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Emerging technologies for detecting food fraud: A review of the current landscape in the 2020s

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A R T I C L E I N F O

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A B S T R A C T

Background: Food fraud refers to the intentional adulteration or misrepresentation of food products for financial gain. It has become a rising global challenge in the 2020s, with significant implications for public health, consumer confidence, and economies. Complex international supply chains, economic pressures, and vulnerabilities exposed by the COVID-19 pandemic have amplified opportunities for fraudulent practices.
Scope and approach: This review examines the state-of-the-art of Emerging Technologies and Digitalization in Foods tackling food fraud. We outline advanced analytical methods, including spectroscopic, imaging, chromatographic, spectrometry techniques, molecular DNA assays, and novel sensor platforms, used to authenticate food and identify adulterants more rapidly and with improved sensitivity. Complementing these instrumental advances are data-driven approaches such as machine learning (ML), other artificial intelligence (AI) tools, and blockchain systems, which enhance pattern recognition, and traceability across the food supply chain.
Key findings and conclusions: Integrating AI-based predictive analytics with traditional and emerging lab methods significantly improves fraud detection, while blockchain and Internet of Things (IoT) innovations enable secure, real-time tracking of food authenticity. This review discusses how mentioned technologies collectively strengthen the ability to uncover fraud, and emphasizes the need for interdisciplinary collaboration, harmonization, and updated regulatory frameworks to support their adoption. It also integrates fraud incidence data (2020–2024), classification by food matrices and global regions, and an exhaustive review of emerging methods and data-processing and pattern-recognition tools. In conclusion, emerging analytical, and digital tools are poised to dramatically reduce food fraud, but sustained investment, and global cooperation are required to fully safeguard food integrity in the future.

1. Introduction

Food fraud refers to the intentional deception of consumers for economic gain by altering or misrepresenting food products, in contrast to unintentional food safety incidents (Spink et al., 2019). It encompasses a wide range of deceptive practices, from adulteration (e.g., diluting or substituting ingredients), and mislabeling, to counterfeiting brands, and falsifying documents (Vinothkanna et al., 2024). These fraudulent acts pose serious risks to public health, and consumer confidence. Notorious fraud incidents illustrate the threat. For example, the 2008 melamine adulteration in infant formula caused 6 deaths, and over 50,000 hospitalizations in China (Brooks et al., 2021), and the 2013 European horsemeat scandal severely undermined consumer trust (Agnoli et al., 2016). Economically motivated adulterants are often unconventional substances, making them harder to detect with routine safety measures (Spink et al., 2019). Food fraud causes substantial global economic damag (Agnoli et al., 2016; Kendall et al., 2019).

A total of 1621 food fraud incidents have been reported from 2020 to 2024 (Fig. 1). **Note: These counts are based on article-level entries from the European Commission's Knowledge Centre for Food Fraud and

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Quality 'Food Fraud News' monthly digests (2020–2024), which reflect media coverage rather than true incident frequency. Details of the literature search, and data retrieval procedures are provided in Supplementary Section S1.** The apparent increase may reflect enhanced detection capacity, driven by improved analytical methods, and data sharing, rather than a sudden spike in fraudulent activity. Enhanced monitoring correlates with higher reported incidence, while limited oversight likely leads to underreporting (Brooks et al., 2021). Conversely, under-detection remains an issue in areas lacking robust controls European Commission [EC] (2018). Thus, as observed in Fig. 1, the apparent rising trend in media-reported food fraud may reflect advances in detection and reporting rather than a true expansion of fraud itself. From 2020 to 2024, the data suggest possible seasonal fluctuations, but signals are not consistent across years; any peaks (e.g., February–May or late summer) should be interpreted with caution. Further statistical analysis is warranted to confirm these trends and explore their underlying causes.

Several trends have heightened the concern about food fraud in the current decade. Global supply chains are longer, and harder to trace, opening more fraud opportunities. Ingredients and products now cross the world, widening the gap between producers and consumers, and making it easier for fraud to go undetected. Economic pressures also play a role during periods of recession or market instability, where fraudsters exploit cost-cutting demands, and supply shortages. On this regard, the COVID-19 pandemic exemplified this vulnerability. Global supply disruptions, spikes in food demand, and reduced inspections in 2020–2021 created ideal conditions for food fraud. For instance, pandemic-related lockdowns, and staff shortages led to fewer food facility audits, lowering the chance of catching illicit activity. Opportunistic actors took advantage by inserting fraudulent products into strained supply chains. These factors have converged to make food fraud a pressing issue in the 2020s. Regulators worldwide have acknowledged the problem's gravity and are calling for stronger preventive measures (Brooks et al., 2021; European Commission, 2021).

In response to this challenge, technological innovations for detecting food fraud have rapidly advanced. This review focuses on the emerging technologies that are transforming food fraud detection, and authenticity verification. We address two main fronts: 1) Analytical methods: cutting-edge laboratory, and field techniques for identifying adulterants, and verifying composition, such as advanced spectroscopic, and chromatographic methods, DNA-based molecular assays, and novel sensor platforms, often coupled with chemometric analysis;, and 2) Data-driven approaches: new digital, and informatic tools that improve fraud detection including Machine Learning (ML) algorithms and other Artificial Intelligence (AI) tools for pattern recognition, blockchain for supply chain traceability, Internet of Things (IoT) based real-time monitoring, and predictive analytics for fraud risk modeling. While contextual background on fraud categories, regulations, and recent statistics is provided for completeness, the core objective of this review is to evaluate these state-of-the-art detection technologies, and their impact.

This paper is organized to transition from context into technological developments. The review begins by summarizing the landscape of food fraud, and its classifications, providing essential background. Next, analytical techniques that have emerged in the 2020s, ranging from spectroscopic imaging, and chromatography, and Mass Spectrometry (MS) combinations to portable on-site testing devices are examined, highlighting their role in enhancing sensitivity, and accelerating food fraud detection. Then, data-centric innovations, including AI-driven detection models, blockchain-based traceability systems, and advanced computational tools are explored, explaining their principles, and applications in food integrity. Finally, the integration of these technologies, and future directions are discussed, emphasizing interdisciplinary collaboration, regulatory evolution, and research gaps.

2. Food fraud categories

Food fraud poses serious risks to food safety, public health, and consumer confidence (Spink et al., 2019). There is no single global definition of 'food fraud', and various organizations use partly overlapping classifications. In this review we follow the European Commission's categories (2021) as a practical reference. To effectively address these challenges, it is crucial to understand the various types of food fraud and organize them into clear categories. Such classifications not only help detect weak points within the food supply chain but also guide the development of targeted strategies to mitigate risks and ensure adherence to regulations.

In the European Union (EU), the Directorate-General for Health, and Food Safety of the European Commission (EC) has established a detailed framework for classifying food fraud, grouping it into five key categories: 1) adulteration, 2) counterfeiting, 3) document forgery, 4) grey market activities, and 5) misdescription (including mislabeling, and misbranding). **Note: Definitions in the subsections below are from EC (2021).** Each category encompasses specific fraudulent practices, and this systematic breakdown is essential for both understanding the issue and taking appropriate action. Fig. 2 provides a detailed summary of this classification, outlining the distinctive fraudulent activities within each category. We selected the EC framework because it was widely used in European monitoring and knowledge-sharing initiatives during the 2020s and aligns with the data sources analyzed later in this review This visual representation complements the EC's framework, emphasizing the need to strengthen food supply chain oversight, enhance regulatory compliance, and restore consumer trust. In highlighting the complexity, and breadth of fraudulent practices, the classification underscores the importance of vigilance, and advances in detection technologies to combat this persistent issue effectively. The lack of a global definition—taken up again in Chapter 6—remains a barrier to harmonized risk assessment and policy metrics.

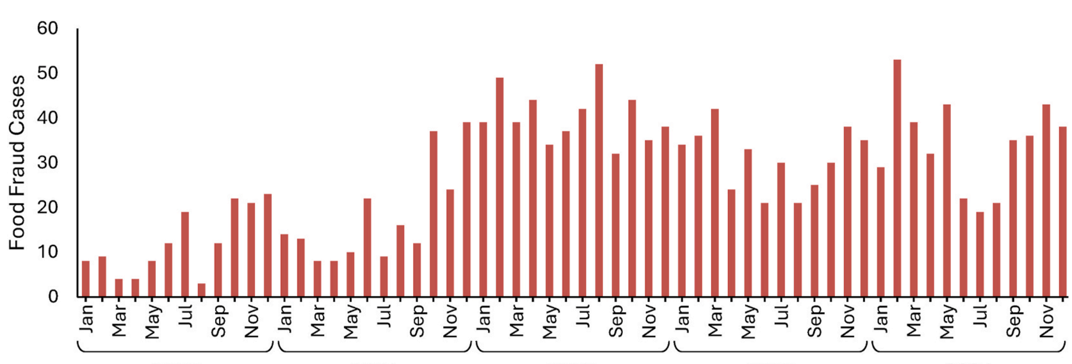

Fig. 1. Evolution of reported food fraud cases worldwide from 2020 to 2024 *(N = 1621)*. Author's own elaboration using data retrieved from EC (2020–2024), which reflect media-reported cases.

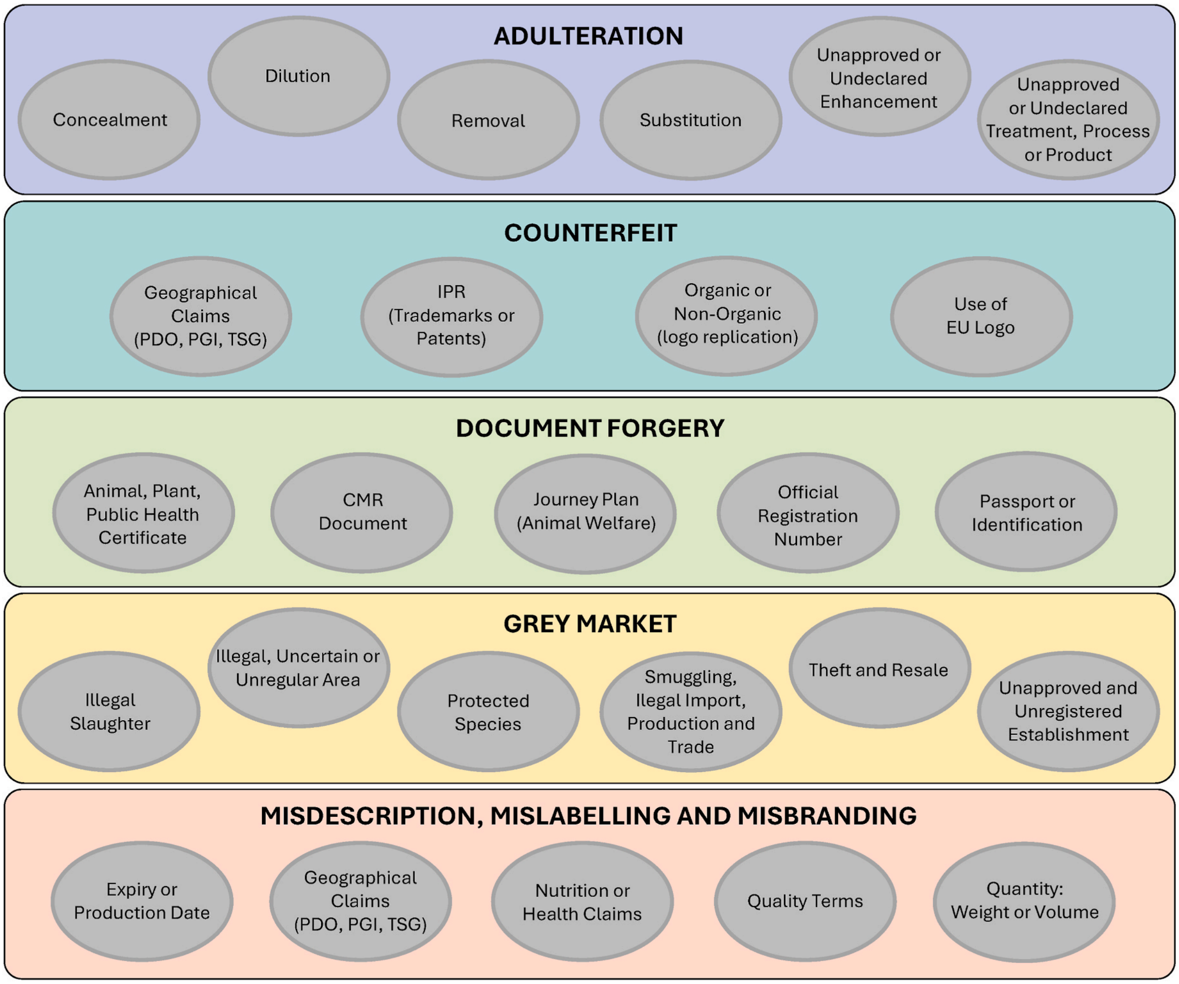

Fig. 2. Food fraud categories used in this review. Author's own elaboration from EC (2021); a synthesis for clarity and not a new taxonomy. CMR, Convention on the Contract for the International Carriage of Goods by Road *(Convention relative au contrat de transport international de Marchandises par Route)*; EU, European Union; PDO, Protected Designation of Origin; PGI, Protected Geographical Indication; TSG, Traditional Speciality Guaranteed.

2.1. Adulteration

Adulteration involves deliberately altering a food product by adding, removing, substituting, or concealing substances to deceive consumers. This practice compromises product quality and safety. This includes, for instance, substituting high-value ingredients with cheaper alternatives, diluting liquids to increase volume, removing key components like omega-3s from fish or masking contamination with unauthorized additives. Other forms of adulteration include the addition of unapproved substances, such as melamine in milk or the use of illegal treatments like unauthorized pesticides or storage methods.

2.2. Counterfeit

Counterfeit fraud entails the deliberate imitation of genuine food products or their packaging to mislead consumers, often involving intellectual property right (IPR) infringements. This includes forging brand names, misusing geographical claims such as Protected Designation of Origin (PDO), Protected Geographical Indication (PGI) or Traditional Speciality Guaranteed (TSG), and unauthorized replication of organic logos or trademarks (false organic claims without logo replication fall under Misdescription/Mislabeling/Misbranding). Counterfeit practices extend to the unauthorized use of certification logos like EU quality marks, undermining the integrity of food labeling systems, and preventing consumers from choosing products based on accurate information.

2.3. Document forgery

Document forgery encompasses the manipulation or falsification of official documentation in the food supply chain, compromising traceability, and regulatory oversight. Common examples include forging health certificates, altering official registration numbers, falsifying animal welfare journey plans, and tampering with transport documentation. Such practices distort compliance systems and facilitate the circulation of fraudulent or unsafe products.

2.4. Grey market activities

Grey market activities refer to the illicit production, theft, and distribution of food products through unauthorized or unregulated channels. This includes smuggling, and illegal imports that bypass safety restrictions, the resale of stolen goods without traceability, and the processing of animals in unsafe or unregistered facilities. Additionally, grey market practices may involve trading in protected species in violation of the Convention on International Trade in Endangered Species of Wild Fauna, and Flora (CITES) regulations, contributing to significant ethical, and safety concerns.

2.5. Misdescription, mislabeling, and misbranding

This category involves the deliberate misrepresentation of a product's attributes to deceive consumers. Fraudulent practices include falsifying expiration or production dates to extend shelf life, exaggerating nutritional or health benefits, and making incorrect geographical claims about a product's origin. Additionally, misleading quality terms like "artisanal", "free-range", or false organic claims without logo replication may be used without justification, alongside inaccurate labeling of weight or volume. These acts result in consumer misinformation and distort market competition.

3. Overview of food fraud in the 2020s

3.1. Geographic distribution

Food fraud is a worldwide issue, but its incidence is unevenly distributed across countries. The data from 2020 to 2024 (Fig. 3A) show that a few countries account for a disproportionate share of reported cases. Notably, Italy has the highest number of food fraud incidents, with over 300 cases (top quintile). India, and Pakistan also rank in the highest quintile, each reporting well over 150 cases. These three countries alone represent the upper 20 % bracket of fraud occurrence globally. A second tier of countries (4th quintile), including Spain, Brazil, Bolivia, Malaysia, Colombia, and Argentina, report a few dozen cases each, while most other nations have relatively low counts (bottom quintiles) (Fig. 3A). This skewed distribution suggests that food fraud is concentrated where high-risk products, and active enforcement intersect. Major producer countries, and trade hubs tend to report more cases, either because fraud is more frequently attempted there, or detection efforts are more intensive (EC, 2020–2024). For example, Italy's prominence may reflect its vigilance, and the vulnerability of premium Italian products (e.g., olive oil, and wine) to fraud. Similarly, India, and Pakistan's high numbers likely stem from recurring adulteration issues in commodities such as spices, tea, and dairy, sectors with substantial economic incentive for fraud, and complex supply chains (Brooks et al., 2021). In contrast, many African countries, and smaller economies report very few cases, which could indicate either genuinely lower incidence or under-detection due to limited monitoring infrastructure (EC, 2020–2024). Europe exhibits a broad spread of cases but with notable regional disparities. Within Europe, Italy stands out as an outlier, followed by Spain with moderately high incidents, whereas most

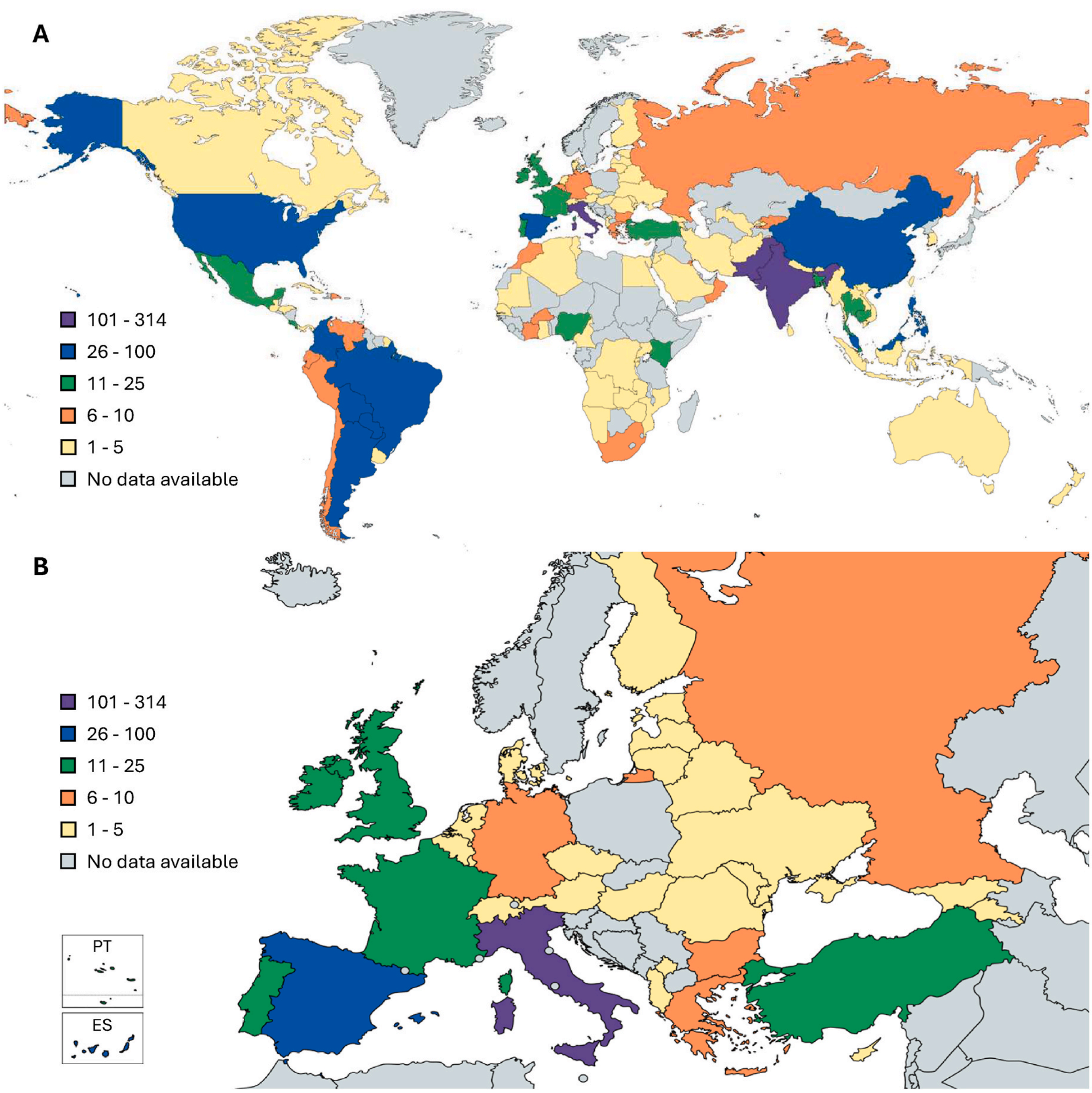

Fig. 3. Geographic distribution of food fraud cases detected in each country from 2020 to 2024. A) World map and, B) European continent. Countries were classified according to the cases in each country *(N = 1621)*. ES, Spain; PT, Portugal. Author's own elaboration using data retrieved from EC (2020–2024), which reflect media-reported cases, and country boundaries from MapChart (https://www.mapchart.net/).

other European countries fall into lower quintiles (Fig. 3B). This indicates that while food fraud is a pan-European concern, its detection is uneven and concentrated in certain countries. One reason is that enforcement intensity, and reporting systems differ. Italy's robust food control system and focus on authenticity (especially after high-profile scandals) contribute to more reported cases (Agnoli et al., 2016). In contrast, some EU members report fewer cases, which may reflect either lower fraud activity or gaps in surveillance. The European continent map (Fig. 3B) highlights these differences, with Western/Southern Europe generally reporting more incidents than Eastern Europe. Globally, the pattern is influenced by trade-related factors. Countries heavily involved in exporting high-value foods (e.g., spices, oils or seafood) often experience more fraud cases, either domestically or upon import by their trading partners. For instance, spice-exporting regions in South Asia have frequent adulteration cases, and seafood-producing nations face issues with illegal fishing, and mislabeling in trade (EC,

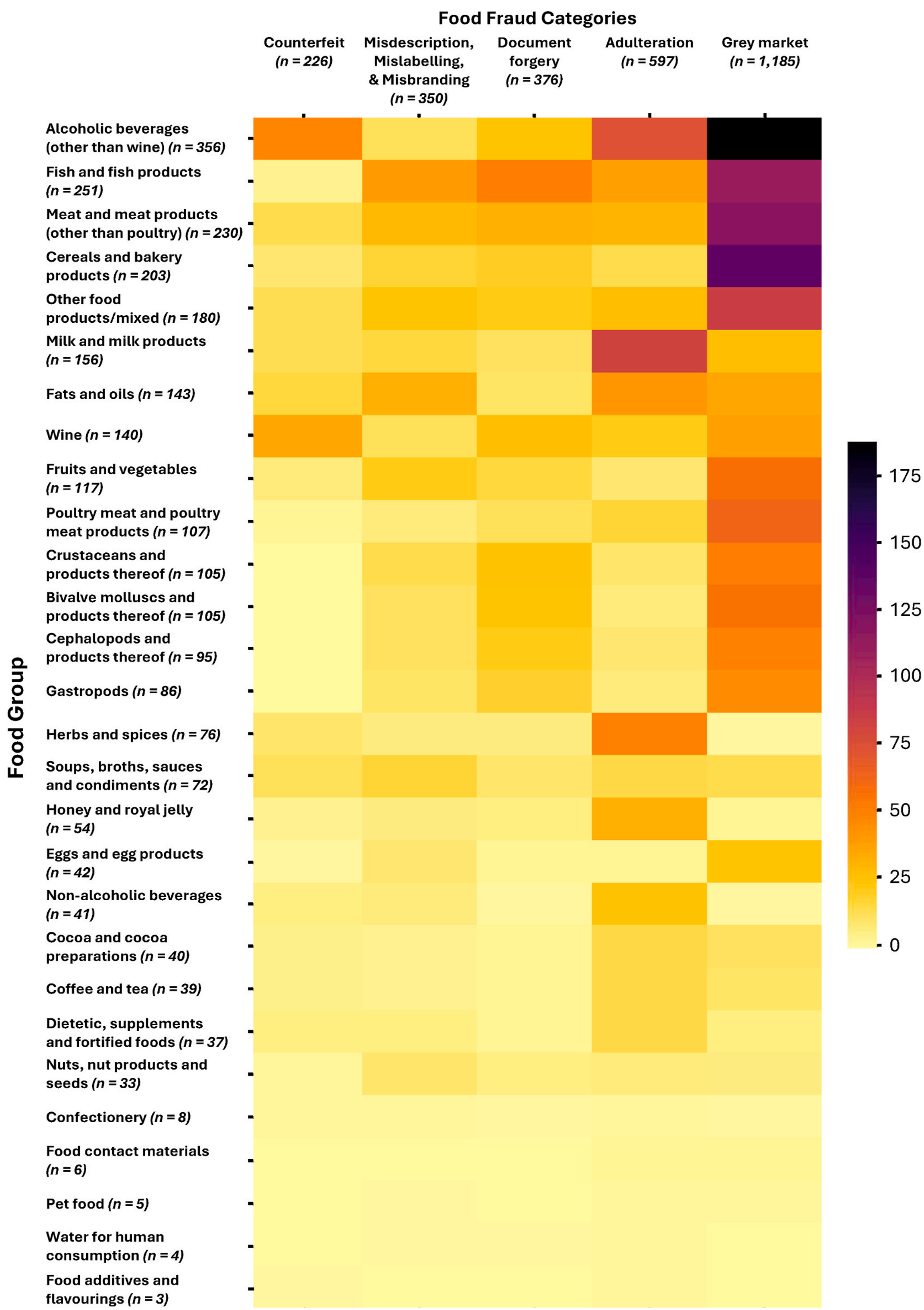

Fig. 4. Heatmap of food fraud cases worldwide from 2020 to 2024, classified by food fraud category and food group *(N = 2734; a single case may be classified in several food groups and food fraud categories)*. Author's own elaboration using data retrieved from EC (2020–2024), which reflect media-reported cases.

2020–2024). In the EU, the free movement of goods, and the coordinated reporting EU Food Fraud Network facilitate the sharing, and detection of fraud cases across borders (EC, 2018). This means a fraud incident originating in one country might be detected, and reported in another, contributing to higher counts in nations that are major importers. Moreover, global supply chain disruptions in the early 2020s (e.g., the COVID-19 pandemic or the Brexit) may have heightened fraud vulnerabilities, as shortages, and new trade frictions presented opportunities for fraudsters (Brooks et al., 2021). In summary, geographic disparities in food fraud reflect a combination of product-specific risks, enforcement effectiveness, and international trade dynamics, as also indicated by EC (2018).

3.2. Fraud categories by food group

The heatmap in Fig. 4 reveals that grey-market activities are the most prevalent form of food fraud globally. Grey-market cases account for the largest share of recorded incidents at 43 % (1185/2734). This category is especially pronounced in certain food groups such as alcoholic beverages (i.e. spirits, and others, excluding wine), which shows the highest incidence, with authorities frequently seizing bootleg alcohol, and smuggled liquor. Staple foods like cereals, and grains, as well as meat, and seafood, also exhibit heavy grey-market activity. These often involve the cross-border movement of products outside official channels like unauthorized meat processing or illegal fishing catches entering the supply chain. The prominence of grey-market fraud reflects how economic gain drives covert trade in high-demand goods, evading taxes, and regulations (EC, 2018).

Adulteration is the second most common fraud type, comprising about 22 % (597/2734) of fraud instances. It is closely associated with particular food groups that offer high profit margins or are easy to dilute. Milk and dairy products stand out: numerous cases involved milk being watered down or tainted with additives to extend volume, echoing longstanding issues in the dairy sector (Ferreira et al., 2025). Fats and oils, notably olive oil, are another prime target, often involving the mixture of lower-cost oils, and sold as premium olive oil (Abamba Omwange et al., 2021). In herbs and spices, adulteration is rampant. Examples include bulking oregano with olive leaves or coloring spices with industrial dyes. Indeed, a large proportion of spice-related fraud cases are adulteration incidents, given spices' high value, and powder form, which facilitate concealment of fillers (Zhang et al., 2019). Honey is similarly vulnerable: It is frequently diluted with sugar syrups or other cheap sweeteners. Honey adulteration is one of the most reported issues in food fraud literature, and regulatory agencies worldwide have been challenged to authenticate honey purity (Bose & Padmavati, 2024). These patterns align with economic drivers i.e., foods that command premium prices (e.g., olive oil, honey or spices) or massive volume (e.g., milk) invite adulteration because substituting with cheaper ingredients yields substantial illicit profit (Spink et al., 2019).

Misdescription/mislabeling, and document forgery together account for a substantial proportion of fraud cases, representing over 26 % (726/2734). They are pervasive in supply chains where origin, species or quality claims affect market value. Seafood is a classic example: in many cases, cheaper fish are mislabeled as expensive species and catch certificates or traceability documents are forged to cover illegal, unreported, or unregulated fishing. Meat products have seen similar issues such as the infamous horsemeat scandal, where horses were passed off as beef in Europe, exemplifies how mislabeling undermines consumer trust (Agnoli et al., 2016). In the 2020–2024 data, document fraud appears often alongside meat and fish cases, indicating ongoing problems with falsified health certificates, and fraudulent transit documents for these animals. Counterfeiting is less frequent overall at 8 % (226/2734), but it is heavily linked to branded, and protected products. Premium wines, and spirits, for instance, are targets of counterfeiters copying labels, and geographical indications, as well as dietary supplements, and specialty foods where brand trust is exploited. This corresponds with reports of fake labeling of origin (e.g., false "organic" or Geographic Indication claims) identified by EU authorities. While counterfeit cases are fewer, their impact on intellectual property, and consumer confidence can be substantial (EC, 2021).

Fig. 4 also highlights which food groups accumulated the most fraud reports. Alcoholic beverages (other than wine) had the highest total incidents among all categories, at 13 % (356/2734), driven largely by grey-market distribution, and adulteration (e.g., illicit liquor production). Fish, and seafood (especially fish products), and meats (excluding poultry) follow, with over 17 % (481/2734). The prevalence in these categories is linked to their complex supply chains, and global trade: seafood fraud often crosses international waters, and meat supply networks involve many handling points, raising opportunities for fraud. Cereal and bakery products also showed a high total at 7 % (203/2734), likely reflecting grain supply chain issues such as fraudulent organic certification or illegal import/export of staple grains. Meanwhile, milk/dairy, oils, and wine form another tier of vulnerability, at 5 % of cases (140, and 156 out of 2,734, respectively), predominantly due to adulteration, and grey-market dealings in these high-value products. Notably, some categories with fewer total cases still face serious fraud concerns. For example, honey and spices do not top the list by volume, but virtually all their reported cases are adulteration-focused, underlining a concentrated risk in those products (Egido et al., 2024). This suggests that every food category has its weak points: staples, and highly traded foods suffer from smuggling, and document fraud, whereas niche high-value foods suffer from ingredient tampering, and counterfeiting.

Clear patterns emerge linking fraud categories with specific products. Economically motivated adulteration is strongly correlated with ingredients-based products (e.g., dairy, oils, honey, spices) where substituting or diluting can be done furtively, and profitably (Abamba Omwange et al., 2021; Egido et al., 2024). Grey-market violations correlate with taxed or regulated goods like alcohol, and meat, indicating fraudsters exploit regulatory gaps, and demand, by passing official channels. Mislabeling, and forgery correlate with products where authenticity is hard for consumers to verify (e.g., fish species, meat origin, coffee quality, etc.), so paper documentation becomes the target for fraud. These correlations are well-documented in food fraud research. For instance, olive oil is notorious for adulteration with cheaper oils, a form of economically motivated adulteration (Abamba Omwange et al., 2021), whereas premium wines, and spirits are prone to counterfeiting labels (fraud capitalizing on brand value). Regulatory discussions echo these findings: authorities emphasize strengthening traceability, and authenticity verification in vulnerable sectors (EC, 2021). Efforts such as improved supply chain transparency, routine authenticity testing, and international information-sharing are being advanced to tackle the specific fraud *modus operandi* seen in each food category (EC, 2018). The alignment between the data and known fraud patterns underscores that food fraud tends to occur at the intersection of high economic gain, and low detection risk. By understanding these patterns (Figs. 3 and 4) regulators, and Food Business Operators (FBOs) can target interventions, like deploying new detection technologies or stricter oversight, to the most at-risk products, and fraud types, thereby mitigating fraudulent practices in the post-2020 landscape.

4. Current trends in food fraud detection, and prevention

4.1. Roles, and responsibilities of the public sector: international, EU, and national levels

Government authorities, representing the public sector, have the role of protecting the health and wellbeing of consumers along the food chain by verifying that the FBOs comply with the law (Codex Alimentarius Commission, 2013). Further to this, authorities are also responsible for ensuring fair practices in the food trade. In this regard, authorities put efforts into enforcing measures against fraudulent practices, acknowledging their serious impacts over public health, and food trade. Failure to prevent and detect fraudulent practices may result in a loss of consumer trust, and confidence in FBOs, and authorities (Agnoli et al., 2016; Kendall et al., 2019; Le et al., 2020; Spink et al., 2019). Furthermore, the costs of food fraud are estimated at 30 billion euros annually for FBOs (EC, 2018). Given these economic, and reputational impacts, prevention is preferable to remediation, and food fraud should be controlled at each stage of the food chain (Brooks et al., 2021; Manning, 2016).

At the international level, efforts to address food fraud have been undertaken by key intergovernmental organizations in public health, food safety, and trade. These include the World Health Organization (WHO), the Food, and Agriculture Organization of the United Nations (FAO), their joint program, Codex Alimentarius, and the World Trade Organization (WTO). The unique international legally binding agreement addressing food safety, and food trade is the Agreement on the Application of Sanitary and Phytosanitary Measures (1994), adopted by the WTO. However, food fraud is not covered in such an agreement, highlighting a regulatory gap that limits international coordination, and enforcement. On the other hand, although not being legally-binding by their nature, Codex Alimentarius' standards are recognized as the international reference to provide benchmarks on food safety issues. While related elements, import/export inspection, fair practices in food trade, traceability and labelling, are addressed, Codex lacks a specific food-fraud standard; a 2023 draft discussion paper is underway.

Building on these instruments, one outcome has been the establishment of the International Food Safety Authorities Network (INFOSAN), a global voluntary network of national food safety authorities coordinated by WHO and FAO (Spink et al., 2019; WHO, 2023). INFOSAN aims to interconnect and offer an official channel of rapid exchange of information during food safety emergencies. Since most fraud cases involve cross-border trade, INFOSAN plays an important role in food fraud detection, and early response. In a survey conducted among the 166 WHO member states, 97 % of the respondents expressed the desire for more guidance, and information on best practices in preventing and managing food fraud (Spink et al., 2019).

In the EU, general food law, Regulation 178/2002, specifically mentions that consumers should be protected against fraudulent, and misleading practices, as well as adulteration of food. Moreover, Regulation 1169/2011, on the provision of food information to consumers, particularly addresses food fraud from a labeling perspective. Together with the regulatory framework, there are several initiatives to combat food fraud in the EU. These initiatives include also the Rapid Alert System for Food, and Feed since 1979 or the EU Agri-Food Fraud Network (EC, 2023), which links the EU member states, the EC, the EC Knowledge Centre for Food Fraud, and Quality with the European Anti-Fraud Office, and the EU Agency for Law Enforcement Cooperation. The former provides an official channel to exchange information on food fraud cases detected between member states, and EU bodies while the latter serves as a platform for also exchanging information and cooperating in front of violations of the EU law of a cross-border nature. The EC's Joint Research Centre (JRC) is also a key-role player by providing evidence-based knowledge, and tools to support EU policies, in this case, against fraudulent practices (EC, 2025a). One example of this is the intention to create a risk-based AI tool to centralize, standardize, and analyze food-related data from different databases to flag anomalies that could indicate fraud (EC, 2024).

On the other hand, in addition to the above-mentioned, several projects have been set up to combat food fraud at EU level. For example, the so-called FOODINTEGRITY project, which was established in 2014 with stakeholders from the EU, China, and Argentina (EC, 2025b). The aim was to address consumer mistrust of food authenticity, and provenance claims in general. The outcomes of the project included the need for increased data sharing between stakeholders, and the development of predictive and preventative measures against fraud. Another recent project is the European Food Fraud Community of Practice (EFF-CoP), established in 2024 (EC, 2025c), which seeks to bring together food fraud researchers, regulators, and industry to combat food fraud through research, and innovation, with the aim of increasing transparency, and confidence in the sector.

At the national level, while some countries consider food fraud to be a crime under the general penal code, such as Germany (Federal Ministry of Justice, 2025) or Spain (Jefatura del Estado, 1995), others include food fraud under general food acts, such as Thailand (Government of Thailand, 1979), or specific food labeling acts, such as Japan (Government of Japan, 2013). Other countries have developed or strengthened the existing regulatory frameworks following fraud crises. For example, in the wake of the 2009 melamine incident in China, which resulted in 6 deaths, and 294,000 cases, the country expanded the scope of existing requirements in relation to the authenticity of powdered infant formula, health food, and food for special medical purposes (Standing Committee of the National People's Congress, 2015). However, other countries have gone a step further in terms of legal initiatives or guidance for FBOs to ensure their successful compliance with the law, and consequent prevention of fraud. In the United States of America, the *Food Safety Modernization Act* (U.S. Congress, 2011) introduced preventive controls to address economically motivated adulteration when it poses a risk to human health. FSMA also requires food business operators to establish food defense plans; however, it is important to note that food defense and food fraud are distinct concepts. Food defense focuses on intentional adulteration intended to cause harm, whereas food fraud is driven by economic gain. Another example is the United Kingdom where, following the horsemeat incident in 2013, the Food Standards Agency (FSA) established the National Food Crime Unit (NFCU), which has prosecutorial powers, and is dedicated to tackling food crime, including food fraud. In this case, NFCU developed a food fraud resilience self-assessment tool for FBOs. Although it is not legally-binding, this aims to guide, and support FBOs prepare, and implement an internal anti-fraud strategy (Food Standards Agency, 2025).

4.2. Roles and responsibilities of the private sector

The private sector plays a significant role in the assurance of product safety, and quality in the context of food commercialization. It is crucial to emphasize that these agents bear the responsibility of ensuring the safety and quality of their food products at each stage of the food chain. In that sense, in the UE for example, FBOs are the legal agents responsible for this matter under Regulation 178/2002 (EC, 2002).

To avoid fraudulent behaviors, the deployment of hybrid strategies combining private and public approaches is an effective measure for both authorities and FBOs. Such approaches include 1) self-regulation, 2) co-regulation, and 3) cooperation. Self-regulation refers to the active participation of FBOs in adopting measures to avoid food fraud, such as codes of conduct, without the participation of authorities. An example of those could be the corporate social responsibility codes, which represent the commitment of FBOs to fighting against fraud (United Nations Conference on Trade & Development, 2017). Co-regulation entails a hybrid combination of permanent public-private partnerships, and actions for the development, and maintenance of formal food co-regulatory efforts, with the objective of enhancing greater compliance of FBOs (Wu, Tang, et al., 2024). In that sense, the Global Food Safety Initiative (GFSI) as a private organization initiative, has addressed food fraud through its accreditation schemes by requiring FBOs to have a food-fraud vulnerability assessment, and mitigation plan in place (GFSI, 2018). In that context, retailers request new suppliers to be GFSI certified. Other examples include the Foundation Food Safety System Certification (FSSC) 22000 Version 5 (Foundation FSSC 22000, 2019), or the International Featured Standards (IFS) product fraud (International Featured Standards, 2023). Finally, cooperation refers to the strategy of combining efforts between authorities, consumers, FBOs or academia to respond to *ad hoc* situations, including training campaigns or development of best practices guidelines. This strategy may include joint development, and implementation of best practices through the cooperation between authorities and FBOs.

5. Emerging technologies in food fraud detection

As seen above, food fraud continues to pose a critical global challenge, undermining public trust, endangering health, and resulting in significant economic losses. To combat this issue, technological advancements in food fraud detection have made significant advances, particularly over the past two decades. Early methods relied heavily on traditional analytical tools such as chromatography, and conventional spectroscopy, which, while accurate, were often slow, costly, and reliant on specialized laboratory settings. In contrast, the 2020s have guided in a transformative era, characterized by innovative, faster, more cost-efficient, and non-invasive approaches for identifying fraudulent practices in the food supply chain (Sharma et al., 2024; Vinothkanna et al., 2024).

A breakthrough in this field has been the fusion of advanced analytical techniques with state-of-the-art data processing, and pattern recognition technologies. While enhancements to established methods like portable devices, and hybrid analytical platforms have been noteworthy, the advent of ML, other AI tools, and multivariate statistical models has truly revolutionized detection processes. These cutting-edge tools not only deliver faster, and more precise results but also enable the analysis of highly complex datasets, yielding robust, and reliable outcomes. Technologies such as Random Forests (RF), Support Vector Machines (SVM), and gradient boosting machines have been particularly impactful, unlocking insights previously inaccessible through conventional methods (Vinothkanna et al., 2024; Yang et al., 2024).

This review underscores the critical synergy between traditional analytical methods, and emerging data-driven tools, demonstrating their combined progress in tackling food fraud. Both established and novel techniques remain pivotal in overcoming this global issue, often working in tandem to validate, and strengthen findings. Over time, all these technologies have been fine-tuned, optimized, and integrated, making detection methods increasingly efficient, affordable, and non-invasive. Table 1 outlines the primary technologies that have advanced or gained prominence in the 2020s, serving as a foundation for the in-depth discussions that follow.

The methods included in this review were selected through an exhaustive literature search, prioritizing those most frequently applied and recognized as rigorous and reliable. The most informative techniques vary depending on the fraud type: DNA-based assays are highly specific for species identification, spectroscopic and sensor-based approaches enable rapid non-destructive screening of adulteration, and chromatography and mass spectrometry remain benchmarks for compositional analyses.

5.1. Analytical techniques

5.1.1. Imaging techniques

Imaging techniques for food fraud detection use visual data to evaluate food authenticity. These methods vary from basic systems, such as mobile phone cameras, to more advanced technologies like Hyperspectral Imaging (HSI), and machine vision systems. HSI captures images across multiple spectral bands beyond the visible spectrum, providing detailed chemical, and physical insights into the food (An et al., 2023). Machine vision systems, which combine cameras with AI, enable fast, and automated inspections to identify fraudulent activities (Saha & Manickavasagan, 2021). The primary objective is to examine the visual properties of food items, providing critical insights into their authenticity, and quality (An et al., 2023). Their development relies on a multidisciplinary approach combining optics, computer science, and food science.

These techniques offer great flexibility, ranging from low-cost solutions like mobile cameras for initial screenings to high-resolution systems for more complex analyses. Imaging techniques can detect various types of food fraud, including adulteration, counterfeit products, misdescription, and misbranding (Mohd Ali et al., 2020).

HSI is widely used for detecting adulteration in quinoa flour (Wu et al., 2023), honey varieties (Cheng et al., 2024), and authenticating maize varieties (Zhang et al., 2024). Multispectral Imaging (MSI), despite its larger bandwidths, and generating less data than HSI, has proven effective in rapid assessment of microbiological quality, and authentication in chicken (Fengou et al., 2024). Machine vision systems combine digital cameras, and AI algorithms to distinguish genuine ginger (Jahanbakhshi et al., 2021b), saffron (Momeny et al., 2023), and turmeric (Jahanbakhshi et al., 2021a). These techniques enhance detection accuracy across diverse food categories.

5.1.2. Spectroscopy-based techniques

Spectroscopy is one of the most utilized approaches for food fraud detection due to its non-destructive nature. Techniques such as optical spectroscopy (e.g., ultraviolet (UV), visible (VIS), Near Infrared (NIR), fluorescence), vibrational spectroscopy (e.g., Raman), and Nuclear Magnetic Resonance (NMR) spectroscopy allow for rapid, and precise analysis of food products. Recent advancements have not only enhanced the sensitivity, resolution, and adaptability of these techniques but also enabled the development of portable devices, facilitating quick, on-site detection. While some techniques still require prior sample separation, these innovations have made spectroscopy invaluable for detecting adulteration, counterfeit products, mislabeling, and misbranding.

UV/VIS/NIR spectroscopy which has been applied for decades, is widely used for detecting adulteration in cereals, and bakery products (Aznan et al., 2022; Teye & Amuah, 2022; Wu et al., 2023), cocoa, and cocoa preparations (Millatina et al., 2024; Santos et al., 2021), egg plasma (Puertas et al., 2023), herbs, and spices (Coqueiro et al., 2024; Qin et al., 2024), and chicken products (Fengou et al., 2024). Traditionally, they required sample extraction, and destruction for analysis. However, recent advancements have introduced portable devices, and in situ sensors, allowing real-time, non-destructive measurements without the need to remove or destroy samples. These innovations make UV/VIS/NIR spectroscopy even more adaptable, and effective for rapid food fraud detection. For example, Fourier Transform Infrared (FTIR) spectroscopy enriches spectral data to authenticate chicken products (Fengou et al., 2024), and FTIR-Attenuated Total Reflectance (FTIR--ATR) specifically authenticates hazelnuts (Torres-Cobos et al., 2024).

Historically, fluorescence analysis faced challenges in non-destructive applications due to the need for separation or dilution in complex food matrices, as is the case for Fluorescence Spectroscopy Enhanced By Double Quantum Dots (Xu et al., 2020), which are techniques that improve sensitivity, and signal stability, allowing for the detection of low-concentration adulterants in complex food matrices. However, Front-Face Fluorescence (FFF) spectroscopy has overcome these limitations, enabling non-destructive analysis of turbid, and solid foods. This technique has been successfully applied to differentiate geographical origins in wine (Wu et al., 2024), adulteration in cassava flour (Kogniwali-Gredibert et al., 2024), extra virgin olive oil (Abamba Omwange et al., 2021; Lozano et al., 2025), and verify milk authenticity (Ullah et al., 2020), among other complex food matrices. Moreover, the Energy Dispersive X-Ray Fluorescence (EDXRF) requires no sample dilution or separation (Ghidotti et al., 2025).

Raman Spectroscopy (RS) excels in characterizing molecular structures, applied to assess milk authenticity (Feng et al., 2024; Ferreira et al., 2025). Moreover, Surface-Enhanced RS (SERS) has expanded the capabilities of Raman techniques, enabling the detection of trace contaminants, and adulterants in crude oil with significantly improved sensitivity (Yao-Say Solomon Adade et al., 2022). Terahertz spectroscopy has shown potential for identifying misbranding in milk powders (Hou et al., 2023), and other food matrices.

Magnetic resonance techniques provide exceptional detail for chemical profiling. Proton NMR spectroscopy (1H NMR) is widely used to analyze molecular structures, and quantify key components, as

Table 1
Relevant emerging analytical techniques, data processing and pattern recognition tools used to detect food fraud in the 2020s, by foodstuff.

Foodstuff	Analytical Technique	Data Processing and Pattern Recognition Tools	Aim	Reference
Alcoholic beverages				
Chinese red wines	EEMF	PARAFAC extracts key components from the 3D EEMF matrix, while PLS-DA, N-way PLS-DA, and Unfolded PLS-DA classify and authenticate samples. N-way PLSR quantifies adulteration levels with high accuracy and precision.	Rapidly identify the geographical origins of Chinese red wines	Wu, Tang, et al. (2024)
European wine	EDXRF	PCA groups patterns, PLS-DA classifies samples, and clustering ensures accurate detection of authentic and fraudulent samples.	Authentication of wines with PDO/PGI labels	Ghidotti et al. (2025)
Wine	HRM-SNP	Melting curves were analyzed using clustering algorithms to distinguish grapevine varieties and wine blends.	Classify different grapevine varieties and quantify their presence in wine blends	Barrias et al. (2025)
Cereals and bakery products				
Durum Wheat	FTIR	PCA for pattern recognition, LDA for classification, and a hybrid PC-LDA approach. Pre-processing methods included mean normalization, SNV, and detrending to correct biases and distortions.	Tracing the geographical origin of durum wheat	De Girolamo et al. (2019)
Maize	HSI	One-Class CNN, PCA, and Band Attention Mechanisms were used to classify maize seeds and detect fraud.	Classify different maize seed varieties	Zhang et al. (2024)
Quinoa flour	Portable HSI in the Vis-NIR range	PLSR creates predictive models; BOSS selects the most relevant wavelengths, while image processing algorithms generate visualization maps to display adulteration levels.	Develop a global calibration model for adulteration detection in quinoa flour	Wu et al. (2023)
Rice	NIR through the packaging and E-Nose sensor	PCA for pattern recognition, ANNs for regression modeling, optimized with BR and LM algorithms	Develop a rapid, non-destructive, low-cost method for detecting rice fraud.	Aznan et al. (2022)
	Pocket-sized NIR	PCA identifies patterns, PLS-DA, LDA, and SVM classify samples, while Synergy Interval PLS and ELM quantify adulteration with high accuracy.	Accurate authentic rice variety identification and adulteration quantification	Teye and Amuah (2022)
	Terahertz spectroscopy	Feature selection algorithms (Relief, RF, mRMR), signal processing techniques (Hilbert Transform, Butterworth Low-Pass Filter), and ML models (SVM, ELM) to enhance spectral data analysis	Detect the adulteration of rice seeds	Hou et al. (2023)
Wheat and cassava flour	FFFS	PCA reduces dimensionality, CA groups in similar samples, and PLS-DA classifies flour mixtures by cassava content. Preprocessing with SNV and Savitzky-Golay filtering improves spectral quality and model accuracy.	Differentiate mixed wheat-cassava flours according to their level of cassava	Kogniwali-Gredibert et al. (2024)
Cocoa and cocoa preparations				
Chocolate	NIR and MIR	PCA groups samples by cocoa concentration, PLSR predicts cocoa content, and preprocessing improves data quality to detect adulteration.	Determine the concentration of cocoa solids in chocolates	Santos et al. (2021)
Cocoa powder	Vis-NIR	PCA classifies samples unsupervised, Random Forest and SVM classify supervised, PLSR and shrinkage methods quantify adulteration, and Boruta selects features to improve accuracy.	Determine the cocoa powder adulteration	Millatina et al. (2024)
	HPLC-MS	PCA identifies natural clusters, PLS-DA classifies and discriminates samples, and chemometric tools process metabolomic data efficiently.	Determine the cocoa powder adulteration	Greño et al. (2023)
Coffee				
Arabica coffee varieties	Smart E-tongue	PCNN for dimensionality reduction and classification, and CA to group and differentiate coffee samples. These statistical techniques helped in recognizing patterns from the voltametric signals generated.	Rapid different bean varieties coffee analysis for quality and adulteration detection.	Almario et al. (2024)
Instant coffee	HPLC-UV-FD	PCA explores data, PLS-DA classifies sample groups, and PLSR quantifies chicory adulteration levels.	Detection fingerprinting to assess the classification and authentication	Núñez et al. (2021)
Roasted and ground coffee	SPME-GC-MS	PCA reduces dimensionality, HCPC clusters samples, PLS-DA validates PCA and enhances differentiation, and Heatmap Analysis visualizes sample differences.	Discriminate Arabica coffee and its main adulterants	Couto et al. (2024)
Eggs and egg products				
Egg plasma	UV–VIS–NIR	PCA reduces dimensionality and detects patterns, while SVM, LDA, and QDA classify egg samples and validate results.	Develop a quicker and cheaper method for fraud detection in egg labels	Puertas et al. (2023)
Fats and oils				
Coriander oil	Portable NIR spectrometer	PCA for exploration, LDA and k-NN for classification, and PLSR for adulterant prediction. Spectral pre-processing used Savitzky-Golay smoothing and first derivatives to improve signal quality.	Coriander oil adulteration	Kaufmann et al. (2022)

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Table 1 (*continued*)

Foodstuff	Analytical Technique	Data Processing and Pattern Recognition Tools	Aim	Reference
Crude palm oil	SERS	PCA identifies clustering patterns, while LDA and k-NN classify and validate adulteration levels in palm oil.	Detecting the validity and adulteration of palm oil with Sudan dyes (II and IV)	Yao-Say Solomon Adade et al. (2022)
Extra Virgin Olive Oil (EVOO)	NIR and EEMF	DD-SIMCA differentiates between authentic and adulterated samples.	Authentication of Argentinean extra-virgin olive oils	Lozano et al. (2025)
	FFFS and UV-FI	PCA detects clustering, SVM classifies olive oil categories, and PLSR predicts quality indicators for accurate detection.	Discriminating adulterated extra-virgin olive oil with virgin olive oil	Abamba Omwange et al. (2021)
Perilla leaf oil	ASAP-MS	PCA and LDA differentiate between authentic and adulterated samples.	Detection of cinnamon oil adulteration in perilla leaf oil	Wu et al. (2025)
Sesame oil	GC-MS and E-Nose	PCA identifies patterns, LDA and QDA classify oils, SVM detects fraud, ANN performs advanced classification, and CA groups similar samples.	Detect sesame oil fraud adding canola oil	Aghili et al. (2022)
Fish, crustaceans and products thereof				
Crustaceans and products thereof	DNA barcoding, DNA mini-barcoding, Bar-RFLP, and Bar-MCA	K2P model for calculating genetic distances and NJ trees and UPGMA tree construction to cluster species based on genetic similarities.	Identify different species of crab	Mazumder and Ghosh (2024)
Basa catfish and Sole fillets and	REIMS	PCA reduces dimensionality and detects patterns, while LDA and Orthogonal PLS-DA classify samples and identify markers.	Discrimination of basa catfish and sole fish	Shen et al. (2022)
Herbs and spices				
Cinnamon	NIR and MIR	PCA detects clustering and reduces dimensionality, PLS-DA classifies adulterated samples, and PLSR quantifies adulterant concentrations in cinnamon.	Detect adulteration in samples of true cinnamon powder	Coqueiro et al. (2024)
Ginger	MVS with a digital camera and controlled lighting	CNN with gated pooling, HOG and LBP extract features, data augmentation expands the dataset, and SVM and GBT classify samples.	Distinguish genuine ginger from fake ginger	Jahanbakhshi et al. (2021b)
Paprika	HPLC-FD	PCA explores data, PLS-DA classifies paprika by origin, and PLSR quantifies adulteration.	Authenticate the geographical origin of paprika	Campmajó et al. (2021)
Pericarpium citri reticulatae	Flash GC E-Nose and FTIR	PCA extracts features, PLS-DA classifies samples, CNN with LSTM predicts age and quality, and preprocessing enhances data accuracy.	Rapid and accurate identification of storage year falsification	Qin et al. (2024)
Saffron	MVS with a mobile phone digital camera	Learning-to-Augment Incorporated Inception-v4 CNN classifies samples, HOG and LBP extract features, PCA reduces dimensionality, and SVM and Ensemble Decision Trees compare performance.	Detection of counterfeit saffron in images captured by smartphones	Momeny et al. (2023)
Turmeric	MVS with a digital camera and controlled lighting	CNN with gated pooling classifies samples, HOG and LBP extract features, data augmentation expands the dataset, and SVM and GBT analyze performance.	Distinguish genuine turmeric from fake turmeric	Jahanbakhshi et al. (2021a)
Honey and royal jelly				
Honey	HPLC-DAD	Chromatograms analyze phenolic compounds, but no specific pattern recognition tools are mentioned.	Generate phenolic profiles for several monofloral Australian honeys to authenticate them	Moore et al. (2025)
	HSI	GANomaly uses deep learning method utilizing GANs to detect fraudulent honey samples.	Generate a method to detect the fraud of New Zealand Manuka honey	Cheng et al. (2024)
	HPLC-UV fingerprinting	PCA groups honey and syrup samples, PLS-DA classifies and clusters, and PLSR quantifies adulterant percentages.	Detect honey frauds based on sugar syrup adulteration	Egido et al. (2024)
	Voltametric E-Tongue	PCA for feature extraction, LDA and SVM for honey classification, and PLSR for predicting physicochemical parameters. Voltametric E-tongue data were processed to improve classification accuracy.	Honey adulteration detection	Ciursa and Oroian (2021)
Meat and meat products				
Beef products	SWNIR–HSI	PLSR coupled with VIP wavelength selection.	Detect pork adulteration in minced beef rapidly and non-destructively.	Chiavaioli et al. (2025)
Chicken products	Multispectral Sensor Chipset	PCA reduces data, classification models are trained, and SVC combines them for prediction.	Discriminate cold chain (frozen) interruption	Turgut et al. (2025)
	FTIR and MSI	PLS selects features and reduces dimensionality, while SVM handles regression and classification.	Rapid assessment of microbiological quality and authentication (i.e., fresh vs frozen/thawed) of meat	Fengou et al. (2024)
Horse meat	ERA and LFS-ERA	Fluorescence amplification curves for real-time ERA and lateral flow strips for LFS ERA, validated against real-time PCR.	Detect horse, donkey, and pig DNA using a fast, reliable, field-ready method	Zhou et al. (2023)
Milk and milk products				

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Table 1 (*continued*)

Foodstuff	Analytical Technique	Data Processing and Pattern Recognition Tools	Aim	Reference
Buffalo milk	FFFS	PLSR builds models for adulteration levels, PCA identifies clusters and reduces dimensionality, and preprocessing improves data quality.	Adulteration of cow milk into buffalo milk	Ullah et al. (2020)
Cow and sheep milk fat	1H NMR	XLStat software processes statistical data and uses NMR signal ratios for clustering and classification.	Fatty acids profile determination, to detect adulteration	Hanganu and Chira (2021)
Cow and goat milk	Potentiometric E-tongue	PCA for feature extraction and milk sample discrimination, and PLSR for predicting fat, protein, and lactose from potentiometric sensor data.	Analysis of milk adulteration	Perez-Gonzalez et al. (2024)
Cow milk	RS	PCA clusters data, ML models classify dairy types and predict fat content, and a fusion model improves accuracy.	Authenticity of food labels in milk	Feng et al. (2024)
Goat milk powder	RS	DD-SIMCA differentiates between authentic and adulterated samples.	Authentication of powder goat milk adulteration with cow milk	Ferreira et al. (2025)
Non-alcoholic beverages				
Apple juice	HPLC-RID	PCA reduces dimensionality and identifies adulteration patterns, while LDA classifies pure and adulterated apple juice.	Identify adulterated apple juice by type and concentration of adulterants.	Yeganeh-Zare et al. (2022)
Kiwifruit juice	Double-QDs-enhanced fluorescence	One-Class PLS detects adulterants, Robust PCA identifies outliers, and data fusion enhances accuracy with fluorescence and quantum dot data.	Detect adulterated juice due to the addition of non-declared ingredients	Xu et al. (2020)
Orange juice	DPV	PCA explores data, PLS-DA and PCA-LDA classify and detect adulteration, and statistical metrics validate model performance.	Authentication of fruit juices	Monago-Maraña et al. (2024)
Nuts, nut products and seeds				
Hazelnut	GC-MS	Combined unfolding of SIM-based extracted ion chromatograms with correlation-optimized warping and PLS-DA for fingerprinting, and PARADISe PARAFAC2 deconvolution coupled with PLS-DA for untargeted profiling.	Authentication of '*Tonda di Giffoni*' cultivar and origin with more than 90 % accuracy	Torres-Cobos et al. (2024)
Pistachio	FTIR-ATR portable and bench-top	Spectral normalization PCA in full spectrum and selected bands, and DA	Non-destructive authentication of pistachio geographical origin	Panebianco et al. (2025)
Other food products/mixed				
Food supplements	FIA-MS	Box-Behnken optimized parameters, Response Surface Methodology modeled factor relationships, StatGraphics performed regression, and ANOVA with Tukey Test identified significant differences.	Evaluate the authenticity of different *C. forskohlii* supplements	Jiménez-Amezcua et al. (2025)
White wine vinegar	LF-NMR	iCOSHIFT was used for spectral alignment, Savitzky-Golay for noise reduction, PCA for data exploration, LDA for classification, and SELECT for variable selection in LDA models.	Discriminating between authentic and adulterated vinegars	Grassi et al. (2024)

1H NMR, Proton Nuclear Magnetic Resonance Spectroscopy; ANN, Artificial Neural Networks; ANOVA, Analysis of variance; ASAP-MS, Atmospheric Solids Analysis Probe tandem Mass Spectrometry; Bar-MCA, Barcode-Melt Curve Analysis; Bar-RFLP, Barcode-Restriction Fragment Length Polymorphism; BLAST, Basic Local Alignment Search Tool; BOSS, Bootstrapping Soft Shrinkage; BR, Bayesian Regularization; CA, Cluster Analysis; CNN, Convolutional Neural Networks; DA, Discriminant Analysis; DD-SIMCA, Data-Driven Soft Independent Modelling of Class Analogy; DPV, Differential Pulse Voltammetry; EEMF, Excitation-Emission Matrix Fluorescence Spectroscopy; EDXRF, Energy Dispersive X-ray Fluorescence; ELM, Extreme Learning Machine; ERA, Enzymatic Recombinase Amplification; E-Nose, Electronic Nose; E-tongue, Electronic Tongue; FFFS, Front-Face Fluorescence Spectroscopy; FIA-MS, Flow Injection Analysis-Mass Spectrometry; FTIR, Fourier-Transform Infrared Spectroscopy; FTIR-ATR, FTIR in Attenuated Total Reflectance; GC, Gas Chromatography; GC-MS, GC coupled with Mass Spectrometry; GAN, Generative Adversarial Networks; GANomaly, Generative Adversarial Network-based anomaly detection; GBT, Gradient Boosting Trees; HCPC, Hierarchical Clustering of Principal Components; HOG, Histogram of Oriented Gradients; HRM, High-Resolution Melting; HRM-SNP, HRM combined with Single Nucleotide Polymorphisms markers; HPLC, High-Performance Liquid Chromatography; HPLC-DAD, HPLC with Diode Array Detection; HPLC-FD, HPLC with Fluorescence Detection; HPLC-MS, HPLC coupled with Mass Spectrometry; HPLC-RID, HPLC with a Refractive Index Detector; HPLC-UV, HPLC with Ultraviolet Detection; HPLC-UV-FD, HPLC with Ultraviolet and Fluorescence Detection; HSI, Hyperspectral Imaging; iCOSHIFT, Interval-based Covariance Shift algorithm; IR, Infrared; K2P, Kimura-2-Parameter; k-NN, k-Nearest Neighbors; LBP, Local Binary Patterns; LDA, Linear Discriminant Analysis; LFS-ERA, Lateral Flow Strip Enzymatic Recombinase Amplification; LF-NMR, Low-Field Nuclear Magnetic Resonance; LM, Levenberg–Marquardt algorithm; LSTM, Long Short-Term Memory; ML, Machine Learning; mRMR, Maximum Correlation Minimum Redundancy; MS, Mass Spectrometry; MSI, Multispectral Imaging; MVS, Machine Vision System; NIR, Near-Infrared spectroscopy; NJ, Neighbor-Joining; NMR, Nuclear Magnetic Resonance; OPLS-DA, Orthogonal Partial Least Squares Discriminant Analysis; PARADISe, PARAFAC2 deconvolution; PARAFAC, Parallel Factor Analysis; PC-LDA, Principal Component Linear Discriminant Analysis; PCNN, Principal Component Analysis assisted by Neural Networks; PCR, Polymerase Chain Reaction; PDO, Protected Designation of Origin; PGI, Protected Geographical Indication; PCA, Principal Component Analysis; PLS-DA, Partial Least Squares Discriminant Analysis; PLSR, Partial Least Squares Regression; QD, Quantum Dots; QDA, Quadratic Discriminant Analysis; qPCR, Quantitative Polymerase Chain Reaction; REIMS, Rapid Evaporative Ionization Mass Spectrometry; RF, Random Forest; RS, Raman Spectroscopy; SERS, Surface-Enhanced RS; SNV, Standard Normal Variate; SPME-GC-MS, Solid-Phase Microextraction GC–MS; SWNIR–HSI, Shortwave NIR and HSI; SVC, Soft Voting Classifier; SVM, Support Vector Machine; UPGMA, Unweighted Pair Group Method with Arithmetic Mean; UV, Ultraviolet; UV-FI, Ultraviolet-Induced Fluorescence Imaging; UV–VIS–NIR, Ultraviolet–Visible-Near-Infrared spectroscopy; VIP, Variable Importance in Projection; Vis-NIR, Visible-NIR.

demonstrated in determining fatty acid profiles in milk (Hanganu & Chira, 2021). This technique is invaluable for distinguishing high value products and detecting mislabeling. Similarly, Low-Field NMR (LF-NMR) is a portable, and cost-effective alternative, offering quick, non-destructive assessments of food quality, and authenticity. It has been successfully applied to detect milk adulteration (Hanganu & Chira, 2021), and verify the authenticity of white wine vinegar (Grassi et al., 2024). Meanwhile, Low-Field NMR (LF-NMR) quantified authenticity in white wine vinegar (Grassi et al., 2024), exemplifying innovative integrations in food analysis.

Overall, the diversification, and refinement of spectroscopy-based methods highlight their strategic role in addressing food fraud. Their non-destructive nature, and growing portability make them essential tools for enhancing transparency, and control along the food supply chain, although their broader adoption still requires overcoming barriers related to cost, standardization, and integration into routine inspection systems.

5.1.3. Separation and chemical analysis techniques

Chromatography and MS are indispensable tools in modern food fraud detection. These technologies enable sensitive, and precise identification of compounds, forming the basis for further analyses. Although used as reference methods, they are destructive, require extensive sample preparation, and skilled operators, and generate chemical waste. Recently, automated instruments combining multiple advanced technologies have emerged to tackle diverse fraud types, and benchmark rapid, non-destructive screening techniques. These tools perform highly accurate analyses to fight various types of fraud. They can detect adulteration by identifying mixed or lower-quality ingredients; counterfeiting by spotting imitation products; document forgery by verifying certificates or labels; grey market activities by identifying unauthorized goods; misdescription by validating claims about a product's origin or composition; mislabeling by checking ingredient lists, and nutritional information; and misbranding by confirming authenticity, and quality claims (Quintanilla-Casas et al., 2025).

Chromatography has been extensively applied in food fraud detection, showcasing its ability to identify compositional subtleties with precision. High-Performance Liquid Chromatography (HPLC) coupled to different detectors has proved effective in uncovering food fraud: **a)** with fluorescence detection (HPLC-FD) detected cocoa-powder adulteration (Greño et al., 2023); **b)** with Diode Array Detection (HPLC-DAD), and with Refractive Index Detector (HPLC-RID) identified adulterated apple juice (Yeganeh-Zare et al., 2022); **c)** with UV-detection (HPLC-UV) confirmed honey authenticity (Egido et al., 2024; Moore et al., 2025). Gas Chromatography (GC) proved effective in identifying sesame oil adulteration with canola oil (Aghili et al., 2022), while the use of solid-phase microextraction coupled with GC enabled precise profiling of Arabica coffee to differentiate it from adulterants (Couto et al., 2024), and the Flash GC combined with E-nose can authenticate herbs, and spices (Qin et al., 2024). These studies emphasize the adaptability of chromatography for detecting volatile, and non-volatile compound irregularities.

MS has proven equally invaluable in detecting fraudulent activities, leveraging advanced modalities for rapid, and accurate analysis. Atmospheric Solids Analysis Probe Tandem MS (ASAP-MS) was utilized to detect cinnamon oil adulteration in perilla leaf oil (Wu et al., 2025), providing a quick, and preparation-free method. Rapid Evaporative Ionization MS (REIMS) distinguished fish species such as basa, catfish, and sole fish (Shen et al., 2022), illustrating its effectiveness in authenticating protein-rich foods. Flow Injection Analysis MS (FIA-MS) enables fast, cost-effective detection of food supplement fraud (Jiménez-Amezcua et al., 2025).

The combination of chromatography, and MS further amplifies analytical capabilities, offering robust solutions for complex fraud cases. Gas Chromatography-MS (GC-MS) was pivotal in detecting sesame oil adulteration (Aghili et al., 2022), hazelnut authentication (Torres-Cobos et al., 2024), merging separation, and molecular identification techniques.

5.1.4. Molecular and genetic techniques

Molecular (i.e. detection of proteins, metabolites, or other biomolecules), and genetic (i.e. analysis of DNA to identify species or origins) techniques have emerged as crucial tools in the fight against food fraud due to their precision, and reliability. These methods leverage the molecular composition, and genetic markers of food products to detect fraudulent practices such as species substitution, origin misrepresentation, and adulteration. Among the most prominent techniques are polymerase chain reaction PCR-based methods, DNA barcoding, immunotechniques, and High-Resolution Melting (HRM) analysis, each contributing to authenticity verification, and fraud prevention. While these techniques have been widely used for food fraud detection, recent advancements in the 2020s have further enhanced their accuracy, sensitivity, and applicability (Silva & Hellberg, 2021).

Beyond traditional qPCR, and multiplex PCR, techniques such as droplet digital PCR (ddPCR), and isothermal amplification (e.g., LAMP) have emerged. ddPCR enhances sensitivity, and quantification accuracy by partitioning DNA samples into thousands of droplets, reducing errors in species detection. This method has been particularly useful for seafood authentication, where precise identification is crucial (Silva & Hellberg, 2021). Similarly, enzymatic recombinase amplification (ERA) with Lateral Flow Strip (LFS-ERA) enables fast, low-cost detection of horse, donkey, and pig DNA in meat products, providing a simpler alternative to PCR (Zhou et al., 2023).

The integration of Next-Generation Sequencing (NGS) has revolutionized barcoding approaches, allowing simultaneous identification of multiple species in a single analysis. High-Throughput Sequencing (HTS) provides broader coverage and is increasingly applied to detect mislabeling in complex food matrices, particularly for seafood (Silva & Hellberg, 2021), and distinguish unauthorized GMOs (Fraiture et al., 2017).

Regarding immunotechniques, the hybridization of PCR with ELISA (PCR-ELISA) has improved food authentication by combining DNA detection with antibody-based specificity. This allows for greater sensitivity in detecting allergens or undeclared animal components. The approach is now being applied in allergen detection, and processed meat authentication (Silva & Hellberg, 2021).

Finally, recent applications of HRM involve its combination with Single Nucleotide Polymorphism (SNP) analysis, allowing finer differentiation of geographical origin claims for premium products like olive oil, and wine (Barrias et al., 2025). HRM's capability to detect subtle genetic variations without sequencing makes it a cost-effective alternative in food fraud detection. For example, this technique helps in identifying specific seafood species based on their unique melting temperatures, which can vary between different species due to differences in their DNA sequences (Silva & Hellberg, 2021).

Molecular and genetic techniques have greatly enhanced food fraud detection by improving accuracy, sensitivity, and efficiency. However, challenges such as high costs, specialized equipment requirements, and data interpretation complexities remain barriers to widespread adoption. Despite these limitations, continued advancements are making these techniques more accessible, and effective in ensuring food authenticity, and consumer trust.

5.1.5. Sensor-based, and other emerging techniques

Sensor-based techniques have gained traction in food fraud detection due to their portability, cost-effectiveness, and rapid analysis capabilities. These technologies are designed to mimic human sensory perception or provide rapid compositional insights, making them useful for on-site applications, and preliminary screening.

The Electronic-Nose (E-nose), and Electronic-Tongue (E-tongue) are notable sensor-based tools that emulate olfactory, and gustatory systems, respectively. The E-nose analyzes volatile organic compounds

(VOCs) using an array of gas sensors, proving its utility in detecting adulteration in essential oils (Aghili et al., 2022), spices (Qin et al., 2024), and wines (Peris & Escuder-Gilabert, 2016). Similarly, the E-tongue evaluates non-volatile compounds, demonstrating success in authenticating honey (Ciursa & Oroian, 2021), coffee (Almario et al., 2024), and milk by identifying deviations in taste profiles due to dilution or substitution (Perez-Gonzalez et al., 2024). While these technologies are highly sensitive, their accuracy can be limited by sensor drift, and the need for calibration tailored to specific food matrices (Mahanti et al., 2024).

Handheld NIR spectrometers have emerged as compact and efficient tools for food fraud prevention. These devices enable non-destructive testing by analyzing the molecular fingerprint of samples through light absorption patterns (Gopal & Muthu, 2024; Li et al., 2024). Recent advances in handheld NIR technology have made it possible to authenticate meat species, verify the geographic origin of grains (De Girolamo et al., 2019), and detect adulterants in oils (Kaufmann et al., 2022), and dairy products in real time (Hebling e Tavares et al., 2022). However, their precision can vary depending on the complexity of the food matrix, and the robustness of reference databases. Similarly, Differential Pulse Voltammetry (DPV) has been applied for fruit juice authentication, analyzing electrochemical fingerprints to detect adulteration (Monago-Maraña et al., 2024).

Microfluidics, another breakthrough technology, integrates analytical processes on a small chip, allowing for rapid, and low-cost detection of adulterants, and contaminants. These systems have been particularly effective in identifying fraudulent practices in high-value foods such as honey (Egido et al., 2024), and fishery products by detecting biogenic amines as an indicator of edibility (He et al., 2020). Genosensors, which exploit nucleic acid hybridization for selective detection, have also been applied in food authentication, providing rapid and specific recognition of target adulterants.

Overall, sensor-based techniques, while not replacing laboratory-based methods, provide valuable, rapid screening, real-time preliminary assessments that enhance supply chain monitoring, and combat food fraud effectively.

5.2. Data processing and pattern recognition tools

5.2.1. Data preprocessing techniques

Data preprocessing is essential in food fraud detection, ensuring raw data is refined for accurate, and reliable analysis. By addressing noise, correcting baselines, and isolating key features, preprocessing enhances the clarity, and usability of spectral, genomic, and imaging data.

Improving data quality begins with techniques to reduce noise, such as the Savitzky-Golay filter (Grassi et al., 2024; Kogniwali-Gredibert et al., 2024), which smooths spectral data while preserving critical details. Baseline correction further refines this data, counteracting distortions caused by instrumental variations or sample inconsistencies, thereby revealing subtle anomalies in products like milk (Ullah et al., 2020). To handle the complexity of high-dimensional datasets, feature selection methods extract the most relevant variables, simplifying models without losing critical information, leaving detailed statistical techniques like Principal Component Analysis (PCA) for later stages.

Together, these techniques form the backbone of reliable data analysis, ensuring subsequent statistical and computational methods can effectively detect fraudulent activities across a range of food products.

5.2.2. Chemometrics, machine learning, and other artificial intelligence tools

Chemometrics, the application of mathematical and statistical tools to chemical data, is indispensable in food fraud detection. Techniques like PCA, Partial Least Squares (PLS) regression, and clustering, though established for decades, remain crucial for simplifying multidimensional data, and uncovering patterns or anomalies, enabling advanced approaches, like ML. By integrating spectral, genomic, and imaging data, chemometrics provides critical insights to identify fraud, evolving alongside computational advancements to tackle challenges like data variability, and the need for robust databases. These methods ensure foundational reliability while supporting the growing complexity of analytical demands (Rodionova et al., 2024).

PCA plays a pivotal role in simplifying high-dimensional datasets, allowing for the identification of critical patterns, and variances in fraud detection across most food groups. For example, it continues to be applied in some studies on alcoholic beverages (Ghidotti et al., 2025), some cereals (Kogniwali-Gredibert et al., 2024; Teye & Amuah, 2022), cocoa, and chocolate (Greño et al., 2023; Millatina et al., 2024; Santos et al., 2021), coffee (Couto et al., 2024; Núñez et al., 2021), eggs (Puertas et al., 2023), fats (Abamba Omwange et al., 2021), fish (Shen et al., 2022), herbs, and spices (Campmajó et al., 2021), honey (Egido et al., 2024), meat (Turgut et al., 2025), and milk (Feng et al., 2024), among many others.

Parallel Factor Analysis (PARAFAC) is another powerful chemometric tool, especially effective in decomposing complex three-dimensional data sets, such as fluorescence matrices having Excitation-Emission Matrices (EEMs) that have been used for fraud detection in wine (Wu et al., 2025), and milk (Ullah et al., 2020).

Clustering methods, including k-means, and hierarchical clustering, are invaluable for grouping samples based on similarity, and identifying anomalies. For instance, in sesame oil (Aghili et al., 2022), clustering revealed distinct chemical profiles indicative of fraud, while in saffron (Momeny et al., 2023) it successfully differentiated authentic samples from counterfeits, underscoring its effectiveness in unsupervised data analysis.

PLS regression is excellent for building predictive models by correlating spectral data with target variables. This technique in combination with spectral techniques continues to give very good results in cocoa (Santos et al., 2021), fats, and oils (Abamba Omwange et al., 2021), herbs, and spices (Campmajó et al., 2021), honey (Egido et al., 2024), milk (Ullah et al., 2020), and non-alcoholic beverages (Xu et al., 2020), thus demonstrating its ability to make accurate, and reliable predictions.

Linear Discriminant Analysis (LDA), and Quadratic Discriminant Analysis (QDA) are classification tools that extend the capabilities of clustering by separating predefined classes in datasets. These methods have evolved to combine with others, such as Partial Least Squares Discriminant Analysis (PLS-DA), which integrates the predictive power of PLS regression with the classification ability of LDA. For example, PLS-DA has been applied in alcohol beverages (Ghidotti et al., 2025), cereals (Teye & Amuah, 2022), herbs, and spices (Momeny et al., 2023), among others. Similarly, LDA has been used in eggs (Puertas et al., 2023), fats, and oils (Aghili et al., 2022), while QDA excels in these groups, offering a more precise analysis through advanced classification frameworks.

Building upon the foundation of chemometrics, predictive techniques powered by ML, and other AI tools emerged. Unlike traditional statistical methods, these approaches focus on leveraging algorithms to predict outcomes and classify data with exceptional precision. ML, and other AI tools are revolutionizing the detection of food fraud, offering tools capable of processing vast, and complex datasets, enabling more accurate, scalable, and efficient analyses across diverse applications. However, challenges such as overfitting, and the small sample size typical in many studies require careful validation to ensure model reliability, and generalizability (Yang et al., 2024).

Supervised learning involves training algorithms with labeled datasets to enable predictions, and classifications. SVM have proven effective in classifying several complex food matrices, such as cereals, and bakery products (Hou et al., 2023; Teye & Amuah, 2022), cocoa powder (Millatina et al., 2024), eggs (Puertas et al., 2023), extra virgin olive oil adulteration (Abamba Omwange et al., 2021), herbs, and spices (Jahanbakhshi et al., 2021b; Momeny et al., 2023), and meat (Fengou et al., 2024). Similarly, RF, Extreme Learning Machine (ELM) or similar techniques have been applied to classify rice (Hou et al., 2023) cocoa powder (Millatina et al., 2024), demonstrating its robustness in handling datasets with diverse features. Decision trees, such as Neighbor-Joining (NJ) trees, Unweighted Pair Group Method with Arithmetic Mean (UPGMA) trees, and phylogenetic trees, have also been used to establish relationships between samples based on spectral, and compositional similarities in fish, crustaceans, and products thereof (Mazumder & Ghosh, 2024). Additionally, ensemble methods like Gradient Boosting Trees (e.g., XGBoost, LightGBM) have shown high efficiency in distinguishing fraudulent food products by optimizing classification accuracy in herbs, and spices (Jahanbakhshi et al., 2021a, Jahanbakhshi et al., 2021a; Momeny et al., 2023).

Unsupervised learning methods explore datasets without predefined labels, uncovering patterns, and anomalies. These methods are particularly valuable for exploratory analyses where classification boundaries are not initially defined. Clustering techniques, such as hierarchical clustering, have been utilized in differentiating Arabica coffee varieties (Couto et al., 2024), detecting adulteration in cocoa powder (Millatina et al., 2024) and identifying different species of crab (Mazumder & Ghosh, 2024) as well as fraud in crude palm oil (Yao-Say Solomon Adade et al., 2022), and cinnamon samples (Coqueiro et al., 2024). Additionally, anomaly detection has been applied to extra virgin olive oil adulteration (Abamba Omwange et al., 2021), identifying distinct patterns indicative of fraud.

Deep Learning (DL) harnesses neural networks, a branch of AI, to analyze complex imaging, and spectral data. Applications include maize seed classification using One-Class Convolutional Neural Networks (CNNs), and Band Attention Mechanisms with HSI (Zhang et al., 2024), and fraud detection in ginger using CNNs with gated pooling, and feature extraction (Jahanbakhshi et al., 2021b). CNNs, such as Inception-v4, have been employed to detect counterfeit saffron (Momeny et al., 2023), and to distinguish genuine turmeric from adulterated samples (Jahanbakhshi et al., 2021a). Similarly, Artificial Neural Networks (ANNs) with NIR spectroscopy, and E-Nose sensors have been used for rice fraud detection, achieving high accuracy through Bayesian Regularization, and Levenberg–Marquardt algorithms (Aznan et al., 2022). Additionally, GANomaly, a DL method based on Generative Adversarial Networks (GANs), has been applied to honey fraud detection (Cheng et al., 2024), showcasing the potential of DL in uncovering intricate patterns in food fraud.

5.2.3. Data fusion, and multi-source integration

Data fusion combines information from multiple sources, such as spectroscopy, imaging, and genomics, to enhance the accuracy, and reliability of food fraud detection. By integrating diverse datasets, data fusion reduces false positives and provides a comprehensive understanding of complex samples. Feature-level fusion, which combines raw data for joint analysis, and decision-level fusion, which merges outputs from individual models, are pivotal approaches in this field (Vinothkanna et al., 2024).

Applications for data fusion are widespread. The integration of spectroscopic and genomic data has proven effective in authenticating fish products, while combining imaging and chemical analyses has been used to identify adulteration in spices, and meat products (Liang et al., 2025).

Practical examples highlight its versatility, Raman spectroscopy combined with a fusion ML algorithm has been employed to detect dairy product fraud, achieving high accuracy in identifying adulterants (Feng et al., 2024). Similarly, HSI coupled with PLS regression has been applied to verify the authenticity of minced beef, showcasing the potential of data fusion in combating food fraud (Chiavaioli et al., 2025).

5.2.4. Big data, and real-time analytics

Big data, and real-time analytics are revolutionizing food fraud detection by enabling the processing of massive datasets, and immediate decision-making. Cloud-based solutions facilitate the storage, and analysis of global data, ensuring comprehensive monitoring of supply chains, and food authenticity. The IoT further enhances real-time detection through smart sensors integrated into food processing systems, enabling continuous monitoring of parameters like temperature, humidity, and chemical composition (Sharma et al., 2024; Zhang et al., 2025).

Cloud platforms allow stakeholders to share, and analyze data in real time, improving transparency, and traceability. For example, IoT-enabled sensors combined with cloud-based analytics have been employed in processed foods to detect adulterants on-site and provide instant alerts. By leveraging IoT, and cloud-based analytics, big data solutions ensure accurate, scalable, and timely interventions in food fraud, solidifying their role in safeguarding food systems (Zhang et al., 2025).

5.2.5. Blockchain for food fraud prevention

Blockchain technology, a decentralized system for storing and verifying data, is revolutionizing food fraud prevention by ensuring transparency, and traceability throughout the supply chain. Its key features, such as immutability, cryptographic security, and distributed accessibility, enable robust data management, reducing opportunities for tampering or manipulation. These capabilities are critical in mitigating fraud, particularly in high-value or geographically certified products (Yang et al., 2024).

Blockchain facilitates decentralized data management, ensuring production, transport, and certification records remain tamper-proof. For instance, supply chain transparency is enhanced by recording each stage of a product's journey, from origin to final distribution, allowing stakeholders to verify claims of authenticity (Yang et al., 2024).

Practical applications demonstrate its effectiveness. In PDO-certified feta cheese, blockchain-based traceability systems improve compliance by securely documenting production standards, and geographical origins. Similarly, blockchain has been used for pomegranate traceability, ensuring authenticity through detailed, and verifiable supply chain records (Tran et al., 2025). These examples highlight blockchain's potential to safeguard the integrity of food products and build consumer trust by offering an unprecedented level of transparency, and accountability.

6. Challenges, and limitations in combating food fraud. Future directions, and innovations

Despite significant progress in analytical technologies, several challenges remain that limit their comprehensive use in detecting food fraud. Non-destructive techniques like HSI and UV/VIS/NIR spectroscopy enable rapid field deployment. Furthermore, emerging FFF spectroscopy, which enables direct analysis of turbid food matrices without any sample preparation, shows great promise, but additional studies are needed to validate its performance across a broader range of food products. However, these methods often fall short of the specificity required for thorough compositional analyses. Destructive approaches such as HPLC and GC-MS provide high sensitivity but require labour-intensive preparation and specialized personnel. Advanced methods like NMR and RS generate complex datasets requiring advanced computational tools and expertise, limiting their wider adoption. The high cost of these technologies restricts their accessibility, confining their use to well-resourced laboratories, and regulatory agencies (Sharma et al., 2024).

Food fraud is aggravated by the lack of uniform regulations, and enforcement frameworks on a global scale. The lack of standardized definitions and testing protocols hinders coordinated international efforts. Regulatory bodies, especially in low- and middle-income countries, often face significant barriers, including limited access to advanced analytical technologies, and insufficient capacity to implement rigorous enforcement measures. In regions dominated by informal or 'wet' markets, especially in parts of Africa, Asia, and South America, challenges are compounded by unregulated trade. While traceability systems have shown progress, they remain inadequate to manage the increasing complexity of global supply chains. These systemic gaps create opportunities for fraudsters, underscoring the pressing need for harmonized regulations, and strategic resource distribution to bolster enforcement capabilities (Vinothkanna et al., 2024).

The transnational scope of food fraud complicates enforcement. Overlapping jurisdictions and differing national regulations hinder cross-border cases. Additionally, the absence of integrated international systems for data sharing, and fraud pattern detection impedes timely, and effective interventions. Trade policies and conflicting priorities delay regulatory action and undermine coordination. Addressing these issues requires strengthened cross-border collaboration through unified frameworks, joint enforcement initiatives, and robust international agreements designed to streamline efforts, and enhance accountability (Zhang et al., 2025).

Food fraud impacts stakeholders across the supply chain. Advanced detection technologies require significant investment, often beyond the reach of small and medium-sized enterprises (SMEs). Although long-term benefits of fraud prevention are clear, high upfront costs often overshadow them, especially in resource-limited settings. To ensure broader adoption, it is crucial to strike a balance between costs and benefits by developing scalable and economically viable solutions (Sharma et al., 2024).

Emerging AI, blockchain, and IoT technologies are revolutionizing food fraud prevention. AI-powered algorithms significantly improve data analysis capabilities, identifying subtle patterns within the complex datasets generated by spectroscopic, and imaging systems. Blockchain provides immutable records that improve supply chain transparency and traceability, reducing fraud risks. Meanwhile, IoT-enabled smart packaging, equipped with advanced sensors, allows for real-time monitoring of environmental conditions, aiding in the early detection of tampering or product degradation. Together, these technologies represent a transformative shift toward a more proactive, data-driven approach to combating food fraud (Sharma et al., 2024).

Nanotechnology offers groundbreaking solutions for detecting food fraud. Nano-sensors for trace adulterant detection are emerging as fast, and reliable tools. Similarly, nano-barcodes, which remain invisible to the naked eye, provide a sophisticated method for verifying the authenticity and integrity of food products. These technologies are effective, cost-efficient, and suitable for large-scale use in commodity markets. The scalability and versatility of nanotechnology-based tools underscore their critical role in advancing the fight against food fraud.

The future of food fraud detection lies in the seamless integration of diverse technologies, including rapid, non-destructive, in-situ methods for raw materials, and final products. Combining spectroscopic techniques with genetic tools, and advanced imaging methods strengthens detection systems, enabling them to address a wider array of fraud scenarios with greater precision. Centralized data platforms that harmonize, and interpret complex datasets further enhance accuracy, and operational efficiency. Achieving these advancements will require close collaboration between academia, industry, and regulatory authorities, fostering innovation, and ensuring the effective deployment of comprehensive detection systems (Vinothkanna et al., 2024).

As technology advances, so do the tactics employed by fraudsters. In the coming decade, increasingly sophisticated methods, such as counterfeit molecular markers, and advanced adulteration techniques, are expected to emerge. Climate change is likely to amplify fraud involving claims of geographical origin, and sustainability, as shifting environmental conditions affect food production. Growing consumer demand for transparency will accelerate the adoption of real-time monitoring systems, while innovations in AI, and blockchain technology will play a central role in shaping the next generation of fraud prevention strategies.

7. Conclusions

in technology are reshaping the fight against food fraud. This review shows combining modern analytical science, and informatics enables more effective fraud detection, and prevention. On the analytical side, techniques like spectroscopy (NIR, FT-IR, Raman), and chromatography coupled with MS have become indispensable for authenticating food products, providing rapid, and highly sensitive identification of adulterants. These methods, once confined to labs, are now increasingly available as portable devices, and kits, bringing testing closer to the supply chain. Data-driven tools, including AI, and ML models can mine chemical and image data to recognize subtle fraud patterns that humans might miss, while blockchain ledger systems secure supply chain information to improve traceability. The synergy between traditional analytical methods and digital technologies (e.g., AI-assisted spectroscopy) has markedly improved both the accuracy and speed of fraud detection. Emerging technologies, from smart sensors to predictive algorithms, make food fraud more detectable, and less attractive to fraudsters.

To capitalize on these technological gains, an interdisciplinary, and cooperative approach is essential. Regulatory agencies should invest in, and adopt these emerging tools within inspection regimes, updating official methods to include rapid field tests, and data analytics. For example, authorities are urged to strengthen routine authenticity testing, and traceability in vulnerable sectors. Sharing information, and best practices across borders (through mechanisms like the Food Fraud Network, and the new European Food Fraud Community of Practice) can amplify the impact of national efforts. The food industry should proactively implement technologies such as blockchain for end-to-end supply chain visibility, and AI-based screening of raw materials to catch anomalies early. Integrating fraud detection into food safety management systems will protect brands, and consumers alike. Researchers and technologists are encouraged to continue developing user-friendly, cost-effective detection devices, and to refine algorithms for even greater accuracy. Collaboration among food scientists, data scientists, and law enforcement experts will be key to staying ahead of increasingly sophisticated fraud tactics.

Looking forward, several avenues hold promises for enhancing food fraud prevention. AI-driven predictive models are expected to play a larger role by analyzing supply chain data, market prices, and historical incidents, ML could predict fraud susceptibility in real time, enabling preventative action before adulterated products enter the market. Similarly, real-time monitoring using IoT sensors (for temperature, authenticity markers, etc.) could alert stakeholders to fraud attempts as they happen, rather than after the fact. These technologies, combined with big data analytics, could shift the paradigm from reaction to prevention. A critical frontier is harmonizing global regulations and standards. Currently, gaps, and inconsistencies in food fraud definitions, and enforcement allow fraudsters to exploit “weak links” in the system. Unified international standards, and stronger cross-border cooperation – for instance, interoperable databases of fraud incidents, and shared analytical methods – would close these loopholes. In summary, emerging technologies provide powerful tools to detect, and frighten food fraud, but their full potential will be realized only through coordinated efforts that integrate innovation with policy. By embracing collaboration, and continuing to invest in technology, and oversight, regulators, and industry can move toward a food supply that is not only safe, and high-quality, but also verifiably authentic, and fraud-free.

Author contributions (CRediT)

•Xavier Marín: Conceptualization, Data curation, Formal analysis, Investigation, Methodology, Project administration, Software, Supervision, Visualization, Writing – original draft, and Writing – review and editing.

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•Guillem Gervilla-Cantero: Writing – original draft and Writing – review and editing.

• Carolina Ripolles-Avila: Supervision.

•Manuel Castillo: Supervision.

Declaration of generative AI and AI-assisted technologies in the writing process

ChatGPT (OpenAI) was employed solely to refine language and style. All scientific ideas, data analyses and conclusions are original to the authors, and no AI contributed to scientific content.

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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Appendix A. Supplementary data

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Data availability

The data is public and can be easily found on the internet.

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