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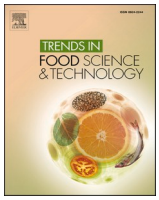

Integrating AI and advanced spectroscopic techniques for precision food safety and quality control

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ABSTRACT

Traditional methods like high-performance liquid chromatography (HPLC) and gas chromatography-mass spectrometry (GC-MS) are widely used in food analysis but often face limitations in detecting trace contaminants at ultra-low levels or in complex matrices. This review highlights recent breakthroughs in food analysis technologies that deliver unprecedented sensitivity and accuracy for consumers' health protection. Among these advances, Wide Line Surface-Enhanced Raman scattering (WL-SERS) has delivered a tenfold increase in sensitivity, enabling the detection of contaminants like melamine in raw milk at concentrations far below conventional thresholds. Mass spectrometry imaging (MSI), particularly matrix-assisted laser desorption/ionization (MALDI-MSI), has made significant progress in spatial resolution, allowing for precise mapping of food constituents and contaminants. Additionally, two-dimensional liquid chromatography (2D-LC) and multidimensional gas chromatography have evolved rapidly, achieving detection as low as 1 ppb in complex food systems. Innovative sensor technologies, such as the Dpyt near-infrared (NIR) fluorescent probe and electrochemiluminescence (ECL) aptasensors, offer rapid and highly sensitive detection, effectively complementing traditional methods. Furthermore, the integration of artificial intelligence (AI) and machine learning (ML) has revolutionized food quality assessment, with models like convolutional neural networks (CNNs) reaching up to 99.85% accuracy in identifying adulterants. Despite these advancements, challenges such as high operational costs, sensor stability and AI's computational demands remain. This review highlights the integration of advanced spectroscopy, AI-driven analysis, and novel sensor technologies, outlining future strategies such as miniaturization, nanomaterial innovations, and standardized protocols. These approaches present transformative pathways for improving the precision, efficiency, and accessibility of food safety and quality management, ultimately enhancing public health protection.

1. Introduction

Food safety and quality control are essential elements of the food industry, directly impacting public health by reducing food-borne illnesses and maintaining the integrity of food products (Liu et al., 2024a). The complexity of modern food supply chains is underscored by the fact that food-borne pathogens are responsible for 31 major illnesses identified in safety reviews (Gallo et al., 2020). Moreover, the World Health Organization reports that food-borne illnesses caused by contaminated food affect 600 million people annually, leading to 420,000 deaths (Akinsemolu & Onyeaka, 2024). Additionally, food fraud, a $30 billion global issue, undermines consumer trust and disrupts market stability (Sharma et al., 2024). Notably, over 70% of consumers express concerns about food safety, placing immense pressure on food

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processing companies, which face increasingly stringent international regulations (Handford et al., 2016). Consequently, stricter regulatory frameworks now impose severe penalties and product recalls for non-compliance. Implementing Hazard Analysis and Critical Control Points (HACCP) strategies is essential for mitigating contamination risks and safe food consumption (Ngure et al., 2024). Furthermore, progressive approaches, including metabolomics, are becoming vital in comprehensive food safety strategies (Mphaga et al., 2024). These developments highlight the critical need for advanced technologies to enhance food safety practices' efficacy.

Over recent decades, food analysis technologies have evolved significantly, transitioning from basic manual methods to sophisticated technological innovations. Initially, early techniques such as visual inspections and simple chemical reactions, offered limited accuracy (Nowak et al., 2021). However, the introduction of instrumental methods like spectrophotometry and chromatography marked a significant shift, allowing for faster and more reliable analysis of food components (Hansen et al., 2024). The latter half of the 20th century witnessed breakthroughs with gas chromatography (GC) and high-performance liquid chromatography (HPLC), which offered unprecedented precision in separating and identifying substances (Beecher, 2024). These foundational technologies laid the groundwork for modern advancements, including nuclear magnetic resonance (NMR) spectroscopy, mass spectrometry and inductively coupled plasma (ICP) spectrometry that enable the detection of trace compounds and bioactive substances with remarkable sensitivity and specificity (Ncube et al., 2024). The shift from these conventional techniques to more advanced solutions has set the stage for further technological integration to address complex food safety challenges.

Among these advancements, biosensors play a crucial role in enhancing smart food traceability systems and improving food safety and security. These devices provide rapid, sensitive, and cost-effective detection of contaminants and pathogens throughout the food supply chain. Recent innovations include nanotechnology-driven, ultra-sensitive sensors capable of detecting contaminants at concentrations as low as 0.1 ppb (Eş & Khaneghah, 2024). Additionally, biosensors that merge biological recognition elements with electronic systems facilitate real-time monitoring with high specificity. This integration allows for better detection accuracy and quicker responses to contamination risks. For example, the development of a gold nanoparticle-based lateral flow biosensor enables visual detection of *Phytophthora infestans* with a detection limit of 0.1 pg/μL of genomic DNA in under 2 h (Meliana et al., 2024). Such advancements help reduce the risk of foodborne illnesses significantly. Adding to these advancements, He et al. (He et al., 2024) introduced a gDNAzyme-enhanced *Clostridium butyricum* Argonaute (CbAgo) detection technique for amplification-free, multiplexed pathogen detection. This method identifies *E. coli*, *Salmonella*, and *S. aureus* at concentrations below 80 CFU/mL within 2 h, enhancing efficiency, quality control, and reducing the likelihood of outbreaks. Fluorescent nanosensors based on carbon dots have further advanced the field by providing affordable and highly sensitive solutions for food quality assessments (Luo et al., 2020). These nanosensors are capable of detecting trace quantities of contaminants and are integrated into portable devices, allowing for on-site testing and making food safety monitoring more efficient (Ouyang et al., 2023). Such advancements enhance the reliability and reach of biosensor technology in real-world applications, reinforcing the importance of rapid and precise food safety practices.

The application of Artificial Intelligence (AI) and Machine Learning (ML) in food quality control has reshaped the industry by enhancing precision in data analysis and monitoring throughout production (Raju et al., 2024). These technologies employ machine learning algorithms to analyze large datasets and detect patterns, boosting the accuracy of food quality detection to above 90% (Saha & Manickavasagan, 2021). Computer vision, powered by deep learning, allows detailed defect detection and product classification based on attributes such as size, color, and shape (Chhetri, 2024). Hyperspectral imaging has also proven effective, detecting chemical compositions and spoilage at the molecular level, while IoT-enabled sensors provide real-time data on crucial parameters like temperature and humidity for immediate intervention (Chhetri, 2024). Electronic nose (e-nose) technology has demonstrated high effectiveness in quality inspection, achieving classification accuracies of up to 96% for distinguishing between fresh and overripe fruit, such as mangoes (Ali et al., 2020). The combination of biosensors with AI/ML technology further amplifies their capabilities, enhancing food safety monitoring. The DRAGON platform, as introduced by Wen et al. (Wen et al., 2024), integrates mesophilic Argonaute (CbAgo)-driven reactions with polydisperse microdroplet reactors and machine learning for rapid and sensitive detection of pathogens. This platform, achieving detection limits of 1–2 CFU/mL and completion in less than 45 min, leverages a random forest regression (RFR) model for improved detection accuracy using dual-parameter inputs like microdroplet area and fluorescence intensity. This hybrid approach ensures a strong correlation between predicted and actual concentrations (R^2 = 0.9922), exemplifying how combining biosensor technology with AI/ML fosters efficient, reliable pathogen detection.

Beyond the integration of biosensors and AI/ML, other innovative methods have also contributed significantly to enhancing food safety and quality monitoring. Hyperspectral imaging, for example, has become so sensitive that even pesticide residues as low as 0.01 mg/kg can be detected (Sindhu & Manickavasagan, 2023). These techniques allow real-time analysis without destruction, accelerating quality control processes and broadening the range of quality assurance procedures. Micro-needle technology is another major advance in maintaining food quality (Faraji Rad, 2023). It allows non-destructive and minimally invasive sampling, leading to faster sample collection and improved contaminants analysis, thereby aiding in meeting regulatory requirements. The detection of water contaminants represents another challenge, as most current methods do not process the sensitivity required by regulations. Regulatory thresholds set by the EPA and the EU are generally in the low ppt range, yet many methods detect only at high levels, around 10 ppm (Ateia et al., 2024). Moreover, the lack of standardized procedures and performance measurements across institutions exacerbates the issue, leading to poor reproducibility and inter-laboratory efficiency (Bayen et al., 2024). Addressing these challenges requires standardizing performance metrics and certifying new technologies to foster broader acceptance and consistency in food safety practices. Such measures can improve uniformity across practices and facilitate the widespread adoption of advanced methods that elevate food safety protocols.

This review critically evaluates recent advancements by integrating spectroscopic, chromatographic, and nanotechnology-based techniques, while exploring the use of AI to enhance biosensor functionality. Unlike prior reviews, which often separate traditional and emerging technologies or neglect sustainability, this work presents a comprehensive analysis with a clear emphasis on novelty. It highlights sustainable practices that maintain high accuracy while minimizing environmental impact. By detailing the novel synergistic effects of AI and machine learning on biosensor technologies, this review provides fresh insights into improving detection speed and sensitivity. Additionally, it identifies critical research gaps, such as the need for eco-friendly solutions and standardized metrics, to inspire future innovations in food analysis. This dual focus on technological novelty and sustainability positions the work as a significant contribution, setting a foundation for robust and forward-thinking approaches to food safety.

2. Advances in food analysis techniques

2.1. Cutting-edge developments in spectroscopic techniques

The significant advancements in spectroscopic techniques have become essential for specific applications, such as food analysis, to enhance the speed and sensitivity of molecular detection. The Wide Line

Surface-Enhanced Raman scattering (WL-SERS) microscope is a key innovation, illustrated in Fig. 1A(a). This advanced device's laser beam delivery system functions in various modes, including wide line (WL) illumination (Fig. 1A(b)) and point focus (Ilchenko et al., 2020). The WL mode, in particular, boosts detection efficiency and accelerates data collection by spreading the laser light over larger areas (Fig. 1A(c)). The WL-SERS demonstrated a remarkable 43-fold increase in signal-to-noise ratio (SNR) and 10-fold LoD enhancement in the limit of detection (LoD) when detecting melamine in raw milk (Fig. 1A(d, e)) compared to the conventional point-focus mode. Furthermore, this system detected p-coumaric acid (pHCA) in ethanol liquid at concentrations as low as 10 μM (Fig. 1 A(f, g)), underscoring the enhanced sensitivity provided by WL-SERS in food safety applications (Ilchenko et al., 2020).

In comparison, combining various spectroscopic techniques has proven effective in improving detection systems. For example, integrating Near-Infrared (NIR) spectroscopy with fluorescence spectroscopy resulted in a high correlation coefficient (R^2) of 0.9742 and a low Root Mean Square Error of Prediction (RMSEP) of 8.02 mg/g for quantifying protein and starch in bean flour. This combination successfully determined protein and starch contents at 19.47% and 85.77%, respectively (Li et al., 2023b). Similarly, combining Raman spectroscopy with NIR enhanced classification accuracy, achieving 96. 6% accuracy in detecting *Corylus avellana* L. (Guo et al., 2024b). These findings demonstrate how combining techniques can increase the precision and reliability of food analysis. Further comparisons reveal that the integration of Laser-Induced Breakdown Spectroscopy (LIBS) with image analysis significantly improved detection capabilities. This combined approach increased the R^2 by 0.1 and decreased the Root Mean Square Error (RMSE) by approximately 0.05 in predicting potassium (K), magnesium (Mg) and phosphorus (P) in bean seeds. The trueness values for K, Mg, and P ranged from 89 to 124%, 82–125% and 73–128%, respectively (Gamela et al., 2020). In contrast, using E-noses combined with spectroscopic techniques for meat quality control yielded an RMSEP of 3.2, an R^2 of 0.920 and a P-value of 0.039 mg/100 g, with a Relative Prediction Deviation (RPD) of 3.59 (Liu et al., 2022).

For trace element detection, Inductively Coupled Plasma (ICP) techniques such as ICP-OES and ICP-MS stand out. ICP-OES can detect elements like zinc (Zn) and copper (Cu) at limits as low as 0.1–10 μg/L, maintaining an average RSD below 5% for reproducibility (Zhou et al., 2024b). ICP-MS is even more sensitive, with a detection limit of 0.001 μg/L (1 ng/L) for toxic elements such as lead (Pb) and cadmium (Cd). This technique has been employed to identify Pb and Cd in chicken meat at concentrations as low as 0.01 μg/kg (An et al., 2024). Another recent work on microplastic detection by Huang et al. (Huang et al., 2023) showcases an integration of holography and polarimetry for microscopy using a single lens. This method records 3D holograms and captures polarization characteristics, such as the Degree of Linear Polarization (DoLP) and Angle of Polarization (AoP), which are less sensitive to scattering. As shown in Fig. 1B, while traditional images can produce distorted images in pure water and milk dispersions, the combined imaging system significantly enhances image contrast and microplastic detection, even in high-turbidity environments (Huang et al., 2023). This innovation is particularly beneficial for environmental monitoring and food safety analysis, where the precise detection of contaminants is crucial. While ICP techniques offer unmatched sensitivity, Atomic Absorption Spectroscopy (AAS) also shows high accuracy, detecting Cadmium (Cd) and mercury (Hg) in food at limits of 0.02–0.04 ng/g, with correlation coefficients above 0.998% and recovery rates of between 85.0% and 111.9% (Jia et al., 2024). However, AAS's sample preparation can be time-consuming, potentially affecting reproducibility and consistency.

In contrast, UV visible spectroscopy remains a valuable tool for detecting contaminants due to its ability to measure light absorption. For instance, cyanide detection using anthraquinone derivatives achieved LOD of 29.48 μM (7.67 ppm), presenting a blue colour for on-site testing. Nanoparticle enhancements have further boosted UV–visible spectroscopy's sensitivity, such as in the detection of staphylococcal enterotoxin A (SEA) with an LOD of 0.2 nM (0.006 ppm) (Rodriguez et al., 2020). Fluorescence-based organoleptic tests like the DEM-H_2S probe for hydrogen sulfide (H_2S) detection in food samples also showed significant promise (Fig. 1C(a)). This probe changes from yellow to red upon exposure to H_2S showing a positive response towards spoilage and shifts fluorescence from weak orange to red (Fig. 1C(b, c)), highlighting its specificity and effectiveness for monitoring spoilage in raw meat (Chen et al., 2024a). In summary, advancements in spectroscopic techniques have significantly enhanced food safety analysis through increased sensitivity and faster detection. The integration of multiple methods, such as NIR with fluorescence or LIBS with image analysis, has been particularly effective in improving accuracy and reliability. However, challenges such as the complexity of method integration and the labour-intensive sample preparation required by techniques like AAS underscore the need for ongoing innovation to further streamline and optimize these technologies for practical applications.

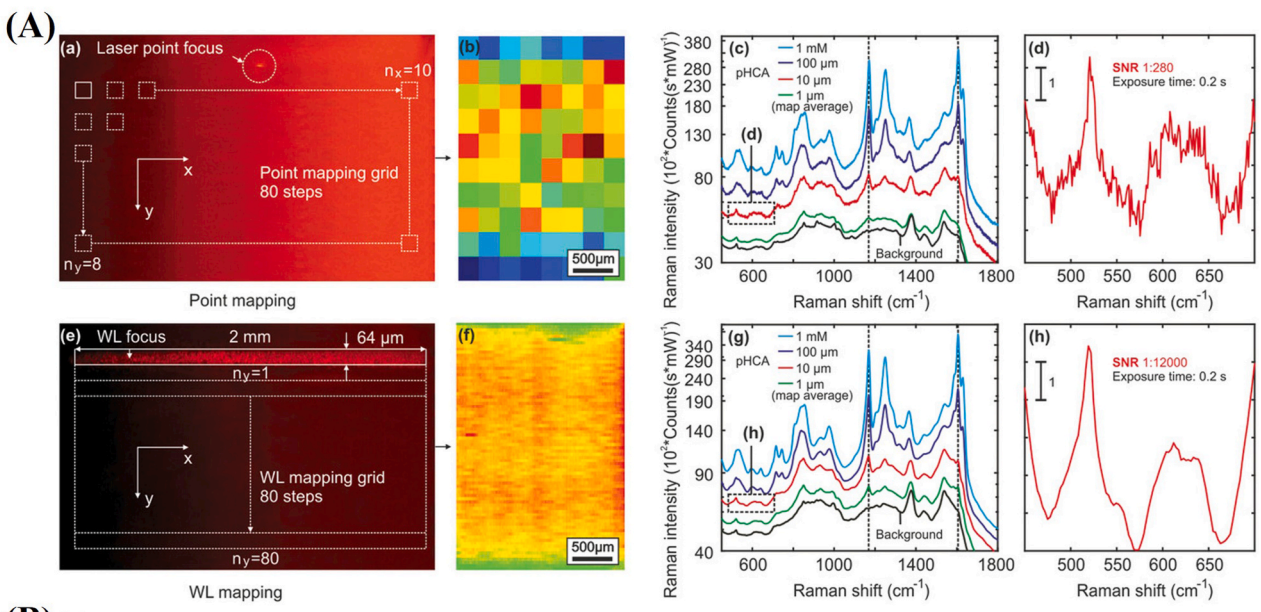
2.2. Breakthroughs in mass spectrometry and imaging techniques

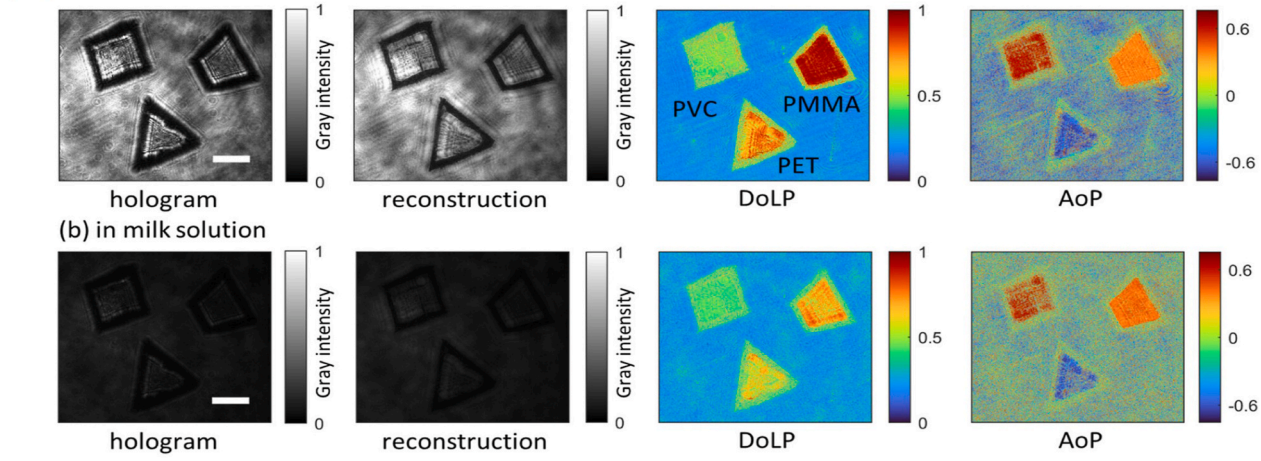
Mass spectrometry (MS) plays a pivotal role in food science due to its high sensitivity and specificity in detecting toxins and analyzing complex food matrices. Techniques such as HPLC-MS/MS and UHPLC-MS/MS stand out for their ability to identify contaminants at very low concentrations, such as ng/mL (Pandey et al., 2023). For example, aflatoxin B1 can be detected in blood at levels as low as 0.05 ng/mL and ochratoxin A in coffee and tea at 0.30 ng/mL, highlighting the robust sensitivity provided by these methods (Ahuja et al., 2023). This level of detection contrasts with recovery rates for other food contaminants, where variability remains a challenge. Ji et al. (Ji et al., 2023) reported recovery rates for mycotoxins in fruits and vegetables ranging from 73% to 120%, with repeatability under 12.9%, illustrating that even advanced techniques face hurdles in matrix effects.

To expand on MS capabilities, Kokesch-Himmelreich et al. (Kokesch-Himmelreich et al., 2022) showcased how mass spectrometry imaging (MSI) can visualize the spatial distribution of food components, offering a more comprehensive analysis. Fig. 1A demonstrated the complementary distributions of a water-soluble disaccharide ($[M + Na]^+$, m/z 365.10544) and fat-soluble cholesterol ($[M\text{-}H_2O + H]^+$, m/z 369.35158). The red marks in Fig. 2A(a) correspond to the disaccharide, while the blue marks in Fig. 2A(b) depict cholesterol, enhancing the understanding of their nutritional values. Compared to traditional MS, which primarily quantifies compounds, MSI adds a layer of spatial data, allowing researchers to observe compound distribution at ppm precision (e.g., 0.68 ppm for disaccharides and 0.62 ppm for cholesterol). Additionally, the visualization of phosphatidylcholine (PC(36:4), $[M + Na]^+$, m/z 804.55138) across the entire tissue in green (Fig. 2A(c)) further demonstrates MSI's capability in mapping ubiquitous compounds within the food matrix (Kokesch-Himmelreich et al., 2022).

In contrast, Kim et al. (Kim et al., 2017) addressed the challenges of sample preparation in MSI. Their findings emphasized that the strip support method better-preserved sample integrity compared to the thaw mount method, leading to more accurate spatial distributions of analyte ions such as choline (m/z 104.12) and phosphocholine (m/z 184.09) are shown in Fig. 2B. This comparison shows that while MSI provides powerful visualization, sample preparation methods significantly impact the accuracy of results, an area that requires ongoing refinement. When considering advanced MS technologies, the use of High-Resolution Mass Spectrometry (HRMS) and tandem MS/MS enhances detection capabilities. For instance, Romero-Sánchez et al. (Romero-Sánchez et al., 2022) reported higher recovery rates (92–111%) for aflatoxin in blood with detection limits as low as 0.05 and 0.2 ng/mL. This contrasts with the variable recovery and repeatability seen in matrix-rich environments (Ji et al., 2023), demonstrating how refined MS techniques like HRMS provide more consistent results.

Further applications of MSI illustrate its multifaceted role in food





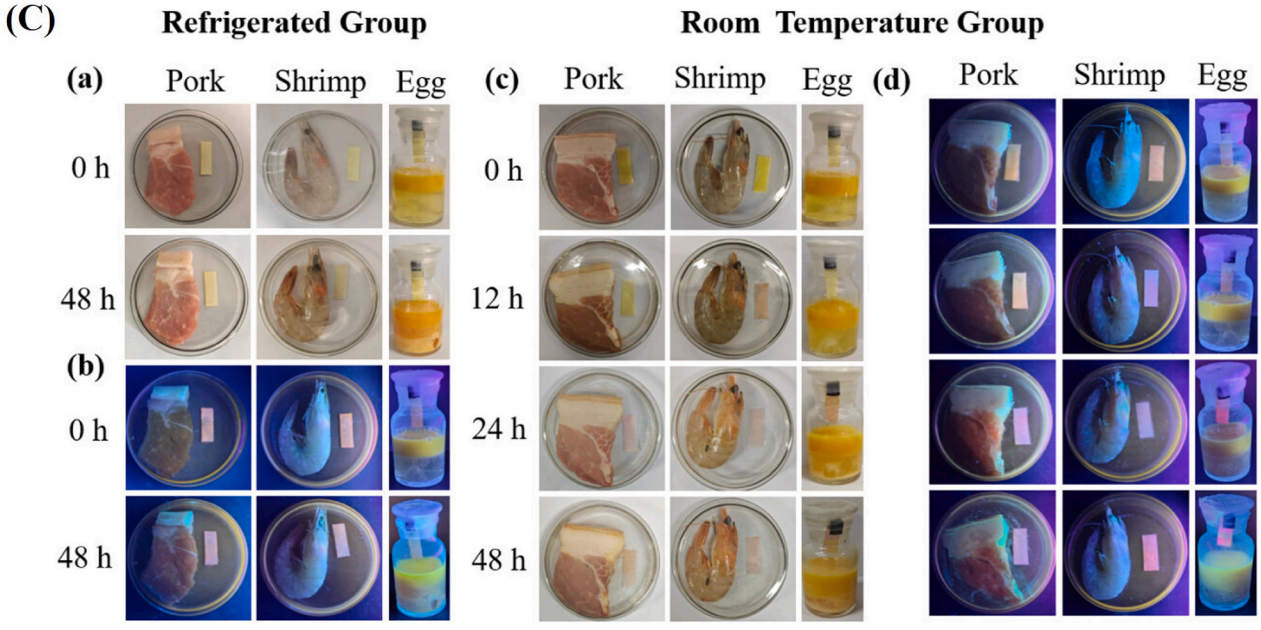


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Fig. 1. (A) Detection of pHCA using different illumination modes: (a,e) Mapping algorithms illustrated under point and white light (WL) laser illumination; (b,f) Surface-enhanced Raman scattering (SERS) maps of pHCA at the 1604 cm^{-1} peak position for point and WL laser illumination; (c,g) SERS spectra of pHCA at various concentrations on Au nanopillars, measured under point and WL illumination modes; (d,h) Zoomed-in spectra of pHCA at a concentration of 10 μm, obtained under point and WL illumination modes. SERS spectra were collected under identical conditions: laser irradiance of 0.2 $mW/\mu m^2$, wavelength 785 nm, exposure time 0.2 s, using a 10 × magnification microscope objective. (B) Degradation of image quality due to scattering and absorption effects in aqueous environments: Holographic and polarimetric images of MP particles shown in (a) pure water and (b) milk solution. (C) Colourimetric and fluorescence changes observed in DEM-H_2S-loaded test strips exposed to H_2S produced during spoilage of pork, shrimp, and egg: Changes monitored at 0 and 48 h under sunlight (a) and UV light (b) in the refrigerated conditions; changes monitored at 0, 12, 24, and 48 h under sunlight (c) and UV light (d) at room temperature. Edited with permission from (Chen et al., 2024a; Huang et al., 2023; Ilchenko et al., 2020). Copyright Wiley© 2020 and ACS© 2023; 2024.

analysis, from quality control to authentication. Zhan et al. (Zhan et al., 2021) successfully used MALDI-TOF/TOF MSI to identify isomeric disaccharides in onion bulbs, detecting them at ppm levels. Maslov et al. (Maslov et al., 2019), applied MALDI-MSI to visualize peptide concentrations in dry-cured ham, which was essential for tracking proteolysis during meat processing. These studies highlight MSI's advantage in mapping molecular distribution, setting it apart from simpler quantification methods offered by traditional MS. Zhao et al. (Zhao et al., 2021) demonstrated MSI's capability in detecting contaminants, such as visualizing and quantifying gossypol in cottonseeds up to 20 μg/g. Comparatively, Goto-Inoue et al. (Goto-Inoue et al., 2019) focused on food authentication, identifying lipid markers in wild versus farmed fish at concentrations of 2–5 μg/g. Fig. 2C shows different metabolite patterns in wild and farmed red sea bream, where farmed fish had significantly higher levels of anserine and carnitine ($p < 0.01$ and $p < 0.05$, respectively). These studies reveal MSI's role in highlighting metabolic differences influenced by diet, which aids in authenticating food sources.

In summary, advancements in mass spectrometry and imaging techniques have significantly improved the detection and analysis of food contaminants, with innovations like MSI providing detailed spatial distributions that traditional MS cannot achieve. While HRMS and tandem MS/MS have enhanced sensitivity and recovery rates, the impact of matrix effects and the need for refined sample preparation in MSI remain challenges. The continued development of these technologies will be essential for advancing food safety and authentication, as they provide comprehensive, reliable, and spatially resolved data crucial for modern food science.

2.3. Insights into recent chromatography technique developments

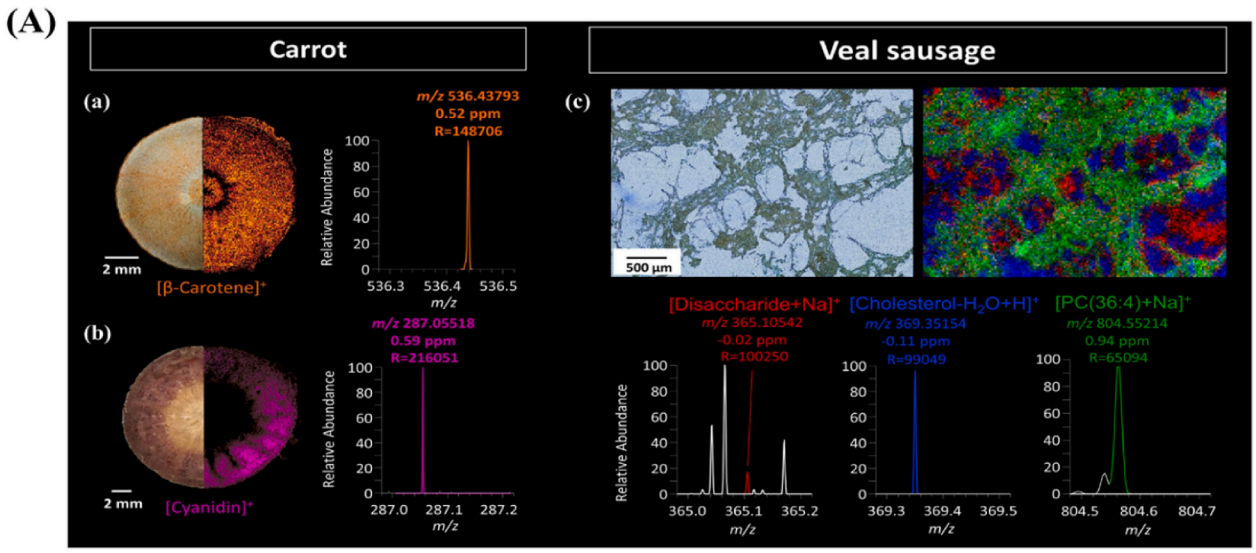
Recent developments in chromatography, such as two-dimensional liquid chromatography (2D-LC), miniaturized LC and high-resolution mass spectrometry (HRMS), have significantly enhanced analytical capabilities across various disciplines (Pirok et al., 2018). These techniques share the common objective of improving sensitivity, resolution and data quality but differ in their specific applications, efficiency, and operational demands. The development of 2D-LC has greatly advanced the ability to separate complex mixtures. For example, Cacciola et al. (Cacciola et al., 2020) demonstrated 2D-LC's ability to detect contaminants like monuron in red wine at limits as low as 0.5 μg/L. This superior separation efficiency is critical when traditional one-dimensional methods struggle to distinguish analytes in complex matrices. However, the complexity of 2D-LC systems introduces challenges, such as potential peak overlap if conditions are not precisely optimized (Mahmoud & Zhang, 2024). This contrasts with the relatively simpler implementation of other methods but highlights the significant benefits in terms of resolution.

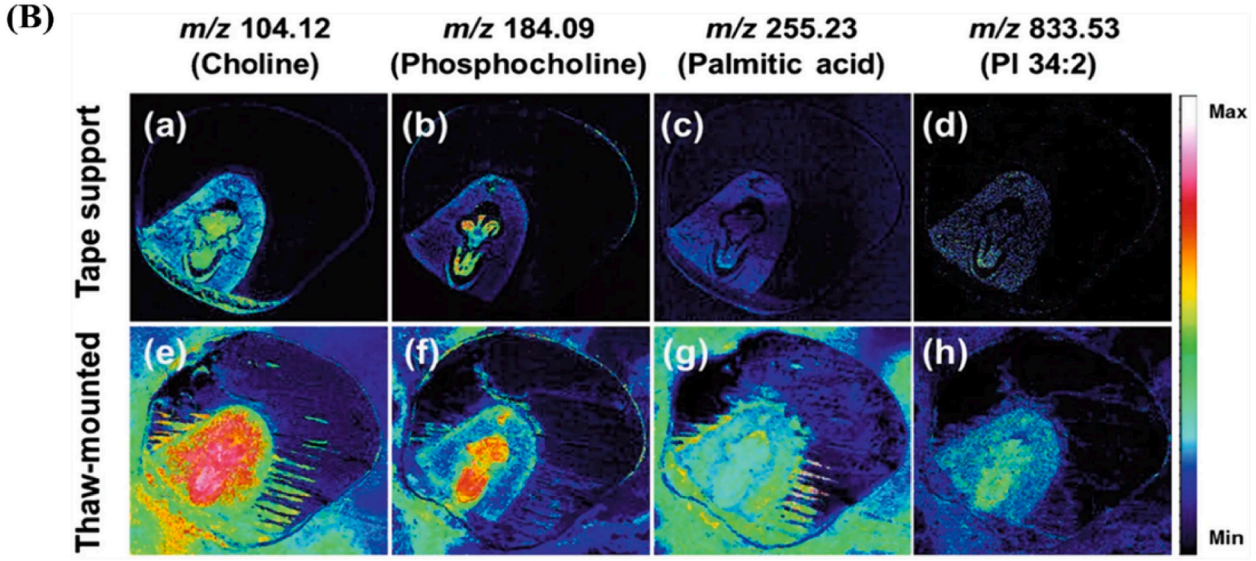
In a similar vein of enhancing analytical performance, Miniaturized Liquid Chromatography (Miniaturized LC) offers substantial improvements in resolution while also addressing sustainability concerns. Ferrero et al. (Ferrero et al., 2019) showcased how columns with diameters as small as 50 μm, packed with sub-2 μm particles, can achieve up to 300,000 theoretical plates per meter. While both 2D-LC and miniaturized LC focus on achieving high separation efficiency, miniaturized LC emphasizes reducing solvent and sample consumption. This miniaturization presents an advantage in terms of environmental impact and cost savings but comes with the trade-off of requiring meticulous management of void volume to maintain sensitivity (Huertas-Pérez et al., 2024). Thus, although both techniques excel in resolution, 2D-LC is better suited for complex sample analysis, while minimizing void volume (V_0), especially in the capillary column connection (Fig. 3A) offers a more resource-efficient approach.

HRMS, especially when integrated with UHPLC, takes sensitivity to new heights. Medina et al. (Medina et al., 2021) highlighted HRMS's ability to detect trace mycotoxins at concentrations as low as 0.001 ng/mL, a level of sensitivity that surpasses conventional methods. Similarly, Du et al. (Du et al., 2018) demonstrated HRMS's efficacy in cereal analysis, reaching detection limits of 0.0013 mg/kg. Compared to 2D-LC and miniaturized LC, HRMS offers unparalleled mass accuracy and the ability to identify analytes with high precision, often exceeding 100,000 resolution points (Li et al., 2021). However, this precision comes at a cost, as HRMS systems are expensive and require extensive calibration and maintenance. In this regard, while 2D-LC and miniaturized LC excel in separation capabilities, HRMS stands out for its precision in mass analysis, making it indispensable for applications requiring exact mass measurements.

Multidimensional gas chromatography (MDGC) provides another layer of advancement, especially for volatile compound analysis. Nolvachai et al. (Nolvachai et al., 2020) highlighted MDGC's strength by identifying 128 volatile compounds in Portuguese bread, compared to only 26 compounds detected using the traditional GC−MS (Fig. 3B(a)). This level of detail is comparable to the intricate separations achieved with 2D-LC but is tailored for gas-phase analyses. Fig. 3B(b, c) illustrates how MDGC provided a detailed aroma profile, highlighting components like 2-furanmethanol and maltol, which contribute to the bread's creamy and caramel notes. Further, the analysis of peaches using super-resolved GC × GC, shown in Fig. 3C(a) revealed 177 compounds correlated to the fruit's quality. The curve-fitting approach used in Fig. 3C(b) ensured retention time accuracy, with %RSD values for the first retention time (1tR) ranging from 0.003 to 0.066% and for the 2tR from 0.305 to 0.551%. Fig. 3C(c) presents centroid representations of the peaks by their positions in the 2D plane, while Fig. 3C(d) shows the deconvolution of coeluted peaks into three distinct peaks. In addition, Fig. 3C(e) demonstrates how MDGC uncovered the presence of minor components like 2-butanol, which were previously masked by larger peaks, emphasizing the technique's sensitivity and power in food analysis. The MDGC technology, for example, has exhibited an improved sensitivity feature. Compared to 2D-LC, MDGC specializes in separating volatile analytes, showcasing exceptional sensitivity for applications like detecting benzene at 0.5 ppb and formaldehyde at 1 ppb (Pua et al., 2023).

In summary, recent developments in chromatography have significantly enhanced the precision and efficiency of analytical methods. While 2D-LC and Miniaturized LC focus on high-resolution separation, the former excels in handling complex mixtures, and the latter emphasizes sustainability. HRMS stands out for its unparalleled mass accuracy and sensitivity but requires extensive resources to maintain. Meanwhile, MDGC offers exceptional performance for volatile compound analysis, highlighting its importance for applications in food quality and safety. Each technique has its advantages and limitations, emphasizing the need for strategic selection based on specific analytical requirements.





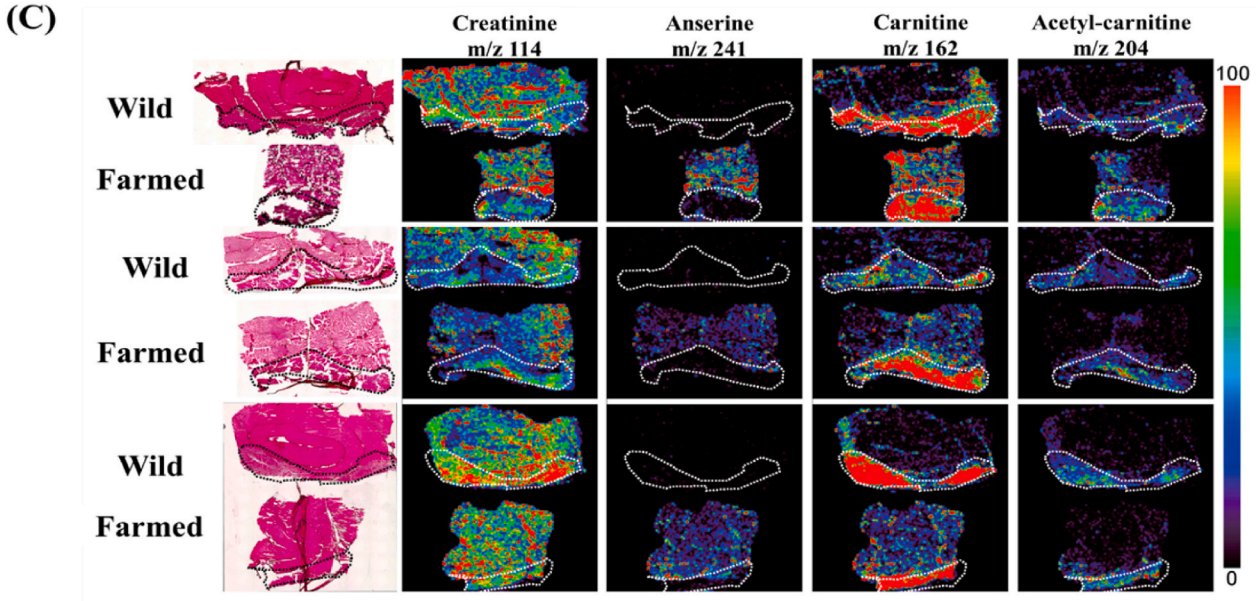


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Fig. 2. (A). MS imaging of components in carrot species and veal sausage: A: Orange carrot: Composite of optical image and single ion image of beta-Carotene ($[M]^+$, m/z 536.43765, displayed in orange), with a pixel resolution of 50 μm. B: Purple carrot: Composite of optical image and single ion image of Cyanidin ($[M]^+$, m/z 287.05501, shown in purple), with a pixel resolution of 80 μm. C: Optical image alongside RGB MS image displaying three components in veal sausage: Disaccharide ($[M+Na]^+$, m/z 365.10544, represented in red), PC(36:4) ($[M+Na]^+$, m/z 804.55138, shown in green), and cholesterol ($[M\text{-}H_2O+H]^+$, m/z 369.35158, depicted in blue), with a pixel resolution of 20 μm. (B). TOF-SIMS images of corn seed tissue demonstrate the distribution of (a), (e) choline, (b), (f) phosphocholine, (c), (g) palmitic acid, and (d), (h) PI 34:2, prepared using both the tape support and thaw-mounting techniques (C). Imaging results obtained via matrix-assisted laser desorption/ionization mass spectrometry (MALDI-MS) showing the distribution of creatinine, anserine, carnitine, and acetyl carnitine in wild and farmed red sea bream. The red muscle is indicated by dotted outlines. Edited with permission from (Goto-Inoue et al., 2019; Kim et al., 2017; Kokesch-Himmelreich et al., 2022). Copyright Springer©2017, Elsevier© 2022 and ACS©2019. (For interpretation of the references to colour in this figure legend, the reader is referred to the Web version of this article.)

3. AI-enhanced food detection and sensor technologies

Ensuring food safety and quality has become increasingly complex due to the rapid evolution of contaminants and the global scale of food production. Traditional detection methods, while effective, often face limitations in speed, precision, and scalability. Recent technological advancements have paved the way for innovative approaches that integrate artificial intelligence (AI) and advanced sensor technologies to overcome these challenges. These tools not only enhance the detection of contaminants but also provide real-time monitoring, improving the overall reliability of food safety processes. By leveraging the capabilities of AI, the detection, analysis, and response times can be significantly reduced, ultimately protecting public health more efficiently.

3.1. Next-generation sensors for food safety and quality control

Recent advancements in sensor technology have significantly enhanced the detection of contaminants and the monitoring of food quality. For example, the near-infrared (NIR) fluorescent probe Dpyt can rapidly detect bisulfite and organic amines, with observable colour changes within just 5 s (Niu et al., 2024). In the context of salmon freshness monitoring, Dpyt was able to identify spoilage at 45 h, providing a visual indication when total volatile basic nitrogen (TVB-N) reached 30.33 mg/100 g (Zhong et al., 2024). This speed and accuracy in detecting spoilage are comparable to the ECL aptasensors developed by Li. et al. (Li et al., 2023a), which demonstrated high sensitivity and specificity for pollutants like kanamycin (KAN) in milk with a limit of detection of 0.43 pM and Vibrio parahaemolyticus (VP) in artificial seawater with an LOD of 1.0 CFU/mL. Both technologies enable real-time monitoring; however, Dpyt provides a quick visual response, whereas ECL aptasensors focus on precise molecular-level detection.

Enhancing this field further, 3D-printed biodegradable hydrogel composite sensors were developed for spoilage monitoring in meat and fish. These sensors, crafted to be pH-responsive and effective across a range from 2 to 13, offer sustainability through their flexibility and biodegradability (Popoola et al., 2024). On the other hand, a dual-mode fluorometric-colorimetric sensor for formaldehyde detection achieves low LODs (0.623 μM and 0.791 μM) and delivers high recovery rates, making it suitable for accurate, on-site formaldehyde analysis (Chen et al., 2024c). Both sensor types emphasize practical application in food safety, but the former stands out for its eco-friendly design, while the latter provides dual detection for increased accuracy.

Incorporating AI into sensor technology, a portable fibre optic fluorescence detection system was created, employing a Radial Basis Function Neural Network (RBFNN) to achieve 100% accuracy in detecting pathogens like ASFV and Salmonella, even in fluctuating environmental conditions (Guo et al., 2025). In contrast, a nitrogen-doped Ti3C2Tx sensor was optimized for real-time monitoring of ammonia, a spoilage marker, with high sensitivity across a range of 100 ppb to 100 ppm (Fan et al., 2024a). The AI-enhanced system excels in adaptive pathogen detection, while the nanomaterial-based sensor is geared towards sensitive monitoring of spoilage gases, demonstrating complementary strengths in the food safety landscape.

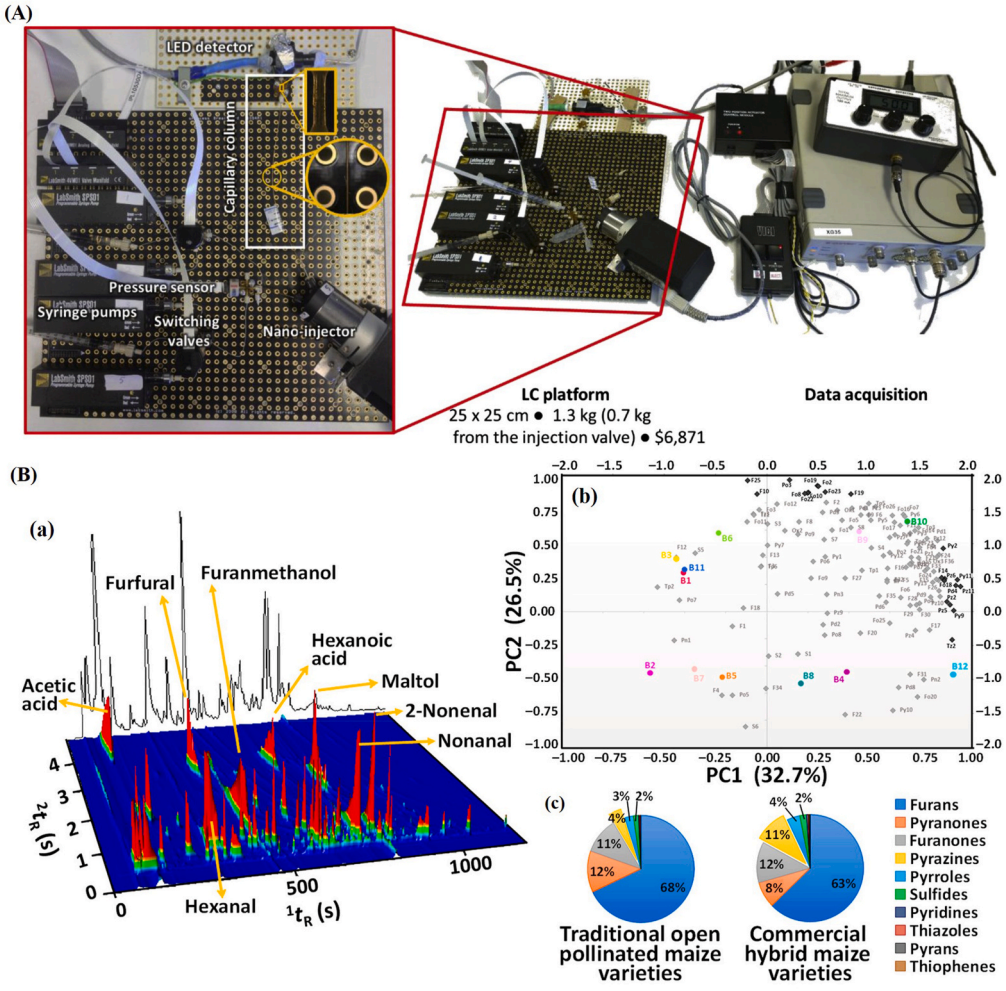
Significant progress has also been made with biosensors, including SAzyme-based designs that demonstrate exceptional sensitivity for food safety and nutritional evaluations (Wu et al., 2024). These biosensors detect analytes like glucose (LOD of 1.2 μM), ascorbic acid (LOD of 0.297 μM), and organophosphates (LOD of 0.87 ng/mL). Additionally, a sensor array can distinguish food preservatives at concentrations as low as 0.4 μM. Comparatively, NIR-II absorption-based biosensors specialize in enzyme-specific monitoring, quantifying myrosinase activity in broccoli with a high degree of precision (18.50 ± 1.58 mU/mg) (Qiao et al., 2023). Another notable advancement is the XDS probe, a red-emitting fluorescent probe formed from a coumarin derivative and rhodanic-CN, selectively responds to hydrogen sulfide (H_2S) (Fig. 4A). This probe accurately identifies H_2S in natural water and beer samples, with detection ranges from 48.13 to 63.13 μM and recovery rates from 98.25 to 105.22% (Shang et al., 2023). The XDS sensor also provides "naked-eye" monitoring of H_2S during food spoilage, with brightness changes over time indicating H2S release rates, making it a practical tool for spoilage detection in real-world scenarios (Liu et al., 2024b).

Further advancements involving material-based sensors such as metal-organic frameworks (MOFs) and covalent organic frameworks (COFs) have enhanced contaminant detection capabilities. For example, MIL-101(Cr) MOFs can adsorb up to 593 mg/g of lead ions (Li et al., 2018), while TpPa-1COFs have an LOD of 0.02 μg/L for pesticides (Wang et al., 2023). The Ag@ZIF-8 core/shell heterostructure nanowires exhibited remarkable SERS detection capabilities for contaminants like thiram and melamine. These necklace-like nanowires, shown in Fig. 4B(a), were synthesized through a simple two-step process that enhanced SERS performance (Fig. 4B(b-i)). The SERS signals for thiram (DTF) were quantifiable at 10^{-7} M with an enhancement factor (EF) of $\sim 1.9 \times 10^7$, while melamine (TTA) detection at 10^{-6} M had an EF of $\sim 1.3 \times 10^6$, as confirmed by SERS spectra in Fig. 4B(j and k). These nanowires demonstrated practical applications, such as detecting DTF residues on the surface of apple peels (Cheng et al., 2021). In addition, the amino-functionalized Al-MOF (NH_2-MIL-53(Al)) nanosensor demonstrated effective fluorescent detection of tetracyclines (TCs) in milk, with fluorescence-quenching efficiencies of 57% for doxycycline (DOX), 69% for tetracycline (TET), and 89% for oxytetracycline (OTC) (Li et al., 2019b).

In summary, next-generation sensors have transformed food safety and quality control through rapid, sensitive, and environmentally conscious technologies. While AI-enhanced and nanomaterial-based sensors offer precise and adaptive detection capabilities, biodegradable hydrogel sensors emphasize sustainability. The integration of advanced materials, such as MOFs and COFs, has expanded the scope of contaminant detection, underscoring the field's evolution towards real-time, practical solutions. These technologies collectively represent a critical advancement in ensuring food safety and quality, providing diverse and powerful tools for modern food analysis. Table 1 offers a comprehensive overview of these advanced sensor methods and their various applications.

3.2. Boosting food chemistry with artificial intelligence and machine learning

The integration of artificial intelligence (AI) and machine learning (ML) is revolutionizing food chemistry, enhancing data processing and prediction capabilities (Yi et al., 2024). For example, AI-based



(caption on next page)

Fig. 3. (A). A diagram and image depict the portable MPLC system. (B). (a) A GC × GC–TOFMS chromatogram of broas, highlighting the major components, and (b) chemometric analysis demonstrating the distinction in volatile profiles between samples made from traditional open-pollinated maize and commercial hybrid maize varieties. The PCA projection depicts the samples (represented by colourful dots) and the variables (shown in grey). (c) Pie charts show the proportion of chromatographic area for each chemical class, with pyrazines accounting for the majority of the variances between samples, indicating off-flavours in the product. (C). The super-resolved data processing method applied to GC × GC–TOFMS analysis of peach samples. Peaks in the modulated chromatogram, (a) are recognized, and the centroid approach is used to establish their precise maxima. This allows for the deconvolution of overlapping peaks in the 3D chromatogram of peach samples (d and e). Edited with permission from (Bento-Silva et al., 2022; Li et al., 2015; Nolvachai et al., 2023, Nolvachai et al., 2020). Copyright Elsevier ©2015, ACS ©2023 and ©2020.

prediction models simplify the analysis of chemical properties and interactions within food matrices, facilitating better predictive accuracy (Wang et al., 2024). Specifically, machine learning methods have proven effective in predicting food freshness, potentially extending shelf life by 30% through better stock management and food quality control (Ayres et al., 2021). In contrast, data mining and pattern recognition methods, such as those used in the Internet of Chemical Things (IoCT), significantly reduce analysis time, especially in contaminant detection and flavour optimization (Prabhu & Urban, 2020). This highlights AI's adaptability; whether it is extending shelf life or ensuring food safety and quality, these applications cater to diverse food industry needs.

High-accuracy detection of food adulterants further showcases AI's potential. Techniques like Support Vector Machines (SVM) and Convolutional Neural Networks (CNN) have achieved impressive results (Nath et al., 2024), with CNN models reaching 99. 85% accuracy in detecting mutton adulteration (Zhang et al., 2022) and 95% accuracy in honey classification (Izquierdo et al., 2020). Although the performance of these models may vary depending on the complexity of the food matrix, their consistent effectiveness across different applications illustrates AI's reliability in combating food fraud. Beyond laboratory settings, AI is also transforming agricultural practices. For example, image-processing robots for harvesting ripe strawberries increase productivity while reducing labor costs. Compared to more data-driven applications like quality or adulteration detection, these practical uses highlight AI's broader impact, demonstrating its benefits from field operations to consumer-level applications (Bouguettaya et al., 2022).

The versatility of AI in food chemistry is well illustrated in Fig. 4C, which analyzes the aroma profile of Brazilian wines. Fig. 4C(a) reveals distinct chemical profiles that differentiate wine types, identifies key analytes using Fisher Ratio Analysis (Fig. 4C(b)), and quantifies compound concentrations through peak area comparisons (Fig. 4C(c)) (Trinklein et al., 2023).

Meanwhile, Fig. 4D demonstrates the combination of optical sensor arrays with machine learning capabilities for detecting and analyzing food. These sensor arrays are designed to identify a wide range of chemicals in food substances, generating multiple variables for each food sample based on their chemical compositions (Peveler, 2024). Machine learning models, such as Support Vector Machines and artificial neural networks, analyze the collected data to identify patterns and categorize the food samples. This analysis provides crucial insights into food quality, authenticity, and safety, enabling applications from manufacturing processes to consumer-level use.

A notable advancement in food safety involves the use of silver nanoparticles (AgNPs) combined with AI, which enhances contaminant detection down to trace levels. AgNP-based biosensors can achieve 97.6% accuracy in identifying pesticide residues (Tun et al., 2022). In another application, AI-powered smart packaging reduces food waste by up to 30% by monitoring freshness in real-time (Barthwal et al., 2024). While AgNP biosensors prioritize precision in contaminant detection, smart packaging focuses on real-time shelf-life management, demonstrating AI's complementary roles in food safety and waste reduction. Moreover, hyperspectral imaging combined with deep learning has shown high effectiveness in detecting food contaminants, with accuracy rates exceeding 95% for cereals. Models developed to detect deoxynivalenol in wheat achieve 92% sensitivity and 90% specificity, offering non-invasive, high-accuracy alternatives for quality assessment (Caratti et al., 2024). Compared to simpler freshness or contaminant analysis methods, hyperspectral imaging provides a comprehensive, non-destructive alternative for quality assessment. AI applications continue to expand, encompassing protein content estimation in cereals, bacterial identification, strawberry ripeness assessment, and olive oil categorization, underscoring AI's widespread influence on food quality and safety. In summary, AI and ML are revolutionizing food chemistry through innovations that span predictive modelling, high-accuracy detection, and practical agricultural applications. The combination of advanced imaging, sensor technologies, and deep learning models offers powerful tools for ensuring food safety and optimizing production processes. For a comprehensive overview of AI and ML methods, including their specific applications, advantages, and evaluation criteria, refer to Table 2.

4. Prospects and obstacles in advanced food analysis

4.1. Critical challenges

Depending on the type of food analysis, various techniques suffer from significant drawbacks that reduce their overall effectiveness and credibility. Surface-Enhanced Raman Spectroscopy (SERS) holds substantial potential but faces several challenges. It is primarily limited by issues such as sensitivity, variability of the substrate, and matrix interference, which can be quite complex when analyzing food samples (Jahn et al., 2017). Wu et al. (Wu et al., 2021) also highlight the limitation caused by the absence of a standardized Raman spectra database, making broader applications more difficult. Despite these limitations, SERS has shown promise in reaching detection limits of 19.87 ng/mL for chlorpyrifos and 38.4 ng/mL for patulin (Guo et al., 2023), although challenges remain. Additionally, Raman spectroscopy is hindered by its inherently weak signal, which accounts for only 10^{-6} of the incident light intensity (Singh & Blümich, 2016). This weak signal complicates the identification of low-concentration analytes, often exceeding the detection limit for certain contaminants, which is around 100 ppm.

Additionally, fluorescence interference poses another significant challenge, causing up to 90% loss of spectral information, which complicates the accurate identification of food components (Xu et al., 2020). Infrared (IR) spectroscopy, on the other hand, is limited by cancelled absorption bands, which can lead to a misclassification rate of 20% within complex food matrices (Fakayode et al., 2020). Furthermore, the sample preparation required for IR spectroscopy may alter the chemical structure of food materials, complicating the interpretation of results. In comparison, Nuclear Magnetic Resonance (NMR) spectroscopy is highly valued for its ability to provide detailed insights into molecular structures. However, NMR is hindered by high operational costs and the need for relatively large sample volumes, making it impractical for routine use. Each method comes with distinct trade-offs. Fluorescence interference impacts data reliability, IR spectroscopy is accessible but prone to structural misinterpretations, and NMR offers precise structural analysis but at a cost that limits its widespread application.

With regards to mass spectrometry, the WPMPI-MS holds potential but has a high detection limit for toxicological standards in serum and lower sensitivity for detecting heavy metals like cadmium, falling short of ICP-MS performance (Chu et al., 2024). Additionally, fragmentation differences complicate the analysis of complex samples (De Vijlder et al., 2018). The cost of mass spectrometry imaging (MSI) instrumentation, which often exceeds $500,000, along with the time-consuming sample

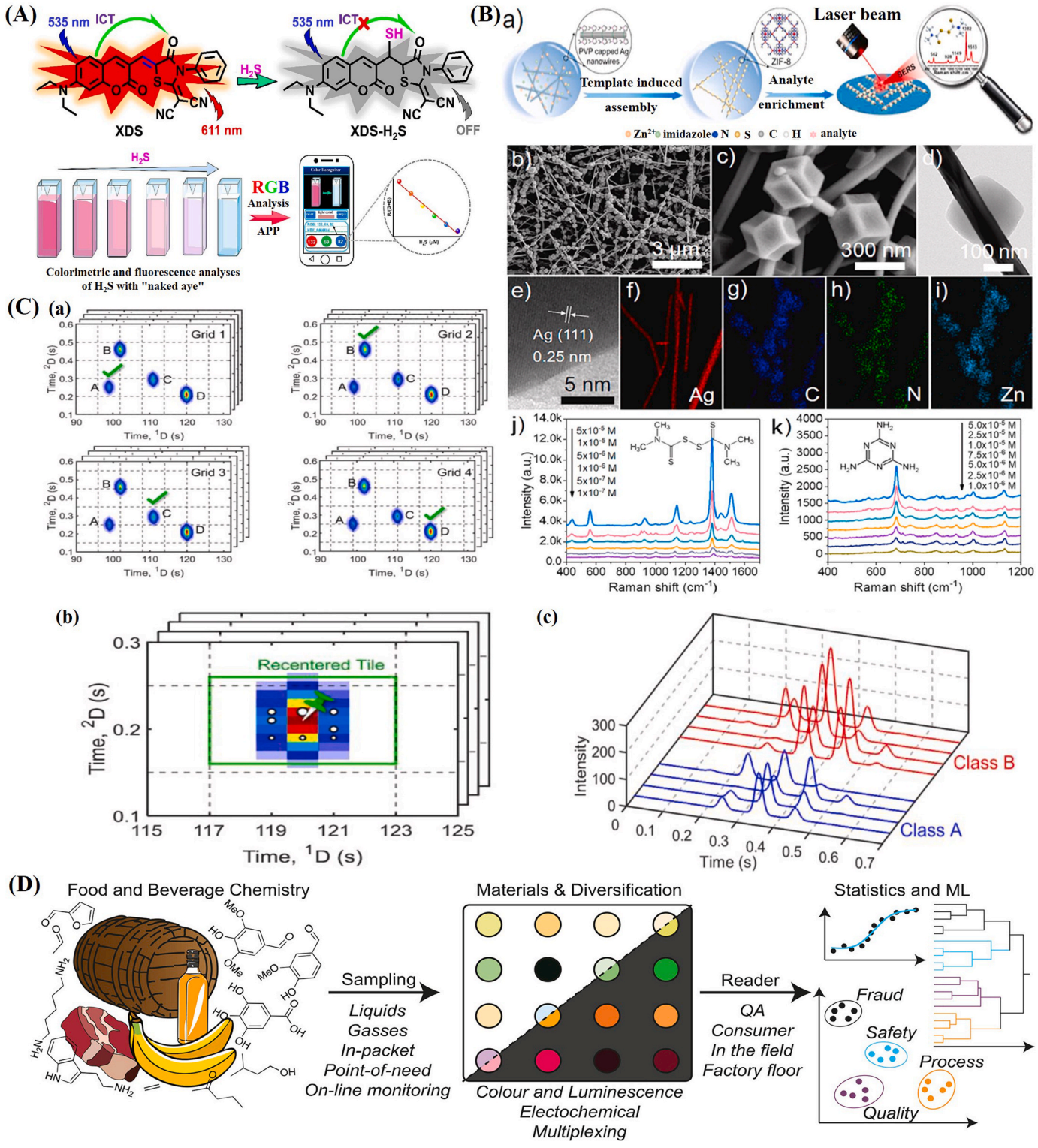


Fig. 4. (A). A proposed method for recognizing XDS's interaction with H_2S and accurately detecting H_2S in real-world samples using a smartphone. (B). (a) Diagram showing the formation process of Ag@ZIF-8 nanowires and the SERS detection process for target analytes; (b), (c) SEM images displaying necklace-like Ag@ZIF-8 nanowires at various magnifications; (d), (e) High-resolution TEM images of a single Ag@ZIF-8 core/shell nanowire; (f)–(i) Elemental mapping of Ag (red), C (blue), N (green), and Zn (cyan) from the same region; SERS detection of thiram (j), and melamine (k) at different concentrations in water using necklace-like Ag@ZIF-8 nanowires. (C). (a). Evaluation metrics based on chromatograms divided according to four tiling schemes. (b). Elimination of redundant hits using pinning clustering algorithms. (c). Use the identified pin locations to delve deeper into the high-fidelity data. (D). Summary of sensing arrays used in food and beverage analysis. Sensing arrays provide unique advantages for analyzing the sensory profiles of food and drinks in a compact format suitable for packaging or factory floor use. Various arrays with diverse outputs can be customized for specific applications and interpreted by either a consumer or an operator monitoring a process. These sensors can be designed for quality control, safety, spoilage detection, or to identify food fraud. Edited with permission from (Li et al., 2019a; Peveler, 2024; Shang et al., 2023; Trinklein et al., 2023). Copyright Elsevier © 2023, © 2019 and ACS © 2023 and © 2024. (For interpretation of the references to colour in this figure legend, the reader is referred to the Web version of this article.)

Table 1
Advanced sensor methods for food safety and quality control.

Category	Analyte	Sample Type	Method	Limit of Detection	Sensitivity	Shelf Life	Response Time	Reproducibility	Reference
Metals	Hg^{2+}	Water	Label-free SERS-based SiO2@Ag sensor	1×10^{-8} M	Linear range (1×10^{-8}-1×10^{-3}M)	–	–	–	Lu et al. (2018)
	Pb^{2+}	Skin toner, AHC toner	SERS-based AuNPs sensor	0.7 nmol/L	Good linear range (0.002–0.075 μmol/L)	–	–	–	Yan et al. (2021)
		complex samples	Spherical nucleic acid fluorescence probe	86 fM	High	Long-term stability expected	–	High	(Li et al., 2022)
	Cadmium	Water	Transgenic Zebrafish Biosensor	0.5 ppm	90%	6 months	10 min	RSD <5%	(Liu et al., 2016)
		Milk	Whole Cell Biosensor	1.0 μg/L	95%	65 days	15 min	RSD <2%	Kumar et al. (2017)
	Arsenic	Water	Electrochemical Biosensor	0.0008 ppb	4.91 μA/ppb	1 year	5 min	95% recovery	Gao et al. (2013)
	Mercury	Water	Transgenic Zebrafish Biosensor	0.1 ppm	95%	6 months	10 min	RSD <5%	Fakayode et al. (2024)
Bacteria	*S. aureus*	Food samples	CRISPR/Cas12a with LFA	2×10^{1} CFU/mL	High	Long-term stability expected	35 min	High	(Zhao et al., 2023)
		Tap water	Electrochemical biosensor based on SDA	8 CFU/mL	High	–	–	RSD ~0.44% and 2.03%	Cai et al. (2021)
	E. coli O157	Pond water	Electrochemical biosensor	0.1 CFU/mL	$0.98 \left(\frac{\frac{\Delta R_{ct}}{R_{ct}}}{\frac{CFU}{mL}} \right) / cm^2$	–	30 min	High	Gangwar et al. (2022)
		Food samples	CRISPR/Cas12a with MOF immunomagnetic beads	6.5×10^{4} CFU/mL	High	Long-term stability expected	–	High	(Zhao et al., 2023)
		Food samples	Electrochemical biosensor	7 CFU/mL	High	94.3% after 30 days at 4 °C	–	Intra:7.2%; Inter: 5.8%	(Li et al., 2020b)
	E. coli	Drinking Water	Electrochemical Method	1 CFU/100 mL	90%	1 year	8 h	RSD <5%	Chorti et al. (2022)
		Spinach leaves	Electrochemical biosensor	1 CFU/mL	High	–	6 h	High	El-Moghazy et al. (2022)
		Food	Smartphone-based optical biosensor	10 CFU/mL	High	6 months	30 min	High	Yang et al. (2022)
	Salmonella typhimurium	Spiked milk	Bio-barcode immunoassay-CRISPR/Cas12a	Single-digit levels	High	Long-term stability expected	60 min	High	(Zhao et al., 2023)
		Food samples	Electrochemical biosensor	1–10 nM	10^{3}–10^{4} CFU/mL	6 months	30 min - 2 h	85–95%	(Silva et al., 2018)
		Food samples	Silver nanoparticles	10^{2} CFU/mL	High	–	2 h	High	Mathelié-Guinlet et al. (2019)
	Bacillus Cereus	Infant Food	DNA-Based Biosensor	10 CFU/g	95%	6 months	30 min	RSD <5%	Izadi et al. (2016)
Pesticides and Toxins	Carbaryl	Tomato	Acetylcholinesterase biosensor	1.9 nmol/L	High	30 days	–	RSD ~2.2%	(da Silva et al., 2018)
	Malathion	Water	Amperometric Biosensor	0.1 ppb	85%	6 months	10 min	RSD <5%	Junior et al. (2021)
	Aflatoxin A1	Peanuts	TSA-PC sensor	2 pg/mL	High	–	15 s	Intraday CV: 8.23–14.83%	(Chen et al., 2023)

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Table 1 (*continued*)

Category	Analyte	Sample Type	Method	Limit of Detection	Sensitivity	Shelf Life	Response Time	Reproducibility	Reference
								Inter-day CV: 11.67–14.13%	
	Aflatoxin B1	Peanuts	Au NR/AFB1−BSA	0.16 ng/mL	High	–	45 min	–	Farka et al. (2017)
		Maize	Label-free immunosensor	0.1 ng/mL	High	–	30 min	High	Ma et al. (2016)
	Mycotoxins (ZEA, DON)	Corn, oats, barley	Quantum dot nanosensor	80 μg/kg (Maize Don)	High	–	5 min	High	Adunphatcharaphon et al. (2022)
	Atrazine	Cherry, tomato, grape	SERS-based aptasensor	–	98.7−106.6%	–	–	–	Jiang et al. (2021)
	Paralytic Shellfish Toxins	Cell-based	Impedance biosensor (neuroblastoma cells)	0.03 ng/mL	High	–	2 h	–	Zou et al. (2015)
	Okadaic Acid	Cell-based	Smartphone-based biosensor (HepG2 cells)	3.41 μg/L	High	–	Real-time	High	Ye et al. (2019)
	Tetrodotoxin (TTX)	Cell-based	Smartphone-based impedance sensor	0.1 ng/mL	High	–	–	High	Tian et al. (2021)
Other Contaminants	Histamine	Fish and shrimp	Enzymatic electrochemical detection using DAO–CS–AuNPs Cry/PB/MWCNTs/SPCE	0.03 μmol/L	1.173 ± 0.076 nA/μmol/L	30 days	–	0.4%–1.2%	Nontipichet et al. (2021)
	Microcystin-LR	Water	Bimodal aptasensor (fluorescence and SERS)	0.50 ng/mL (fluorescence), 0.77 ng/mL (SERS)	–	–	–	–	(Li et al., 2020a)
	Nutrients	Food Products	Optical biosensors	–	High signal-to-noise ratio	Varies	Varies	High	Yang et al. (2022)

preparation, limits its widespread adoption (Shen et al., 2024). To make MSI more practical, Spengler (Spengler, 2015) suggest improvements in ionization techniques and the development of more user-friendly software. Two-dimensional liquid chromatography (2D-LC) offers valuable analytical capabilities but introduces its difficulties, such as sensitivity loss from analyte dilution at high flow rates. For instance, during red wine analysis, excessive flow rates diluted trace components, making it difficult to detect low-concentration contaminants (Cacciola et al., 2020). Miniaturized LC systems, while promising, still struggle with technical challenges like elevated back pressure, which can exceed 600 bar (De Vos et al., 2016). Desmet et al. (Desmet et al., 2020) emphasize the necessity of precise pressure control, as micro-LC columns operating at 1 μL/min can generate pressures around 400 bar.

In addition, High-Resolution Mass Spectrometry (HRMS) adds complexity due to matrix effects and intricate sample preparation requirements. Techniques such as QuEChERS and solid-phase extraction (SPE) help manage matrix effects but increase analytical complexity and cost (Kanu, 2021). Yu et al. (Yu et al., 2023) note that the vast data volumes produced by HRMS necessitate advanced software for processing, while Chaker et al. (Chaker et al., 2020) highlight the shortcomings of peak area-based quantification. Dusza et al. (Dusza et al., 2022) suggest that emerging methods for estimating ionization efficiencies are promising, although they remain under development. IoT sensor networks are becoming increasingly important in food analysis, but stability, specificity, and long-term reliability are significant challenges (Luo et al., 2023). Mayer et al. (Mayer & Baeumner, 2019) report that while 60–70% of sensors achieve the necessary stability and specificity, around 40% experience significant drift within six months, leading to data loss. The cost of wearable and point-of-care sensors, ranging from $100 to $500, is another barrier, especially in resource-limited settings (Ozturk et al., 2023). Furthermore, the environmental impact of disposable sensors is concerning, with electronic waste projected to increase by 25% by 2023 if proper recycling measures are not implemented (Valdés et al., 2021). AI and ML are revolutionizing food analysis by increasing speed and accuracy. However, these methods come with challenges, such as achieving reliable accuracy rates (Shaikh et al., 2022). Li et al. (Li et al., 2024) note that AI systems may only reach 70% accuracy in real-world applications, which is lower than the 85–90% accuracy of traditional methods. The “black box” nature of AI algorithms complicates their reliability, as the underlying decision-making processes are often unclear (Quinn et al., 2022). Additionally, training deep learning models is energy-intensive, making them unsuitable for low-energy environments. Data variability, remains a pressing issue, as up to 30% of learning data can be incorrect, further impacting AI performance (Souza et al., 2020).

In summary, food analysis techniques are evolving rapidly but continue to face critical challenges. SERS struggles with signal weakness and fluorescence interference, IR spectroscopy is prone to misclassification, and NMR is cost-prohibitive. Mass spectrometry, while powerful, is limited by high costs and fragmentation issues, while chromatography techniques grapple with pressure and sensitivity concerns. Even IoT-based sensors and AI systems have hurdles, including stability, energy demands, and data reliability. Addressing these challenges is essential for the continued advancement of food analysis technologies, balancing precision, cost, and practical applicability.

4.2. *Future innovations*

Food analysis stands on the cusp of transformative advancements, driven by the integration of cutting-edge spectroscopic techniques, innovative biosensing technologies, and the latest developments in artificial intelligence and machine learning (Meira et al., 2024). These advancements promise to improve the accuracy and efficiency of food analysis, which is critical for ensuring the safety and quality of food products. One of the most promising advancements in the development of optical biosensors, illustrated in Fig. 5A. These biosensors employ

Table 2
Critical evaluation of AI and ML techniques in food detection: Applications and accuracy.

Aspect	Technique	Application	Benefits	Examples	Performance metrics	References
Flavor enhancement and consumer preference analysis	Machine Learning	Predicting flavor profiles	Enhanced understanding of consumer preferences	Cotton-candy grapes, specialty tomatoes	Models explained 25% more variation in sweetness	Ferrão et al. (2023)
	AI-Driven Flavor Profiling	Enhancing flavor profiles in food products	Improved product development	AI used to develop a new flavor for a snack brand	Consumer Acceptance: 80–90% positive feedback Flavor Consistency: Variability <5%	(Yu et al., 2018)
	Machine Learning Algorithms	Flavor enhancement in food products	Increased consumer acceptance	Flavor optimization in beverages	30% increase in consumer acceptance	Zeng et al. (2023)
Food quality assessment and authenticity verification	AI Decision-Making Tools (PLS-DA)	Quality assessment and decision-making	Enhances accuracy in quality classification and benchmarking	Classification of hazelnut quality based on aroma profiles	Successful discrimination of product qualities	Caratti et al. (2023)
	Convolutional Neural Networks (CNN)	Identifying species and quality of food	High accuracy in classification	Identifying species in caviar	Accuracy: 95%, F1 Score: 0.93	Al-Habsi et al. (2024)
	Convolutional Neural Networks (CNN)	Detection of food spoilage	High accuracy in image classification	Spoilage detection in fruits and vegetables	95% accuracy in spoilage detection	Ge et al. (2023)
	Advanced Computer Vision (CNN)	Automated inspection of food products	Real-time defect detection and classification	Using CNNs for visual inspections of packaged foods	Defect detection accuracy improved to 98%	Chotwanvirat et al. (2024)
	Image Recognition	Visual inspection of food products	Improved accuracy in detecting defects	Automated system detects bruises on fruits	Accuracy: 95% False Positive Rate: <5% False Negative Rate: <2%	Feng et al. (2024)
	Computer Vision	Automated inspection of food products	Reduces human error and increases efficiency	AI systems inspecting fruits for quality	Inspection speed: 100 items/min, Defect detection rate: 95–98%	(Chen et al., 2024b)
Data analysis, representation, and model training in food science	Machine Learning Algorithms	Analyzing complex datasets from GC × GC results	Facilitates the identification of patterns and correlations in large datasets	Use of AI for rancidity level assessment	Median % RE values for key compounds: octanal (406), 4-heptanone (646), γ-hexalactone (69), 2-heptanol (633.5)	Squara et al. (2023)
	Machine Learning	Predictive analytics for food safety risks	Early detection of potential hazards	Predicting outbreaks based on historical data	Accuracy: 85–95%, Precision: 80–90%, Recall: 75–85%	Charlebois et al. (2021)
	AI Smelling Machine	Monitoring aroma blueprints in food products	Objective evaluation of aroma profiles; supports consumer preference analysis	Development of an expert system for key-odorants	OAV values visualized in log10 scale; TGT samples-maintained aroma characteristics longer	Squara et al. (2023)
	SMILES Notation	Encoding chemical structures for model training	Facilitates the representation of complex chemical data	Use of SMILES for various antioxidants	Enhanced model performance through data augmentation	Kou et al. (2023)
	Data Augmentation	Enhancing training datasets for better model accuracy	Addresses overfitting, improves model robustness	Augmenting with stoichiometric ratios in SMILES	Increased predictive accuracy from $R^2 = 0.01$ to $R^2 = 0.90$ with fine-tuning	(Ayres et al., 2023)
Detection of pathogens and contaminants	Biosensors combined with ML	Monitoring foodborne pathogens	Rapid detection, reduced reagent use	Detection of pathogens in various food products	98% detection rate for pathogens	Cui et al. (2020)
	Deep Learning	Rapid identification of foodborne pathogens	Faster response to contamination risks	Deep learning model identifies Salmonella in 2 h	Sensitivity: 95–99% Specificity: 90–98% Time to Detection: 1–4 h	Garcia-Vozmediano et al. (2024)
	Artificial Neural Networks (ANN)	Detection of pathogens in food	Rapid and reliable detection	Salmonella detection in poultry	50% reduction in detection time	Zalnezhad et al. (2022)
	Optical SVM	Detection of antibiotics in milk	High sensitivity and specificity	Kanamycin, Ampicillin, Oxytetracycline, Sulfadimethoxine	Detection accuracy of 95% for multiple antibiotics	Pérez Santín et al. (2021)
	Machine Learning Algorithms	Predicting food safety risks	Improved predictive accuracy, data-driven insights	Predictive models for foodborne disease outbreaks	92% accuracy in predicting outbreaks	(Deng et al., 2021)
Automation and real-time monitoring in food handling	Deep Convolutional Neural Network (DCNN)	Monitoring meat freshness	High sensitivity, integrated detection system	PAN-NSS color sensor	98.5% accuracy in freshness prediction	(Guo et al., 2020)
	IoT Sensors	Real-time monitoring of food storage conditions	Ensures optimal conditions to prevent spoilage	Smart refrigerators that monitor temperature	Response time: <1 min, Data accuracy: 95–99%	Yousefi et al. (2019)
	Delta Robots	Packaging of fresh fruits and vegetables	High practicality and low cost	Delta robots in packaging lines	Increased packaging speed by up to 30%	(Liu et al., 2020)
	Edge AI	Continuous monitoring of food storage conditions	Immediate alerts for temperature or humidity breaches	IoT sensors monitoring cold chain logistics	Response time to breaches reduced to under 5 min	Hernandez-Jaimes et al. (2023)

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Table 2 (*continued*)

Aspect	Technique	Application	Benefits	Examples	Performance metrics	References
	Fuzzy Logic Systems	Monitoring food safety standards	Real-time monitoring and alerts	Monitoring temperature and humidity in storage	20% reduction in spoilage incidents	Sonwani et al. (2022)
	Bayesian Neural Network	Evaluating sensory quality	Incorporates uncertainty in predictions	Sensory evaluation of ice cream flavors	Accuracy: 88%, Sensory score improvement: 15%	(Yu et al., 2018)
Nutritional and predictive analysis	Support Vector Machines (SVM)	Nutrient content prediction	Efficient processing of large datasets	Predicting fat and protein content in dairy	90% prediction accuracy	Tan et al. (2019)
	Machine Learning	Assessing nutritional content	Enhanced understanding of food composition	ML model analyzes nutrient levels in new recipes	Nutritional Accuracy: 95%, User Engagement: 70%	Samad et al. (2022)
	Deep Learning Models (Neural Networks)	Predictive analytics for food safety	High accuracy in identifying patterns of contamination	Using neural networks to analyze historical outbreak data	Reduction in foodborne illness rates by 40%	Tao et al. (2021)
	AI Algorithms	Forecasting foodborne illness outbreaks	Helps in proactive measures to mitigate risks	Models predicting E. coli outbreaks	Prediction accuracy: 80–90%, Time to intervention: 1–2 days	Zar et al. (2024)
Supply chain transparency and traceability	Distributed Ledger Technology (Blockchain AI)	Comprehensive tracking of food supply chains	Immutable records enhance accountability	Implementing blockchain for tracking organic produce	Traceability time reduced to under 30 min	Menon and Jain (2021)
	Blockchain	Tracking food supply chain	Enhances transparency and accountability	Blockchain for tracking farm-to-table processes	Traceability time: <1 h, Data integrity: 100%	Kamilaris et al. (2019)
	Anomaly Detection (Supervised Learning)	Identifying fraudulent food products	Early detection of fraud and mislabeling	Using supervised learning to detect anomalies in food labeling	Fraud detection accuracy improved to 95%	Sharma et al. (2024)
Consumer engagement and regulatory compliance	Chatbots and Virtual Assistants	Providing food safety information to consumers	Improves consumer awareness and education	Chatbots answering food safety queries	User satisfaction: 90–95%, Response accuracy: 85–90%	(Li & Zhang, 2023)
	Machine Learning Algorithms	Dynamic risk assessment and forecasting in food production	Proactive risk management and mitigation	AI models predict contamination risks and potential recalls based on environmental data	Risk assessment time reduced by 60%, Prediction Accuracy: 85–90%, Response Time: 30–50%	Taiwo et al. (2024)
	Natural Language Processing (NLP)	Analyzes reports and feedback for food safety insights	Identifies risks and provides real-time insights	Analyzes FDA reports and social media for food safety issues.	Compliance rate: 90–95%, Risk accuracy: 80–90%, Response: <1 h Sentiment Accuracy: 85–90%	(Abid et al., 2024; Zhou et al., 2024a)
	Data Mining	Ensuring compliance with food safety regulations	Streamlined compliance processes	Data mining identifies compliance gaps in audits	Compliance Rate: 95% Audit Efficiency: 40% reduction in time	Kleboth et al. (2022)

highly sensitive optical detection techniques, leveraging a broad surface area for effective binding, often enhanced with nanoparticles to boost signal detection (Mat Yeh et al., 2024). This technology is particularly vital for detecting trace amounts of harmful substances, such as UAV pork DNA, even in complex, multi-ingredient food matrices. The data generated by these biosensors can be further processed using AI, enabling the rapid identification of patterns and anomalies for faster, more accurate results. Real-time analysis provided by optical biosensors is crucial for food safety and quality assurance, highlighting the value of integrating nanotechnology and AI to mitigate safety and authenticity concerns (Zhou et al., 2024c).

In contrast, SERS is progressing through the development of aptamer-based sensors and the creation of comprehensive Raman spectra databases (Hassoun et al., 2024). These advancements aim to overcome challenges posed by complex food matrices, improving measurement reproducibility and efficiency. SERS benefits from the use of novel nanomaterials and optimized substrate designs that reduce interference and enhance measurement precision. While both optical biosensors and SERS emphasize sensitivity, SERS particularly focuses on addressing the challenges of reproducibility and data accuracy in intricate sample environments. IRES is also witnessing significant advancements aimed at increasing resolution and refining sample preparation techniques to maintain food integrity (Xuesong et al., 2024). This is especially critical for multicomponent samples, where maintaining precision and reliability is a challenge. IRES focuses on optimizing spectral clarity, which makes it valuable for detailed chemical characterization. While SERS and IRES share the goal of enhancing analytical accuracy, they differ in their primary emphasis: SERS improves reproducibility through advanced nanomaterial designs, whereas IRES seeks to optimize spectral resolution and sample handling. The miniaturization of spectroscopic equipment is another crucial area of innovation, particularly for on-site testing (Dirks & Poole, 2022). Portable Near-Infrared (NIR) devices, for example, have made significant strides but still face limitations, achieving around 85% sensitivity compared to conventional laboratory instruments (Tang et al., 2020). This highlights a common challenge across spectroscopic techniques: balancing portability with analytical precision. Both SERS and NIR are striving to close the performance gap between field and laboratory settings, albeit through different strategies, SERS through material advancements and NIR through device optimization.

On a separate front, machine learning and artificial intelligence are set to further revolutionize food analysis. Techniques like Convolutional Neural Networks (CNNs), and MobileNetV3 have shown impressive classification accuracies of over 95% in various applications (Deng et al., 2024). These models excel in pattern recognition and provide faster, more precise analysis. However, challenges such as overfitting and the need for hyperparameter optimization remain obstacles to achieving model interpretability and reliability. Innovations in AI-powered food detection systems are exemplified in Fig. 5B by Fan et al. (Fan et al., 2024b), where technologies like DCF-YOLOv8s, which use deformable convolutional layers and CloFormer attention mechanisms, have enhanced meal identification and recognition. Fig. 5C provides further

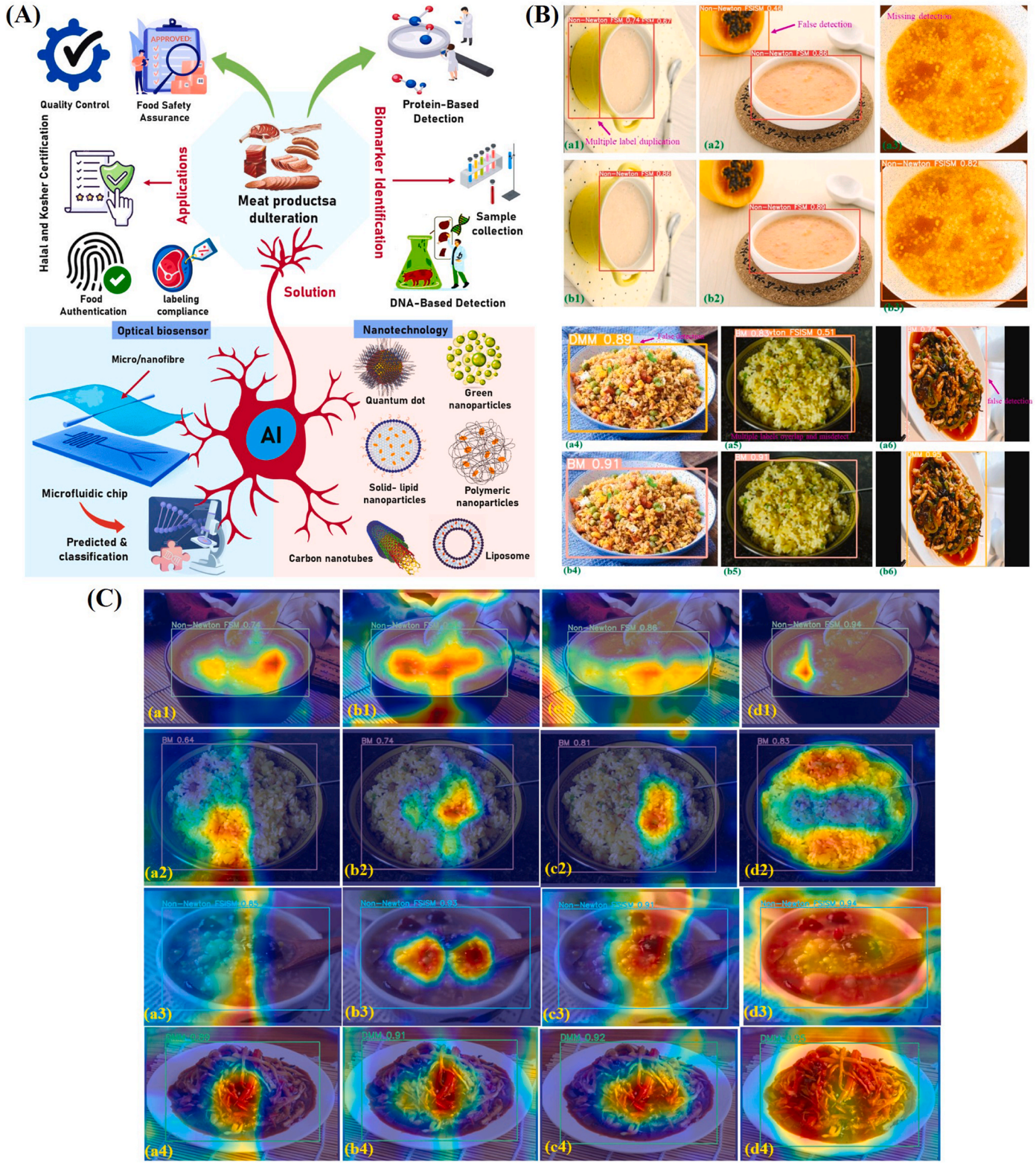

Fig. 5. (A). The process for developing an optical biosensor that integrates AI and nanoparticles for detecting and classifying DNA and proteins associated with pork is outlined. (B). A comparison of detection outcomes between the DCF-YOLOv8s model and the YOLOv8s model: images (a1) to (a6) show results detected by the YOLOv8s model, while images (b1) to (b6) show results detected by the DCF-YOLOv8s model. (C). Grad-CAM comparisons between the proposed DCF-YOLOv8s model and baseline models: letters a, b, c, and d represent the Non-Newtonian FSM, BM, Non-Newtonian FSISM, and DMM, respectively. Numbers 1, 2, 3, and 4 correspond to the feature maps from the baseline YOLOv8s model's backbone, the feature maps generated after introducing the CloFormer module to the YOLOv8s model, the feature maps after incorporating deformable convolution into the YOLOv8s model, and the feature maps from the backbone of the proposed DCF-YOLOv8s model, respectively. Edited with permission from (Fan et al., 2024b; Mat Yeh et al., 2024). Copyright Elsevier© 2024.

insights into AI's role in food quality management, showcasing improvements in detection speed and precision. Unlike spectroscopic techniques, AI models can process vast datasets and integrate multimodal inputs, offering comprehensive insights into food safety and quality. Nevertheless, AI-driven approaches require robust validation to address issues related to data heterogeneity and model transparency (Fan et al., 2024b). The integration of AI with spectroscopic techniques, such as using deep learning models to interpret complex spectral data, has shown promise in boosting analytical accuracy and efficiency. However, ensuring model reliability and maintaining interpretability are critical challenges that need to be addressed. As food analysis technology evolves, there is an urgent need for standardized methods and comprehensive spectral databases. Currently, only about 30% of research groups report adhering to standard protocols (Guo et al., 2021), underscoring the need for improved collaboration and data-sharing practices to achieve consistent and reliable results.

Despite the high initial costs of implementing advanced food analysis technologies, the potential economic benefits are significant. Enhanced quality control, fewer product recalls, and improved regulatory compliance are among the advantages (Belianinov et al., 2018). The global food testing market is expected to reach $20 billion by 2025 (Hassoun et al., 2024), highlighting the economic incentive for continued investment in these technologies. Although implementation is resource-intensive, the long-term gains from increased efficiency and reduced waste often outweigh initial expenditures. Overall, the future of food analysis will be driven by the convergence of advanced spectroscopic techniques and AI/ML innovations. Spectroscopic methods are evolving to improve sensitivity, resolution, and portability, while AI and ML are transforming data interpretation and decision-making processes. Overcoming challenges related to model reliability, device performance, and standardization will be crucial. Ultimately, these advancements aim to ensure food safety and quality management, providing actionable, economically viable insights validated through rigorous testing and collaborative practices.

5. Conclusion

Recent advancements in food analysis technologies have significantly enhanced the ability to detect contaminants and ensure food quality monitoring with improved speed and sensitivity. Innovations such as Wide Line Surface-Enhanced Raman Scattering (WL-SERS) and Inductively Coupled Plasma Mass Spectrometry (ICP-MS) have set new benchmarks in sensitivity, with WL-SERS offering notable advancements in melamine detection and ICP-MS enabling the detection of toxic elements like lead at ultralow levels. Chromatographic techniques like two-dimensional liquid chromatography (2D-LC) and High-Resolution Mass Spectrometry (HRMS) coupled with Ultra-High-Performance Liquid Chromatography (UHPLC) have proven effective for analyzing complex food matrices, although their high cost and complexity remain significant barriers to widespread use. Significant progress has also been made in sensor technology. Near-infrared (NIR) fluorescent probe Dpyt and electrochemiluminescent (ECL) aptasensors offer rapid and precise detection capabilities, enhancing real-time food safety monitoring. AI and machine learning (ML) have revolutionized food quality assessment, achieving remarkable accuracy levels, such as over 99.85% in detecting food adulteration. Despite these advancements, challenges persist. WL-SERS still struggles with weak signal strength and matrix interference, while techniques like HRMS and MSI are hindered by expensive instrumentation and complex sample preparation. Furthermore, 2D-LC systems face issues related to high back pressure and sensitivity loss, while sensor technologies require improvements in stability and affordability. AI and ML models demand extensive datasets and computational power, and the lack of transparency in AI decision-making processes remains a concern. The future of food analysis will likely depend on the strategic integration of spectroscopy, sensor technologies, and AI/ML systems. Enhancing sensor stability, reducing costs, and improving the interpretability of AI models will be crucial. Miniaturization and standardization of devices are expected to play a key role in making these technologies more accessible and operationally efficient. As advancements continue, a coordinated effort to address these challenges will be essential to further enhance the reliability and effectiveness of food safety and quality control methods.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Nomenclature

WL-SERS	Wide Line Surface-Enhanced Raman Scattering
LIBS	Laser-Induced Breakdown Spectroscopy
ICP-OES	Inductively Coupled Plasma- optical emission spectrometry
MSI Mass	Spectrometry Imaging
WPMPI-MS	Wide-Pore Matrix-Protected Ionization Mass Spectrometry
MALDI-TOF/TOF	Matrix-Assisted Laser Desorption/Ionization - Time of Flight/Time of Flight
LC-ESI-MS/MS	Liquid Chromatography - Electrospray Ionization - Tandem Mass Spectrometry
2D-LC	Two-Dimensional Liquid Chromatography
MDGC	Multidimensional Gas Chromatography
NIR	Near-Infrared
ECL	Electrochemiluminescence
LOD	Limits of Detection
SNR	signal-to-noise ratio
RMSEP	Root Mean Square Error of Prediction
RSD	Relative Standard Deviations
DoLP	Degree of Linear Polarization
TVB-N	Total Volatile Basic Nitrogen
AI	Artificial Intelligence
ML	Machine Learning
CNN	Convolutional Neural Networks

(*continued on next page*)

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IoCT	Internet of Chemical Things
SVM	Support Vector Machines
NLP	Natural Language Processing
FRA	Fisher Ratio Analysis
PLS-DA	Partial Least Squares Discriminant Analysis
ANN	Artificial Neural Networks

Data availability

Data will be made available on request.

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