface sensor based on quasi-BIC for detection of additives in infant formula. *Nano.* 2024;14(10):883.
170. Qiu SS, Wang J. The prediction of food additives in the fruit juice based on electronic nose with chemometrics. *Food Chem.* 2017;230:208–214.
171. Fu DL, Zhang BW, Deng JJ, Ding L, Li HB, Liu XH. Theoretically optimized molecularly imprinted gel-encapsulated sea urchin-shaped bionic enzyme serves as a green artificial antibody for the selective recognition of vanillin in desserts. *Sensors Actuators B Chem.* 2024;403:Article 135114.
172. Scharinger M, Kuntz M, Scharinger A, Teipel J, Kuballa T, Walch SG, Lachenmeier DW. Rapid approach to determine propionic and sorbic acid contents in bread and bakery products using ¹H NMR spectroscopy. *Foods.* 2021;10(3):Article 526.
173. Zhao Y, Xu YJ, Jing XH, Ma W. SERS-active plasmonic metal NP-CsPbX₃ films for multiple veterinary drug residues detection. *Food Chem.* 2023;412:Article 135420.
174. Ye MY, Lin XF, Li J, Chen XW, Ying DC, Wu SJ, Wang ZP, Duan N. Dual-mode aptasensor based on P-CeO₂NR@Mxene and exonuclease I-assisted target recycling for malachite green detection. *Food Chem.* 2024;451:Article 139399.
175. Liu Y, Xu LL, Zeng SG, Qiao F, Jiang W, Xu Z. Rapid detection of mussels contaminated by heavy metals using near-infrared reflectance spectroscopy and a constrained difference extreme learning machine. *Spectrochim Acta A Mol Biomol Spectrosc.* 2022;269:Article 120776.
176. Lin YK, Gao JX, Tu YJ, Zhang YX, Gao J. Estimating low concentration heavy metals in water through hyperspectral analysis and genetic algorithm-partial least squares regression. *Sci Total Environ.* 2024;916:Article 170225.
177. Chen Q, Yao L, Yao BB, Meng XZ, Wu Q, Chen ZR, Chen W. Low-cost signal enhanced colorimetric and SERS dual-mode paper sensor for rapid and ultrasensitive screening of mercury ions in tea. *Food Chem.* 2025;463:Article 141375.
178. Shao YN, Wang YT, Zhu D, Xiong X, Tian ZA, Balakin AV, Shkurinov AP, Xu D, Wu YM, Peng Y, et al. Measuring heavy metal ions in water using nature existed microalgae as medium based on terahertz technology. *J Hazard Mater.* 2022;435:Article 129028.
179. He PY, Fu XL, Wang CH, Gou YJ, Cao FJ, Tian HW, Ma SX, Liang YY, An T, Li GL. Rapid and highly sensitive detection of trace chromium and copper in tea infusion using laser-induced breakdown spectroscopy combined with electrospinning technology. *Sensors Actuators B Chem.* 2025;423:Article 136740.
180. Teodoro KBR, Shimizu FM, Scagion VP, Correa DS. Ternary nanocomposites based on cellulose nanowhiskers, silver nanoparticles and electrospun nanofibers: Use in an electronic tongue for heavy metal detection. *Sensors Actuators B Chem.* 2019;290:387–395.
181. Zhang MS, Guo WC. Simultaneous electrochemical detection of multiple heavy metal ions in milk based on silica-modified magnetic nanoparticles. *Food Chem.* 2023;406:Article 135034.
182. Li J, Deng JH, Bai X, Monteiro DDN, Jiang H. Quantitative analysis of aflatoxin B₁ of peanut by optimized support vector machine models based on near-infrared spectral features. *Spectrochim Acta A Mol Biomol Spectrosc.* 2023;303:Article 123208.
183. Guo Z, Zhang J, Dong HW, Sun JS, Li SL, Ma CY, Guo YM, Sun X. Spatio-temporal distribution patterns and quantitative detection of aflatoxin B₁ and total aflatoxin in peanut kernels explored by short-wave infrared hyperspectral imaging. *Food Chem.* 2023;424:Article 136441.
184. Teixido-Orries I, Molino F, Femenias A, Ramos AJ, Marín S. Quantification and classification of deoxynivalenol-contaminated

- oat samples by near-infrared hyperspectral imaging. *Food Chem.* 2023;417:Article 135924.
185. Liu W, Deng HY, Shi YL, Liu CH, Zheng L. Application of multispectral imaging combined with machine learning methods for rapid and non-destructive detection of zearalenone (ZEN) in maize. *Measurement.* 2022;203:Article 111944.
186. Zhao Z, Ren M, Zhang W, Chen Z, Zhang L, Qu X, Shi J, Xia W, Xu X, Yang Y. SERS-lateral flow immunoassay based on AuNR@ag@ SiO₂-AuNP assembly for ultra-sensitive detection of deoxynivalenol in grain. *LWT.* 2024;212(15):Article 117015.
187. Liu W, Zhao PG, Wu CS, Liu CH, Yang JB, Zheng L. Rapid determination of aflatoxin B₁ concentration in soybean oil using terahertz spectroscopy with chemometric methods. *Food Chem.* 2019;293:213–219.
188. Feng YZ, Cheng GB, Wang Z, Wu K, Deng AP, Li JG. Electrochemiluminescence immunosensor based on tin dioxide quantum dots and palladium-modified graphene oxide for the detection of zearalenone. *Talanta.* 2024;271:Article 125740.
189. Machungo C, Berna AZ, McNevin D, Wang RSL, Trowell S. Comparison of the performance of metal oxide and conducting polymer electronic noses for detection of aflatoxin using artificially contaminated maize. *Sensors Actuators B Chem.* 2022;360:Article 131681.