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Nondestructive Techniques for Detecting Food Adulteration: A Comprehensive Review

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***Abstract*— Food adulteration poses a global challenge to food quality and safety it requires effective detection methods. This paper addresses the difficulty in detecting varied types and quantities of adulterants in varied food products and emphasizes the importance of contemporary detection procedures like high-performance liquid chromatography (HPLC) and gas chromatography-mass spectrometry (GC-MS). The need for rapid, non-destructive, and accurate detection methods is highlighted. The paper provides an overview of nondestructive analysis techniques and their application in screening for food adulteration, examining their effectiveness in recent years. Additionally, it explores prospects, variations in data interpretation, and discrepancies among different methodologies.**

***Index Terms*— Nondestructive Techniques, Detection of Food Adulteration, Type of Adulteration, Hyperspectral imaging,**

I. INTRODUCTION

The significance of food safety and quality is escalating in both developed and developing nations, driven by a growing demand for improved food standards and the implementation of stringent safety regulations. These challenges have a direct impact on our daily lives, emphasizing the importance of ensuring that our food is not only safe but also of high quality. Safe food is synonymous with healthiness, harmlessness, and suitability for consumption. The realm of food safety encompasses various issues, including adulteration, toxicity, the addition of foreign substances, pesticide residues, and the use of illegal additives.

Food serving as a vital energy source for all living organisms has a crucial and influential role in their development and preservation. The quality of the food we consume significantly influences the body's ability to obtain the necessary nutrients. A major threat to public health arises from food adulteration or fraud, often motivated by economic considerations. As we strive for better food standards, it becomes imperative to address these challenges to ensure not only the safety of our food but also its inherent nutritional value, contributing to the overall well-being of individuals and communities alike. The shady business of messing with our food is making some people a lot of money, but it's putting us at risk. They play with many foods like milk, wheat, shellfish, oils, drinks, and honey. Even the fruits and veggies we buy might not be safe because they could have harmful stuff on them. There are different ways they mess up the quality of food. Sometimes, they take out important things from it, or they use cheaper stuff to make it look better. This sneaky practice is called food messing. It tricks us into buying not-so-great food, and on top of that, it can make us sick.

The current era witnesses a thriving food adulteration industry that reaps substantial profits. The pursuit of illicit

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gains by shop owners, sellers, and other individuals poses a significant threat to the well-being of consumers. Commonly consumed items such as dairy products, wheat, shellfish, oils, alcoholic beverages, and honey frequently fall victim to adulteration. Furthermore, the perceived purity of fruits and vegetables in markets is not guaranteed, as they may contain harmful chemicals and pesticides. In several ways, the food's quality is diminished including the removal of essential components and the deceptive practice of presenting lower-quality food as superior, collectively termed food adulteration. Food quality can face various challenges, extending beyond adulteration to include natural contamination during the food processing stages. Microbial damage, such as bacterial or fungal contamination, may negatively impact the quality and safety of vegetable and fruit products. Furthermore, the decomposition of dairy goods, sensitive drinks, and additional food items is additionally referred to termed food contamination. Essential for nourishment and enjoyment, food contains carbohydrates, water, fats, and proteins (FAO/WHO, 2007) [1]. Throughout history, the risk of adulteration or the deceptive blending of cheaper substances with food has persisted. India, in particular, is grappling with concerns over food safety attributed to prevalent adulteration and contamination of essential food items, posing risks of diseases or poisoning [2].

A. Type Food adulteration

Food adulteration is divided into two primary types. The first type is when people purposely and knowingly add something to food called Intentional food adulteration. The second type encompasses unintentional or accidental interference, where individuals unknowingly or without awareness contribute to the alteration [3].

1. Intentional Adulteration

The intentional modification of food, termed "purposeful adulteration," entails the incorporation of substandard ingredients closely resembling the original items, making detection challenging. These contaminants may stem from biological or physical sources and are employed to either diminish the costly ingredients, thereby boosting profits, or increase the volume of the food by incorporating ingredients like starch, flour, sugar, oils, water, milk, and even potentially harmful materials such as sand, chalk powder, molasses, stones, brick powder, ergot, chicory, roasted barley powder, ground papaya seeds, etc., to enhance their essential nutrients [3]. Purposeful adulteration stands out as the most dangerous form of food tampering, as it permits nutrients to be eliminated and the introduction of foreign elements by individuals driven by profit motives, prioritizing financial gain over the well-being of consumers [4]. According to the study of the first publicly available database created in the US to gather information on risk factors associated with food fraud, the seven foods most vulnerable to deliberate food fraud motivated by money are olive oil, milk, honey, saffron, orange juice, coffee, and apple juice. [5]. The table 1 below details about some food items and their adulterations with their impact on human body.

TABLE 1: SIDE EFFECTS OF INTENTIONAL ADULTERATION

Food Items	**Adulterants**	**Impacts on the Human Body**
Butter, Ghee, & Cheese	Vanaspati, Starch Powder, And Potato Mash	Diseases of The Digestive System and Stomach
Coffee Ground	Powdered Tamarind with Chicory Seeds	Diarrhea
Honey	Corn Syrup, Dextrose, Molasses, & Sugar	Stomach Ailments
Jaggery	Chalk Powder, Washing Soda	Vomiting And Other Gastrointestinal Issues
Turmeric Powdered	For Instance, Residues of Pesticides, Metallic Material, Arsenic, Lead, Artificial Colors, Sawdust, Chalk Dust, And Metallic Yellow Dye.	Intestinal Problems and Cancer
Pepper	Both Dried Papaya Seeds and Berries	Skin And Gastrointestinal Irritations, As Well As Allergic Responses
Tea	Synthetic Coloring Agents	Disease Of the Liver
Edible Oils	Artificial Colors, Mineral Oil, Castor Oil, And Karanja Oil	High LDL cholesterol, Allergies, Paralysis, Gallbladder Cancer, And Cardiac Arrest
Cinnamon Sticks	Bark Of Cassia	Mouth Sores, Low Blood Sugar, Liver Issues, and an Elevated Risk of Cancer
Seeds Of Cumin	Sawdust, Colored Grass Seeds, And Charcoal Dust	Stomach Ailments
Grains	Weed Seeds, Straw, Dust, Stones, Pebbles, Broken Grain, etc.	Diseases of the Liver, Bodily Poisoning, etc.
Mustard Seeds	Seeds Of Argemone	Spasms In the Abdomen, Sluggishness, And Increased Excretion
Curd And Milk	Water With Powdered Starch	A Stomach-Related Problem
Sugar	Chalk Powder, Washing Soda, Urea, etc.	Gastrointestinal Issues with Renal Failure

2. Incidental adulteration

There is a chance that food and drink products might get contaminated if there are inconsistent nutritious methods used from the point of manufacture through the point of consumption. Unintended adulterants encompass substances like pesticide residues, mouse droppings, larvae in food, and other contaminants. Accidental metal contamination, including arsenic, lead, or mercury, remains a conceivable risk. Animals such as rodents and insects can significantly compromise food safety by introducing inadvertent adulterants such as excreta, bodily secretions, and bacterial decay. Commonly identified unintentional adulterants include pesticides, DDT (dichloro-diphenyl-trichloroethane), and residues on plant products, as highlighted in the research conducted [6]. The acceptable level for DDT in food typically stands at three ppm, a threshold rarely surpassed [7].

II. Literature Survey

The review of the literature must begin with an examination of the various approaches used to identify food adulteration, with a focus on principal component analysis (PCA) dimensionality reduction and optimum band image selection. Although these methods have been effective in detecting food adulteration in certain cases, a more holistic approach is required for a thorough investigation of the food industry.

The study done by Bansal et al. [8], was found to expand their inquiry beyond the confines of original trials, recognizing the need to adhere to systematic survey guidelines. The research not only delves into various methods of food adulteration and the associated health hazards but also examines the available detection techniques. A notable focus is placed on the exploration of molecular techniques for identifying biological adulterants in food [9].

Similarly, the study done by Banerjee et al. [9] centers on the detection of common contaminants and current developments in methods for identifying food fraud. Bhargava et al.'s comprehensive investigation [10] further contributes to the understanding of quality assessment in fruits and vegetables through methods such as feature extraction, segmentation, classification, and preprocessing.

In addressing the broader landscape of challenges in the food sector, Zhou et al. [11] highlight the application of deep learning methodologies. Their research extends to diverse areas, including food recognition, calorie calculation, quality detection of various food items, and tackling issues related to the contamination and food supply network. The examination of deep neural networks' superior architectures underscores the significance of deep learning in addressing the multifaceted challenges faced by the food industry. This literature review aims to synthesize insights from various studies, shedding light on the methodologies employed in detecting food adulteration and the broader challenges and advancements in the field.

III. Overview Of Food Adulteration Detection Methods And Techniques

The detection of contaminated food requires the use of both advanced technologies and basic optical procedures. It is vital to conduct necessary quality control evaluations of fruits, vegetables, and dairy products to guarantee that adulterants are not present in consumables. The two main kinds of techniques used to identify food adulteration are shown in Figure 3.

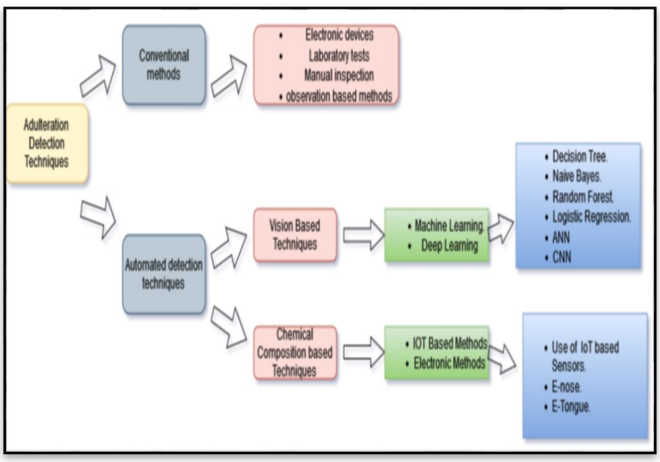

Figure 1: Food adulteration Detection Methods [26]

The diagram shows different types of adulteration detection techniques used in the food industry. It's divided into three main sections: Conventional Methods, Vision-Based Techniques, and Machine Learning.

A. Conventional Methods

These are traditional techniques that rely on human observation and physical tests.

- *Manual inspection:* This involves visually inspecting food for signs of adulteration, such as discoloration, unusual texture, or the presence of foreign objects.
- *Laboratory tests:* These are chemical or physical tests that can be used to identify specific adulterants in food. For example, a test might be used to detect the presence of added sugars or fats.
- *Observation-based methods:* These rely on changes in the food's sensory properties, such as taste, smell, or texture, to indicate adulteration. Numerous laboratory tests are conducted to verify the absence of adulteration in the product. For example, various pH indicators are applied to change the color of the meal, indicating the presence of adulterants. Diverse substances are employed to ascertain the adulteration status of food items. As an illustration, tincture iodine is utilized to determine the presence of starch in milk and milk products [24].

B. Automated Methods

Automated methods use technology to detect food adulteration without manual intervention. Here's a breakdown of the three main types:

- *Vision-Based Techniques:* Imagine food inspectors with superpowers of sight. These techniques use digital cameras and image analysis to see what human eyes might miss.
  - *Electronic devices:* These devices can be used to detect changes in the color, texture, or shape of food. For example, an X-ray machine might be used to detect foreign objects in food.
  - *Adulteration detection software:* This software can be used to analyze images of food and identify signs of impurity.
- *Machine Learning:* This is a type of artificial intelligence that can be used to automatically detect adulteration in food. Machine learning algorithms are trained on large datasets of labeled images of adulterated and non-adulterated food. Once trained, the algorithms can be used to identify adulteration in new images with a high degree of accuracy.
  - *Analyzing images:* Similar to vision-based methods, algorithms learn to identify subtle signs of tampering or low quality in food images.
  - *Analyzing chemical data:* Through the analysis of extensive datasets including both unaltered and contaminated food, these algorithms acquire the ability to identify atypical patterns in chemical profiles, indicating possible issues.
- *Artificial neural networks (ANNs):* These are complex algorithms that can learn to identify patterns in data.
- *Convolutional neural networks (CNNs):* These are a type of ANN that are specifically designed for image recognition.
- *Decision trees:* These are tree-like structures that can be used to make decisions based on data.
- *Random forests:* These are ensembles of decision trees that can improve accuracy and robustness.

Advantages of Automated Methods

- Objectivity refers to the ability to remove human bias and subjectivity, resulting in consistent and reliable outcomes.
- *Rapid and Efficient***:** Capable of swiftly and automatically analyzing substantial volumes of food.
- *Precision:* Certain methods can identify minute alterations that are imperceptible to the unaided vision.

Disadvantages of Automated Methods

- *Expense:* The process of installing and up keeping advanced technology might incur high costs.
- *Complexity:* Demands specialized knowledge and skills for operation and interpretation of outcomes.
- *Narrow Focus:* Each approach excels at identifying some forms of adulteration, but not all.

Table II outlines various methods of food adulteration and the corresponding detection techniques. For example, papaya seed adulteration in pepper is detected through color analysis and specialized imaging. Turmeric adulteration with sawdust is identified using an acid-based color test. Chicory in coffee is detected through sinking behavior and specialized light tests. These detection methods ensure food safety and purity.

TABLE II: VARIOUS FOOD SAMPLES AND METHODS FOR DETECTING ADULTERANT.

Food Sample	Adulterant	Method of Adulterant Detection			Ref.
		Physical	Biochemical	Molecular	
Madagascar pepper	Seeds for papaya	The smaller, ovoid, and either greenish-brown or brownish-black papaya seeds in color, can be distinguished from pepper seeds.	Near-infrared hyperspectral imaging. Mid-infrared spectroscopy	SCAR	[12]
oil and mustard seed	Rape seed, ragi, and argemone seeds/oil (Argemone mexicana)	The surface of mustard seeds is smooth. The argemone seeds can be distinguished from other seeds by close inspection because they have a grainy, rough surface and are black. When crushed, the argemone seed is white, whereas the mustard seed is yellow.	Plates made from TLC contain large absorbing elements, while HPTLC plates include much smaller absorbing materials.	Real-time polymerase chain reaction	[13,14]
Turmeric powder	Sawdust with a Color of metal yellow.	When turmeric is present, it causes a pink hue that appears right away in a test tube once a few drops of strong hydrochloric acid are applied and disappears after being diluted with water. Metal yellow will be present if the color persists.	TLC quantifications rely on optical comparisons or spot intensity comparing methods, that may lack precision in practical applications.	RAPD	[15]
Cinnamon	Hazelnut, almond shell dust, cassia, aromatized and powdered beechnut husk, and	________	_______	SSCP; sequencing	[16]
Coffee	Chicory	After adding water to a glass, sprinkle coffee granules on top. Quickly, fennel starts to grow on the water's surface, while coffee floats. The chicory particles that descend produce a vibrant array of hues as a result of the substantial quantity of caramel present.	Mid-infrared (MIR) spectroscopy	In-the-moment PCR	[17]
Tea	Iron flakes, leather flakes, and cashew husk	once a small portion of the sample has been distributed on paper, place a magnet on top of it. Particles of iron have been incorporated into the magnet. Construct a paper on the sphere. Once the sphere has been released, incorporate a minuscule quantity of the sample. the emission of a charred leather odor in the presence of leather particles.	GS-MS	Specific PCR It's of 5S rRNA	[18]
Oats	Wheat contamination	______	_____	Species specific PCR	[19]
Olive oil	Cheaper oils.	Verification of virgin olive oil's authenticity and origin	MIR spectroscopy	SCAR AFLP/ RAPD	[20]
Milk	Water, Urea, Iron and zinc	Since milk doesn't contain glucose or inverted sugar and can be easily tested with urease strips, it is contaminated if the glucose test results are positive.	ELISA and Fourier Utilize techniques such as transform infrared spectroscopy and multivariate analysis, pulsed-field gel electrophoresis, as well as MIR and NIR spectroscopy.	PCR based method, ribotyping, Real-time PCR	[21]
Meat	Metal, glass stones, bones	____	Enzyme-Linked Immunosorbent Assay (ELISA)	PCR-RFLP	[22]

Juices	Cheaper solid ingredients (particularly sugars)	The Brix test can accurately quantify the ratio of solids to water in fruit juice. Subsequently, the ratio that was observed is compared to specified standards.	Proton nuclear magnetic resonance (NMR) spectroscopy and liquid chromatography-mass spectrometry (LC-MS), Fourier Transform Infrared Spectroscopy (FT-IR)	———	[22]

TABLE III: INFRARED SPECTROSCOPY USED FOR FOOD ADULTERATION DETECTION.

Sample	Detection Technique	Spectral Range	Data Processing	Accuracy in % (R2 or R)	Ref
Ganoderma lucidum spore oil	FT-NIR	12400-4000 cm-1	Clustering technique and RVM	93.7	[27]
Peanut oil	MIR	4000 - 400 cm-1	Partial least squares class model (PLSCM), Soft independent modeling by class analogy (SIMCA)	97	[28]
Soybean oil	corn, sunflower, both of them, and sesame oil flavors	4000 -400 cm-1	MIR	0.99	[29]
Rosehip oil	Sunflower, corn, and soybean oils	4000 - 600 cm-1	Partial least squares-discriminant analysis	100	[30]
pure coconut oil	GC-SAW and FTIR systems	3020 - 3000 cm-1	Primary lateral sclerosis	0.99	[31]
Pure coconut oil	Fourier-Transform Mid-Infrared	4000 - 650 cm-1	discriminant analysis-Partial least squares	100	[32]
Neem and flaxseed oil	FTIR	4000 - 600 cm-1	PLS	0.998	[33]
Fish liver oil	FTIR	4000 - 650 cm-1	Principal component analysis; Primary lateral sclerosis	0.99	[34]
Almond oil	FTIR	4000 - 600 cm-1	Partial least squares	0.994	[35]
virgin extra olive oil	FTIR	3200 - 650 cm-1	Partial least squares	0.99	[36]
dietary oil	Fourier transform infrared spectroscopy	1550 - 650 cm-1	discriminant analysis-Partial least squares	100	[37]
Butter	Attenuated total reflection Fourier transform infrared	4000 - 650 cm-1	Partial least squares	0.99	[38]
Cod liver oil	Attenuated total reflection Fourier	4000 - 650 cm-1	discriminant analysis-Partial least squares	0.99	[39]
soybean oil	Major Incident Response	4000 - 650 cm-1	Non-performing loans - discriminant analysis	94.3	[40]
safflower oil	Major Incident Response	1800 - 650 cm-1	N-way partial least squares regression discriminant analysis	96.3	[41]
safflower oil	NIR- Major Incident Response	6000 - 4540 cm-1 and 1800 -650 cm-1	Least-squares support-vector machines	98.1	[42]
Honey	Vis-NIRS	400 ~ 600nm; 1500 ~ 2000nm	HCA; PCA; LDA; PLS	0.985	[43]
Coffee	NIR	400–2500nm	PLSR	=0.97	[44]
Pork	NIR	12500 ~ 3800 cm-1	PCA, PLS	0.9776(Liver); 0.986(Chicken)	[45]
Milk powder	NIR	11100 ~ 5880cm-1	PCA, SIMCA, PLS, SVR	100	[46]
Milk powder	NIR imaging	7500 ~ 4000cm-1	CLSI	0.60	[47]
Black pepper	DRIFTS	4000 ~ 400 cm-1	PCA, GA-SVM, PLS-DA	98(GA-SVM); 96(PLS-DA)	[48]

Table III presents a comprehensive overview of food adulteration instances and detection methods. Each entry includes the sample name, the adulterant investigated, the detection technique (Physical, Biochemical, or Molecular), the spectral range of Infrared Spectroscopy used, data processing techniques, and the accuracy achieved. Notable examples include FT-NIR for Ganoderma lucidum spore oil, MIR for Peanut oil, and FTIR for various oils like rosehip, fish liver, and almond. The reliability percentage signifies the effectiveness of these methods in consistently identifying contaminants. References provided offer further insights into the detailed procedures and findings associated with each entry.

TABLE IV: FOOD ADULTERATION DETECTED USING RAMAN SPECTROSCOPY AND RAMAN IMAGING TECHNIQUES.

Sample	Method of Detection	Spectral Range	Data Processing	Accuracy in % (R2 or R)	Ref.
Olive oil, Sesame oil	Raman spectroscopy utilizing coherent anti-Stokes	3200 - 2400 cm-1	Ratio of intensity (I=C-H/IC-H)	0.95	[49]
Almond oil	Raman Spectroscopy	2400 ~ 250 cm-1	Map of the distribution of Raman spectral vibration band intensities	-	[50]
EVOO	Raman Spectroscopy	1800 - 800 cm-1	discriminant analysis-Partial least squares	0.99	[51]
Butter	Spectroscopy using Raman	3745 - 200 cm-1	discriminant analysis-Partial least squares	0.99	[52]
virgin extra olive oil	Raman at Short Range Standoff	2350 ~ 250 cm-1	Map of the distribution of Raman spectral vibration band intensities	-	[53]
Honey	Raman spectroscopy	1820 - 270 cm-1	PLS-DA	91.1(HFCS); 97.8 (MS)	[54]
Fresh coconut water	Raman spectroscopy	2579 - 408 cm-1	PCA, PLSR	0.99	[55]
Onion Powder	Raman Spectroscopy	3200 -170 cm-1	PLSR	0.96	[56]
dehydrated milk	Chemical imaging Raman	2881-103cm-1	The linear analysis	0.99 (Melamine and urea)	[57]
Pistachio nut granules	Raman hyperspectral	3700 - 200 cm-1	PCA, PLSR	95.79	[58]

Table IV showcases the effectiveness of Raman spectroscopy and Raman imaging in detecting food adulteration. By analyzing scattered light, this method reveals unique characteristics of food composition. For instance, it accurately detects adulterants in olive oil and sesame oil by assessing vibration intensity ratios, as indicated by R^2 values. This technique is also applied to analyze almond oil, EVOO, honey, fresh coconut water, onion powder, dried milk, and pistachio nut granules, ensuring precision in detection. The table provides a concise summary of detection technique, vibration range, data processing method, and corresponding accuracy for each case, demonstrating the utility of Raman spectroscopy in verifying food purity and quality.

TABLE V: TECHNIQUES FOR DETECTING FOOD ADULTERATION: HYPERSPECTRAL IMAGING (HSI), LASER-INDUCED BREAKDOWN SPECTROSCOPY (LIBS), SPECTRO FLUORIMETRY (FS)

Sample	Techniques	Range	Pre-processing	Accuracy in % (R2 or R)	Ref.
Wheat flour	HSI	1000 ~ 2200 nm	PCA	0.94	[59]
OWF	HSI	900 – 1700 nm	PLSR, PCR, PCA, FMCIA	0.9	[60]
Egg Precipitate	HSI	400 – 1000 nm	Support Vector Machine, PLSR	SVM= 90, PLSR= 0.9	
Milled Beef	VNIR-HSI	400 – 1000 nm	PLSR, PCR, MLR	0.98	[62]
Salmon	HSI	390 – 1050 nm	PCA, SFMN	96.7	[63]
Wuchang rice	HSI	380-1000 nm	PCA, Support Vector Machine	99.2	[64]
Beef	LIBS	___________	PCA, PLS	0.99(Pork); 0.99(Chichen)	[65]
Milk	LIBS	186 -900 nm	PCA, PLSR	0.99(Caprine); 0.99(Ovine)	[66]
Pistachio nut granules	LIBS	___________	PCA, PLS	Rgreen bean2=0.99; Rspinach2=0.99	[67]
EVOO	SFS	240–700nm	Regression analysis	0.97	[68]

Butter	SFS	240–700nm	LDA	100	[69]
Peanut oil	SFS	400–500nm	LDA	95	[70]
Walnut oil	NIR and FS	4000 ~ 650cm-1; 370–700nm	SIMCA, PLS	0.985(NIR); 0.988(FS)	[71]
COA oil	NIR and FS	10000 ~ 4000cm-1; 380–700nm	OPLS	91	[72]

Table V offers insights into advanced techniques like Hyperspectral Imaging (HSI), Laser-Induced Breakdown Spectroscopy (LIBS), and Spectrofluorimetry (FS) for detecting food adulteration. These methods utilize sophisticated analysis to assess the composition of various food samples. For example, HSI's use in wheat flour analysis achieved an accuracy of R^2=0.946 with a spectral range of 1000 ~ 2200 nm and Principal Component Analysis (PCA). Additionally, LIBS is effective in analyzing beef and milk, while FS is employed for walnut oil and peanut oil examination. Application of preprocessing methods like Support Vector Machine and PLSR enhances accuracy, ensuring the integrity and quality of food products.

TABLE VI: ELECTRONIC NOSE (EN) AND ELECTRONIC TONGUE (ET) USED FOR DETECTION OF FOOD ADULTERATION.

Sample	Detection method	Range of spectra/Feature	processing data	Accuracy in % (R2 or R)	Ref.
Virgin coconut oil	EN	Profile of volatile chemicals	PCA; PLS	0.91	[73]
EVOO	EN	Profile of volatile chemicals	Peak signal-noise ratio	_____	[74]
Lard	EN	Volatile chemical profile	Bagged Tree; Simple Tree, KNN	95.6	[75]
Peonies seeds oil	EN and ET	Volatile chemical profile	Peak Signal Noise ratio, Linear Discriminant Analysis	100	[76]
Argan Oil	EN and ET	Properties of smell and taste	Support Vector Machine, Peak Signal Noise ratio	100	[77]
Soybean oil	EN and ET	Properties of gaseous substances that are easily evaporated and their levels of individual constituents.	Peak Signal Noise ratio, Primary lateral sclerosis	0.843	[78]
EVOO	SPME-fast gas chromatography solid-phase microextraction-mass spectrometry and headspace electronic nose	Volatile compounds.	Peak Signal-to-Noise Ratio (PSNR), Discrimination Index, Partial Least Squares (PLS)	0.99	[79]
Honey	VE-tongue	qualities of flavor	PCA, SVM, and HCA	100	[80]
Honey	VE-tongue	qualities of flavor	PLS-DA, MLR	83.3	[81]
Honey	EIS	Electrical parameters might change.	Maintain a record of any modifications performed related to the system characteristics.	_____	[82]
Tomatoes Juices, Fresh	EN and ET, fusion techniques.	Analysis of odor and taste characteristics	CDA, Lib-SVM, PCR, PCA	100	[83]
Milk	ET	Electrical conductivity change	Peak signal-noise ratio	_____	[84]
Milk	EIS (Employee Information System)	0.5-700 KHZ	Artificial Neural Network	94	[85]
Coffee	A vision system and ET	Features of flavor and appearance	Peak Signal Noise ratio, PLS Linear Discriminant Analysis	0.97	[86]
Fresh peanuts	EN	Detects and analyses odor properties	PLSR, Support Vector Machine	0.94	[87]

Table VI provides a succinct overview of Electronic Nose (E-nose) and Electronic Tongue (E-tongue) technologies' application in detecting food adulteration, assessing olfactory and gustatory attributes. For instance, E-nose accurately identifies virgin coconut oil adulteration through volatile compound analysis using PCA and PLS techniques, achieving a high accuracy of R^2=0.91. Similar methodologies are employed for detecting adulteration in various food items such as olive oil, lard, peony seed oil, soybean oil, and coffee, demonstrating the effectiveness of these electronic sensing techniques in ensuring food genuineness and quality.

IV. Discussion

Each technique for detecting food adulteration has specific strengths and applications. Near-Infrared (NIR) and Mid-Infrared (MIR) Spectroscopy (Table 3) excel in analyzing oils and spices but may require advanced equipment and expertise, particularly beneficial for dietary items like oils. Infrared Spectroscopy (Table 4) offers adaptability across a broad range of culinary items but may lack precision in some cases, suitable for various food samples due to its versatility. Techniques like Hyperspectral Imaging (HSI), Laser-Induced Breakdown Spectroscopy (LIBS), and Spectrofluorimetry (FS) (Table 5) demonstrate exceptional accuracy in identifying specific substances across a wide range of food samples but may necessitate sophisticated equipment and expertise, highly proficient in discerning precise chemicals, adaptable to various food items. The Electronic Nose (E-nose) and Electronic Tongue (E-tongue) (Table 6) have the advantage of capturing distinct scent and taste qualities, suitable for a diverse array of food items, exceptional at identifying adulteration through olfactory and gustatory characteristics, though accurate interpretation may require specialized knowledge.

V. Conclusion

The article thoroughly examined the viability of non-destructive analytical techniques in detecting food adulteration. Despite the outlined potential, practical implementation faced notable challenges, particularly in terms of method development and sensitivity. Studies indicated suboptimal performance in terms of low levels of detection (LoD) for adulteration, with varying calibration performances at low concentration ranges. Various techniques were employed successfully to identify different types of impurity, though some limitations arose from examining different methods on the same sample. The complexity of detection increased when auxiliary materials, such as nanomaterials, were introduced, and high-performance devices proved to be costly. The paper emphasized the importance of optimizing approaches for specific sample detections based on different concepts, urging the need to focus on a particular objective rather than generalizing across various food samples. The intricate nature of detection using techniques like Raman spectroscopy highlighted the challenges associated with auxiliary materials and expensive equipment. Despite these challenges, the study underscored the critical need to carefully select analytical methods tailored to specific sample characteristics. Thoroughly comparing various nondestructive analysis methods, the paper emphasized their collective potential to detect food adulteration without compromising sample integrity. Different detection methods were found to be suitable depending on the quality of the food, with infrared spectroscopy, Raman spectroscopy, and the E-nose approach identified as particularly advantageous in terms of cost-effectiveness and wide-scale applicability. The overall conclusion emphasized the significant potential these nondestructive analysis methods hold for addressing the issue of food adulteration in diverse settings.

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