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Frauds in organic foods: An update on strategies of detection, challenges and management

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Abstract

Food fraud poses a significant challenge within the global food supply chain, with apprehensions regarding aspects such as food safety, authenticity, and efficiency. Currently, food fraud prevention is emerging as a unique food research area due to the unpredictability and potential economic gain to fraudsters. However, food fraud incidence/ events are increasing. Due to globalization of production and distribution, modern food fraud events could be massive in scale as they have both regional and global impact.

In this minireview, we have described the basic organic food landscape, concept of food fraud, and its types. Emphasis has been given to the various validated methods of identification of food frauds and techniques employed for their detection. Methods such as spectroscopy, chromatography, and DNA -/chemometric -based techniques. Further, the application potential of recently developed AI-based techniques is also briefly discussed. In a separate section, food fraud issues related to herbs and spices have been dealt with a focus on various sensitive detection methods based on DNA technology and illustrated with a subset of specific spices and organic Honey.

Keywords: Food Fraud; Organic Food; Detection Strategies; AI Detection; Spices; Organic Honey

1. Introduction

Fresh and processed foods produced by organic farming fall under the category of organic foods [1]. They are cultivated without using any synthetic fertilizers or pesticides and are not genetically modified organisms (GMO). The serious health concerns due to various factors such as pollution and misuse and abuse of synthetic fertilizers and pesticides in commercial farming has prompted interest among the consumers for organic foods. Once a farm is converted to organic methods, it helps to increase biodiversity; reduce chemical contaminants; reduces soil, air and water pollution; improve soil microbial health; and improve the health of farmworkers and livestock. Considering the role of harmful agricultural chemicals in food chain, the organic diet could prove healthier than a conventional one. In recent decades, the industry has grown into a multibillion-dollar industry with characteristic production, processing, and supply chain management systems. About 191 countries practice organic agriculture in an area of 76.4 million ha (1.6% of the total global cultivated area) and another 29.7 million ha as wild collection area with 3.7 million organic producers and a market of about 136 billion USD [2]. Australia has the highest area of about 36 million ha. Region- wise distribution of area under organic agriculture is depicted in Figure 1.

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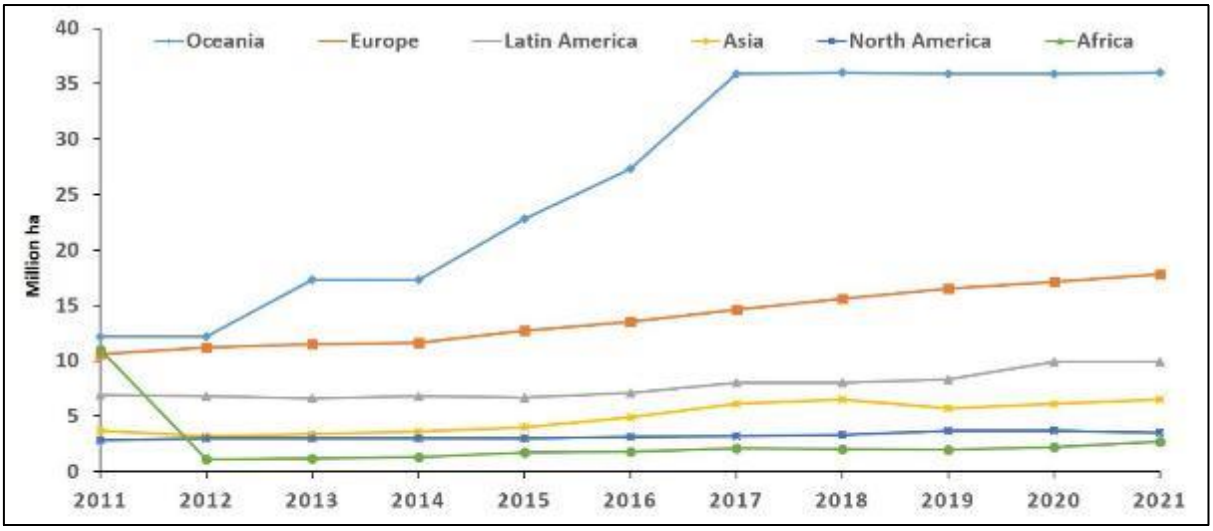

[Source data: FIBL World of Organic Agriculture annual reports]

Figure 1 Progressive area under organic agriculture

In the last decade, the area under organic agriculture has grown at a mean CAGR of 52.32%. Among the regions, highest CAGR of 81.81% was recorded in Asia while it was lowest in Oceania (37.76%) showing a plateau since 2017. However, Oceania constitutes >40% of organic agriculture area in the world. During the same period, number of organic producers have doubled from 1.8 million in 2011 to 3.7 million in 2021 whereas the organic market has grown from 49.4 billion€ to 124.8 billion€ at a CAGR of 43.43%. The per capita consumption of organic foods has increased from 7.05€ to 15.7€ which is very significant. In India, the area under organic agriculture (organic +wild harvest) hovered around 3.5 to 5.7 million ha during 2014-2021. However, with the Government interventions, during 2021-2022, the area almost doubled to 9.12 million ha with a CAGR of 20.74% and a total production of 3.4 million tons [3].

1.1. Food Fraud

According to CX/FICS 18/24/7 notification of Food and Agriculture Organization [4], food fraud is "any deliberate action of businesses or individuals to deceive others in regards to the integrity of food to gain undue advantage. The fraud could be intentional wrongful description of origin of food and its composition; adultery of the foods with cheaper substitutes; non-disclosure of some ingredients and unapproved enhancers; forging the brands, labels and product names with similar sounding terms, composition; and excessive marketing of unreported product etc. to deceive the customer for economic gains. Most common foods prone to fraud are olive oil, milk, honey, saffron, orange juice, apple juices, grape wine, coffee, tea, herbs, spices, vanilla extract and fish. According to [5], the most common types of food frauds include i] adulteration, ii] tampering and mislabeling; iii] over-run; iv] theft; v] diversion; vi] simulation; and vii] counterfeit.

1.2. Types of frauds in organic foods

As discussed earlier, there is a sudden spurt in area under organic agriculture from 37.2 million ha in 2011 to 76.4 million ha in 2021. Further, another 29.7 million ha of wild harvest area makes the total area to around 106 million ha. The trade in organic foods has increased at an exponential pace as they are considered as healthier and eco-friendly. On the other hand, the certification systems and establishment of formal functional regulatory set ups had to gear up suddenly to meet this growing demand. This gap has exposed the vulnerability of this segment for food frauds. Bannor et al (2023) [6] reviewed the available literature from SCOPUS on food fraud during 2010-2023 and found that as many as 7 publications reported fraud in organic foods.

People are wary to purchase organic food due to lack of confidence about its genuineness. The problem of fraud and mislabeling occurs when a Food Business Operator (FBO) marks a product as organic while it contains non-organic ingredients or where the organic production standards are not adhered to in the production process. Therefore, it becomes important to check if the food labelled as "organic" is genuinely organic.

Adulteration: Adulteration is a subset of food fraud for economic gains that involves intentional substitution or incorporation of a substance in a product to increase its apparent value or reduce production costs [4].

Mislabeling: Mislabeling is making falsified claims for economic gain. In august 2019, USD 12 million worth of raspberries were intercepted at Chile border [actually produced in China] with fake organic declarations and fraudulent documentation [7].

Concealment; Concealment is non-disclosure of the low quality of agri inputs, food ingredients or product.

Substitution: Substitution is replacing an ingredient, or part of the product, of high value with another ingredient, or part of the product of lower value. There is a vast scope for such frauds as production of organic food is expensive and detection of organic and non-organic is only through labeling and faith. Any food commodity produced by both methods could be easily mixed and labeled as organic. As long as non-organic foods are produced keeping in mind the good agricultural practices, they would be usually free from harmful chemicals and thus go undetected.

Unapproved enhancers; adding unknown and undeclared materials to food products to enhance the quality attributes.

Dilution: Dilution of the contents is by mixing a high value ingredient with a similarly low value ingredient to reduce manufacturing costs.

Counterfeiting: Counterfeiting is selling produce with established brand name or packaging method, manufacturing method, constituents for economic gain.

Grey marketing: Grey marketing is disposing off the unreported or unsold produce without proper certifications [Table 1]

Table 1 Various Categories of Food Fraud

Substitution Method Comprises of substitution of inferior substances and removing the valuable ones
Dilution This method is to increase the volume of food products like the addition of water to milk.
Artificial enhancement Involves Coloring a food product or addition of an ingredient to make it look more appealing. [e.g. Addition of Sudan dye to enhance the color of paprika]
Counterfeiting To mimic something original to deceive consumers to trust that fake is of equal or greater value than the original thing. For example, dried flowers and dyed onion being sold as saffron.
Mislabelling Intentionally wrong labelling of the food product for financial gain with the intention of deceiving the consumer concerning what is originally packaged.
False marketing Advertising false statements for the sale of food product.

2. Methods for Identification of Food Fraud

Because of the complex nature of the factors underlying food fraud issues and their global economic impact, researchers have constantly reviewed this phenomenon in recent years. Testing methods have been developed and can be classified as either targeted or non-targeted based on the degree of vulnerability and type of fraud committed. When the adulterants are known or the suspect food contains naturally occurring markers [physical, biological, or chemical] that can reveal its identity or purity, targeted analysis is used. However, a non-targeted analysis is useful when the adulterating elements are either new or have not been detected previously, because a targeted approach will not detect them [6, 8]. These involve physical, chemical, and biological approaches.

Physical methods for detecting food adulteration include microscopic and macroscopic visual structure examination, as well as physical parameter analysis such as morphology, texture, solubility, bulk density, etc.

Chemical Methods: Liquid or gas chromatography in combination with mass spectrometry is the most commonly used chemical testing technique today because it allows for the detection of analytes at low concentrations, even in extremely complex food matrices. NMR spectroscopy is a fingerprinting technique that can identify the physical and chemical properties of atoms within a molecule as well as provide structural information. NMR spectroscopy can be used to investigate a wide range of sample types, such as solids, liquids, and complex mixtures.

Biological techniques: Adulterants, which are biological molecules, are best detected using DNA-based molecular methods. Adulterants in food are identified using three methods: Polymerase Chain reaction (PCR), sequencing, and hybridization-based approaches.

3. Techniques for Detecting Food Fraud

Numerous researchers have recently developed and proposed newer validated methods for authenticating food products on the market that are more robust, effective, and efficient, thereby contributing to a significant reduction in the global incidence of food fraud. Several researchers have extensively investigated and reviewed these methods [6, 9, 10, 11]. Food is frequently authenticated through processes that determine whether the product matches the information on its labels and complies with the rules and regulations for consumption.

Currently, the most common analytical techniques used in food product authentication are spectroscopy, chromatography, chemometrics, DNA, and artificial intelligence-based methods. These methods are discussed briefly below:

3.1. Spectroscopy technique

The spectroscopy method is a popular and promising method for food authentication and fraud detection. A wide range of techniques viz., Terahertz spectroscopy, Laser-Induced Breakdown Spectroscopy, Hyperspectral Imaging (HSI), Nuclear Magnetic Resonance (NMR) Spectroscopy, Fourier transformed infrared (FTIR), Raman Spectroscopy, Near Infrared (NIR) Spectroscopy, Vibrational Spectroscopy, and UV-Vis Spectroscopy are extensively used in identification of food frauds. They have been employed to detect and authenticate a variety of food products, including tea [12], honey [13], olive and sesame oil [14, 15], Rice and sugar [16, 17]. Furthermore, spectroscopy techniques are effective in detecting antibiotics, microorganisms, toxins, additives, and other potentially harmful substances in meat, dairy, and eggs.

The wide popularity of spectroscopic techniques as a primary tool for combating food fraud has been attributed to its dependability, speed, low cost, convenience, and small size, which makes it preferable to make quick decisions to prevent food fraud in agricultural marketing [18]. Several key benefits of using spectroscopic techniques are their ease of use, non-destructive nature, lack of sample preparation requirements, and ability to yield fast, accurate, and repeatable results. After obtaining the data through these methods, multivariate analysis is performed using a range of statistical and chemometric tools to better classify adulterated samples and establish the authenticity of original food products. To circumvent this limitation, numerous chemometrics or data analytics techniques have been created.

Several researchers opine that the creation and application of new prediction models in the future will depend heavily on these techniques. There are still several barriers, though, that prevent these technologies from being widely used in both academic and business contexts. It is essential to select the most effective acquisition strategy for the food item. This includes the selection of appropriate technique, such as NIR, IR, NMR, or fluorescence spectroscopy, and sample presentation, such as transmission, absorbance, reflectance, excitation or emission, and so forth. Because the spatial variability of components in heterogeneous foods can be differentiated using site-to-site spectroscopic fingerprint specificity, (HIS) technologies can be a legitimate substitute for point spectral scanning. HSI technologies based on NIR have been widely used for food quality assessment and authentication, particularly for animal-based products.

Chromatography methods are regarded as more powerful and advanced than spectroscopy techniques mainly due to their high accuracy. Chromatography methods include liquid chromatography (LC), gas chromatography (GC), supercritical fluid chromatography, and high-performance Layer Chromatography (HPLC). The techniques were primarily used to detect the toxicity and bioaccumulation of environmental contaminants in food and beverages [19]. However, these methods have been employed to determine the origin of products such as olive oil [20] and recently to detect unapproved additives in rice products and food supplements [21]. Some of the major disadvantages of using the chromatography technique include the cost of the machines and equipment, besides the fact that it is time-consuming and does not provide instant results.

3.2. DNA-Based Technique

Analytical methods based on DNA are among the most effective tools for detecting and authenticating a wide range of food products. These methods comprise of several techniques such Restriction Fragment Length Polymorphisms (RFLPs), Random Amplification of Polymorphic DNAs (RAPDs), Amplified Fragment Length Polymorphisms (AFLPs), Simple Sequence Repeats (SSRs), DNA Bar Coding, and Single Nucleotide Polymorphisms (SNPs). Adulterants in food products such as seafood [22, 23, 24, 25] and processed foods such as food supplements and maitake [10], have been detected using these methods [26]. These techniques have also been used to detect rice product mislabelling and to identify adulterated aromatic rice varieties [27].

3.3. Chemometric based technique

The chemometric-based techniques developed comprise of three major types of neural networks viz., Convolutional neural network (CNN), partial least squares (PLS), and interval-PLS (iPLS) [28]. These techniques are frequently used in conjunction with spectroscopy-based techniques to determine species substitutions in foods such as chicken flour [29], prawns [30], and olive oil [31]. Further, Christmann et al. 2022 [20] have combined gas chromatography hyphenated with ion mobility spectrometry (GC-IMS) with chemometric techniques to detect the geographic origin of olive oil and evaluated its reliability and accuracy. This technique was also used in conjunction with other multivariate regression analyses to detect egg types and sizes.

3.4. AI Based techniques

Artificial intelligence-based methods have enormous potential in food and agricultural quality, particularly in detecting adulteration and defects [32]. The potential of AI-based methods for detecting food fraud has recently been reviewed [33, 34]. Several AI-based techniques, including Artificial Neural Network (ANN), Deep learning (DL), Fuzzy logic (FL), Support vector machine (SVM), and Random Forest (RF), have recently been developed for rapid assessment of food quality attributes. AI techniques have been shown to improve detection accuracy by enabling data dimensionality reduction, feature extraction, and data and sensor fusion. Interestingly, combining AI algorithms with sensors has yielded positive results ranging from 81.2 to 100% accuracy.

In principle, AI in food adulteration detection trains algorithms to detect compositional changes by keeping a database of genuine and counterfeit items. These variations are now being used to create models that can detect whether or not a food product has been tampered with. This method holds a lot of promise for detecting adulteration in a non-destructive manner that human examination or standard laboratory procedures would miss. These methods have been shown to be effective in a variety of situations, including identifying adulterants, tracing the geographic origin of food products, preventing mislabeling and the use of unauthorized additives in food products such as drinks and edible oil, and detecting defects in fruits, meat, and processed foods [34].

These methods are briefly discussed below

Deep learning (DL): In recent years, DL has seen exponential growth in adulteration and defect detection. The number of layers in a neural network is referred to as deep learning. A deep learning algorithm is a neural network with more than three layers, including inputs and outputs [35]. ANNs have been used to detect adulteration in extra virgin olive oil [36, 37], with hyperspectral images [38, 39], with Raman microscopy [40, 41], and in some other agriculture and food quality-related applications. Currently, CNN methods are the state of the art in image pattern recognition and are being successfully used for food adulteration detection and quality evaluation of agricultural products [42, 43]

Fuzzy logic was used in a wide range of food quality applications viz., the classification of pineapple quality [44], prediction of poultry egg production [45] determination of the frying rate of sunflower oil [46], classification of wine quality [47] and the detection of external defects in olive oil [48]. In the food and agricultural industries, support vector machines (SVM) are widely employed to address classification issues. SVM is an optimization-based model that is used to evaluate the quality of agricultural and food products, including tomatoes [49], sea cucumber [50], adulterated cheese [51] and blueberry [52].

Random forest [RF] is a popular supervised technique for regression and classification that is based on the ensemble learning algorithm. Decision trees, the building blocks of RF, are simple to construct, apply, and interpret. Decision trees are good at classifying the data that was used to create them, but they fall short when it comes to classifying new samples. A combination of radiofrequency (RF) and near-infrared spectroscopy [53], digital imaging [54], vision systems [55] and differential scanning calorimetry [41] were used for food quality and adulteration detection.

3.5. Predictive model – Bayesian Networks (BN) model

Food fraud can affect food processing at the primary and secondary levels as well as other points in the food supply chain. The most fraudulent reports concerned beverages, dairy, and meat products, which were often processed as fakes, diluted, artificially enhanced, mislabeled, or substituted. The most widely used adulterant to modify food and beverage products is still chemicals.

BN are probabilistic graphical models that represent a set of known variables and their probabilistic dependencies. These models use the relationship between variables to compute the probability [56]; Several researchers have used to detect food fraud in both primary and secondary food processing as well as other stages within the food supply chain [57]. Regional databases like the Economically Motivated Adulteration incidents (EMA) and the Rapid Alert System for Food and Feed (RASFF) have been used to test several approaches to predicting food fraud using Bayesian Networks (BN) [58]. These researchers used Ge Nie Modeler (Bayes Fusion, LLC) to create the BN model, which was based on 715 notifications from the Food Adulteration Incidents Registry (FAIR) database from 1979 to 2018. 71.3% of the adulteration points and 63.8% of the food fraud type were accurately predicted by the model. In addition to providing useful implications for the food industry, food authorities, and food integrity researchers, BN models can be used to calculate probability. It would be possible to expand the BN model to determine which food categories fraudsters target.

3.6. Global Databases assess for food fraud vulnerability assessments

Several databases accessible in the public domain serve as vital resources for food fraud assessments. Essentially these provide valid information on various aspects related to a) databases on various commodities and ingredients as well as b) food fraud risk and vulnerability assessments. Some of the data sources are provided in Table 2.

Table 2 Major Data sources for food fraud vulnerability assessments

Used by Members of the EU Food Fraud Network system not operating in the public domain; Member States can use it voluntarily for transmitting information related to fraud cases concerning more than one Member State
Decencies Food Fraud Database Database originally set up and operated by the US Pharmacopeia, subsequently acquired by Decencies; Subscription-based database contains nearly 10 000 food fraud related records
Food Adulteration Incidents Registry [FAIR] Database operated by the Food Protection and Défense Institute [FPDI] – University of Minnesota Compilation based on both historical and current events involving economically motivated and intentional adulteration of foods on a global scale. Information related to incidents occurring more than 5 years ago are free of charge.
Horizon Scan Subscription based; original objective was to monitor emerging food safety issues, subsequently extended to cover adulteration and food fraud.
Food Fraud Risk Information Database Open-access database, online consultancy provided by Food Fraud Advisors, Develops/ implements food fraud prevention systems.
European Media Monitor [EMM] and JRC Food Fraud Report Open-access; has a specific section for food fraud-related news items collected globally; Digests the information and publishes a summary of food fraud incidents each month.
Used by Members of the EU Food Fraud Network system not operating in the public domain; Member States can use it voluntarily for transmitting information related to fraud cases concerning more than one Member State

4. Food Fraud: Herbs and Spices

Herbs and spices are particularly vulnerable to FF due to their widespread global trading. Spices, in particular, have extensive and complex supply chain systems due to limited production and processing in specific geographic regions, high economic value, and functional benefits, making them especially vulnerable to fraudulent activity [59, 60]. As a result, these items require increased monitoring, and numerous organizations throughout the world have created regulatory criteria to control their quality/authenticity and identify potential adulterants.

The production of spices is accompanied by a number of processing steps [such as grading, cleaning, separating, drying, roasting, grinding, and granulating], packing, long-term storage [for the majority of the spices], and distribution, which includes middlemen, export, wholesale and retail markets, auctions, and middlemen [61]. Scams and improper handling can happen at any point in the industrial process as well as in the food chain. With 81% of global output, Asia has dominated the international market for spices, followed by Africa, Latin America, and the Caribbean [8].

Since spices are most frequently delivered in powder form, there is a moderate risk of fraud.

Adulterations of herbs and Spice/spice products are being carried out by substitution, dilution, removal, unapproved/undeclared enhancement and concealment, and unapproved/undeclared treatment, process, or product [62]. In the case of the addition of components, these could reduce the quality and alter the composition of the food itself, potentially causing health risks to consumers. For both herbal and spice products, adulteration by incorporation of non-declared or nonpermitted components is of great relevance. It consists of the inclusion of any substance not legally declared, not authorized, or present in a manner likely to mislead the consumer, being an imitated and/or reduced quality product. There have been several reports of high-value spices being adulterated. For example, paprika powder has been found to contain lead oxide, oregano to have olive leaves, and cumin to contain almond peel and peanut husk. Adulteration with foreign materials: dried papaya seed in black peppercorns; chalk powder in turmeric [63]; dried red beet pulp in chilli powder [64]; or using material of lower quality of the same product, such as adding old and spent spices with fresh product.

Adulteration can also happen when inedible plant pieces called extenders are added to increase bulk, such as stamens in pure saffron [60, 65]. In order to hide the true quality of the spice products, chemical additives such as artificial flavorings and colors viz., Sudan red dye I–IV in paprika and metanil yellow in turmeric [66], are generally used [67]. Unlawful food dyes also include Sudan red and metanil yellow dyes, as well as other colors including malachite green and rhodamine B [8]. These dyes have the potential to various adverse health effects such as neurotoxicity, genotoxicity, and cancer.

In the past two decades, a range of different detection methods developed has been used in the determination of the authenticity of both herbs and spices. These include spectroscopy ultraviolet-visible (UV), near infrared (NIR), mid-infrared (MIR), Raman isotopic analysis, chromatography, electronic nose, polymerase chain reaction (PCR), enzyme-linked immunosorbent assay (ELISA) and thermal analysis. Although these methods are efficient and accurate, in some situations, they are often time-consuming, and expensive. Techniques such as NIR are of great industrial interest, due to their speed, efficiency, and environmentally friendly.

The use of DNA technology for food authenticity [68, 69] and, more especially, for plant material [70, 71] has been thoroughly examined. More modern analytical approaches, which are frequently used in conjunction with machine learning algorithms, authenticate herbal material by using proteins, metabolites, or DNA, either targeted or untargeted. DNA-based approaches are extremely specific, sensitive, and cost-effective instruments since their targets' genetic makeup is unaffected by environmental or physiological influences. These methods take advantage of DNA variability between species, and the majority of them include a PCR to amplify DNA. Species-specific PCRs targeting a product-specific nucleotide sequence are particularly appealing because of their sensitivity, specificity, repeatability, and capacity to detect low target amounts.

In the past few years, the use of DNA barcoding has become increasingly popular for identifying animal as well as plant species [71, 72]. This method is most effective when used on a single species. However, if the sample includes multiple species, the barcoding regions from each species may be amplified, making the Sanger sequencing step's sequences challenging to understand. Moreover, Next Generation Sequencing (NGS), a high-throughput sequencing technology, provides a solution to this issue through meta-barcoding. Additionally, whole genome sequencing is becoming feasible and may be used in conjunction with NGS to detect food adulteration. However, the data available for this method is rather limited.

DNA barcoding is a rapid, reliable, sensitive technology for a wide range of food commodities, including highly processed foods, because it allows for the creation of reference databases, increasing the likelihood of it becoming a routine test for food quality and traceability [73]. DNA purity and integrity are critical concerns for DNA barcodes, which can be a test constraint because poor-quality DNA reduces amplification success. With today's fast-paced food chain, the ability to quickly screen large quantities of samples for purity is critical. This technique has substantial relevance as a screening tool, with the potential for a confirmatory assay to estimate the purity of herbs.

A recent study [74], has described a broadly applicable approach viz., DNA accounting which allows for the detection of substitution of biological materials based on digital PCR. Fraud is detectable in a sample, and employing this approach it allows simultaneous measurement and forecasting of the number of genome copies Interestingly, authors have provided, proof of concept by presenting the analysis of 141 samples of Saffron [*Crocus sativus*] from across the European market by DNA accounting and the verification of these results by NGS analysis This method has also been used for the detection of adulterants in saffron , and chilli adulteration in black pepper [75].

Application of some of these techniques for specific spices are exemplified below

Cinnamon: Cruz-Tirado et al., 2023 [76] have published a paper outlining their methodology for creating classification models based on NIR-hyperspectral imaging [NIR-HSI] combined with chemometrics to classify *C. verum* and *C. cassia* sticks. In several health products, cinnamon is used in the form of powder, bark, or oil (CEO). There are two types of cinnamon available in the market: genuine cinnamon and fake cinnamon. In comparison to false CEOs, actual CEOs are more expensive and contain more phenolic and aromatic compounds, making them harder to locate in the market. False CEOs are used as adulterants because they have sensory qualities that are comparable to those of real ones.

Numerous techniques, including sensorial, physical, and analytical methods—with a focus on the last one, which is more investigated because it makes use of DNA barcoding, spectroscopy, chromatography, and electronic nose techniques—either separately or in conjunction with the chemometrics technique [77].

Ginger: There are several adulterants used for ground ginger, and screening methods are thought to be effective non-targeted analysis tools for spotting adulterated ginger. The separation of pure black pepper powder from tainted pepper samples containing black pepper husk, papaya seeds, pinheads, and chilli powder has been accomplished with NIR spectroscopy [78]. Non-targeted screening techniques are still in their infancy as a practical tool, but their advantages over food fraud make them one of the best tools for fighting ginger fraud.

Oregano: A culinary herb that is most frequently used in Mediterranean cuisine and pizzas. The main producers of oregano reside in the USA, Mexico, Greece and Turkey. Unlike most herbs, oregano has a convoluted history because its true nature is so elusive. In addition to the grouping of several botanical genera—Origanum (Lamiaceae) from the Mediterranean and Lippia (Verbenaceae) from Mexico—this is also partially caused by the Origanum genus's high degree of variability. Mexican oregano is much more flavorful than Mediterranean oregano, which may be because the two types of oregano have different amounts of essential oils in their leaves. Mexican oregano leaves have an essential oil content of approximately 3-4%, whereas Mediterranean oregano leaves have an essential oil content of around 2–2.5%.

Two methods were developed- one using chemometrics to analyze data in conjunction with FT-IR screening, and the other using LC-HRMS to identify biomarkers and detect adulterants that are frequently used. 78 samples from various retail and online sources were subjected to the two-tier testing strategy. The two tests agreed 100% that adulterants were present in over 24% of the samples that were tested [79].

Paprika: Paprika powder is a widely consumed spice, making it an attractive target for adulteration, which is not easily detected. In this study, a portable NIR spectrometer was used for fast detection of paprika adulteration. Benchtop NIR spectrometer has been used for the analysis of some spices such as black pepper [80], saffron [81], onion and garlic powder [82, 83] and oregano [79]. On the other hand, advanced techniques allow miniaturization of optical components without excessive loss of performance. NIR spectrometer are powerful instruments offering several advantages for nondestructive, online, or in situ analysis: small size, low cost, robustness, simplicity of analysis and portability [84].

In a recent study [85], the adulteration of paprika with potato starch, acacia gum, and annatto was quickly screened for using a portable NIR in conjunction with chemometric techniques of partial least squares regression (PLSR) and partial least squares discriminant analysis (PLS-DA). With a specificity of more than 90% and an error rate of less than 2%, partial least squares-discriminant analysis (PLS-DA) effectively distinguished adulterated samples from pure samples and identified the type of adulteration in these samples. This method appears to be promising for accurately identifying and measuring spice adulteration. When testing for additional ingredients and unintentional adulterants, NIR spectroscopy can yield reliable results for paprika authentication.

Future research should focus on developing confirmatory and screening methods based on the characteristics analysis of specific spices, such as ginger. It is important to pay equal attention to spice products that are marketed at lower prices and sold in large trade volumes, as well as those that are extremely valuable.

5. Organic Honey

Honey consumption has witnessed a surge after Covid-19 pandemic due to its numerous health benefits and the demand of organic honey is on rise. Organic honey is produced from the nectar of organically grown plants by Honeybees with no antibiotic treatment. The authorized certification bodies certify the organic honey/agri-produce.

Being a high value item, honey bags 3rd position as most faked food in the world and organic honey has become a sweet illusion. The authenticity of honey and presence of pesticide residues in organic honey is a complex issue that has sparked significant interest. Though some data about organic honey w.r.t floral origin, physicochemical parameters, microbial safety and bioactive compounds is available [86, 87, 88, 89], the data on full characterization of organic honey is still limited. Basa Cesnik et al (2019) [90] have analyzed honey from organic and conventional production in Slovenia. Around half of the samples, including both organic and conventional, contained residues of drugs (amitraz, compos, thymol) primarily used to control Varroa mites. However, levels were higher in conventional honey. There are studies, which showed that organic beekeeping practices significantly reduce pesticide exposure in honeybees and their products. Kanga et al. (2019) [91] compared the pesticide residues in conventionally-managed and organically-managed hives in Florida. No pesticide residues were found in honey samples collected from organically managed hives while amitraz, a formamidine was detected in honey collected from conventionally managed hives. Pollen and Wax from both types of apiaries contained pesticides, but levels were generally higher in conventionally managed hives. Lazarus et al. (2021) [92] from Croatia compared honeys from certified organic and conventional beekeepers. Conventional honeys frequently contained traces of synthetic acaricides used to control beehive diseases, like compos and amitraz. No other pesticides, antibiotics and PCBs were detected in any organic honey samples.

While organic certification standards strictly prohibit the use of synthetic pesticides in honey production, trace amounts of pesticides can sometimes be detected due to environmental contamination or soil can retain pesticide residues for years, even after transitioning to organic practices, highlighting the need for further research on broader environmental factors affecting honey quality. Chiesa et al. (2016) [93] investigated the presence of pesticides and persistent organic pollutants (POPs) in organic honey produced in various regions of Italy. The research revealed traces of pesticides found in most honey samples, including insecticides (diazinon and compos), often used in apple and citrus orchards. In their another study in 2018, POPs, specifically polychlorinated biphenyls (PCBs), polybrominated diphenyl ethers (PBDE), and polycyclic aromatic hydrocarbons (PAHs), were found in all the honey samples, regardless of location highlighting the ubiquity of these environmental pollutants. Interestingly, no antibiotics or neonicotinoid pesticides were detected in any of the honey samples. However, the detected levels were below the established safety limits and this information stresses on choosing suitable locations by beekeepers for organic production. Also, traces of pesticides including insecticides used in orchards near industrial site were found by Panseri et al. (2020) [94] in most samples of organic honey. Notably, no residues of pesticides like glyphosate, gluconate, aminomethylphosphonic acid (AMPA) were found. PCBs were identified in all samples, regardless of origin. Importantly, the study didn't detect any antibiotic residues in the honey samples.

In addition to safety concerns of Honey with traces of pesticides and antibiotics, the authenticity of organic honey in terms of adulteration with foreign syrups is gaining importance. With the advancement in the analytical techniques, the type of adulteration is also changing accordingly to escape the detection. A notable example being a shift from C4 sugar (corn or cane syrups) adulteration to C3 sugar (beetroot or rice syrup) adulteration. Therefore, it is becoming challenging and there is a dire need of sophisticated analytical tools. Isotopic signatures [EA-IRMS and EA-LC-IRMS], HRMS and NMR-based Honey-Profiling is being widely used to catch hold of this kind of honey fraud [95, 96, 97, 98].

6. Conclusion

Since supply chains in the herb and spice industry tend to be long, complex and pass through many countries, they provide numerous opportunities for criminals to carry out economically motivated adulteration. There is a growing concern in the food industry over the introduction of hazards from food fraud and greater concerted actions are needed to be put in place to detect it. A large global food industry such as the herb and spice sector is under constant threat from fraudsters. With the increasing trend of food adulteration, fast, reliable, sensitive and validated analytical detection techniques are required to be put in place. The need becomes more stringent in Herb and spice industry as well as organic food supply Chains owing to their higher value and constant demand /growth of this food sector. With highly valuable condiments such as saffron, oregano, vanilla, turmeric and paprika, huge amounts of money can be made by carrying out adulteration of these products at the expense of the consumer.

Compliance with ethical standards

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Disclosure of conflict of interest

The authors declare no conflict of interest.

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