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Systematic Review

A Systematic Review of the Use of Electronic Nose and Tongue Technologies for Detecting Food Contaminants

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Abstract

Sensor operations in the food industry are faced with several major challenges, including in sensitivity, selectivity, accuracy and rapid detection. Among emerging technologies, e-nose and e-tongue systems have attracted much attention from researchers. This review examines 112 studies published from 2004 to 2025, and examines the functionalities and performance in detecting various food product-associated analytes. The sensitivity of e-nose and e-tongue systems was analyzed using various data processing techniques. Recent research and development in leading countries (i.e., China, United Kingdom, Columbia, India, Portugal, Spain, Hungary, Ireland) was examined. The findings indicate that principal component analysis (PCA) was the most widely used technique, while more articles were published in 2021. Worldwide research contributions showed China at the forefront of e-nose studies (26.7%) and Spain leading in e-tongue research (30%). The highest sensitivity values were 99.0% for the e-nose in 2015 and 100% for the e-tongue in 2012. In specific applications, the e-nose achieved a maximum average sensitivity of 15% in apple analysis, while the e-tongue achieved a maximum average sensitivity of 40.5% in water samples. Furthermore, the review presents an in-depth discussion of key parameters, including food sample types, citation rates, analysis techniques, accuracy, and sensitivity, with graphical representations for enhanced clarity.

Keywords: food safety; e-nose; e-tongue; analytical methods; data processing techniques; electrochemical sensor; contaminants; principal component analysis (PCA)

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Received: 14 May 2025
Revised: 1 July 2025
Accepted: 16 July 2025
Published: 19 July 2025

Citation: Zia Ul Haq, M.; Singh, B.; Fuku, X.; Barhoum, A.; Tian, F. A Systematic Review of the Use of Electronic Nose and Tongue Technologies for Detecting Food Contaminants. *Chemosensors* **2025**, *13*, 262. https://doi.org/10.3390/chemosensors13070262

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1. Introduction

Food security and integrity issues are important topics in food science because of the significant and potentially harmful effects of food adulteration on human health [1]. As a result, customers and food manufacturers share the objectives of guaranteeing authenticity [1]. The following major challenges are encountered by food production enterprises: (a) to optimize resource allocation to minimize investment cost, and to use advanced scientific and technological methodologies to improve quality control, (b) to

efficiently and precisely determine the shelf life and storage requirements, (c) to identify the unique features of the product to enhance its appeal and preference among consumers [2]. Hence, to cover these challenges, the current study is based on data from 112 published research articles sourced from Google Scholar and ScienceDirect. The targeted research questions covered in the current review include the following: (a) Which analysis types (PCA, LDA, BPNN, etc.) are mostly employed in the e-nose and e-tongue for food contaminant analysis? (b) Which technology among the aforementioned is most preferred for the monitoring of food contaminants? (c) What future directions are suggested for improving sensitivity in food contamination monitoring? A key novelty of this review lies in incorporating graphical representations of various parameters such as author countries, food samples, citation rates, and accuracy (sensitivity) amongst a comparative discussion. This review aims to facilitate global research collaboration, highlighting challenges and future perspectives in e-nose and e-tongue technology for food quality assessment. By addressing existing limitations, it seeks to advance the practical application of these technologies in the food industry.

Due to various health issues, public awareness of food safety concerns has been increased. The FAO/WHO (Food and Agriculture Organization/World Health Organization) have joint information strategies regarding the functional roles of food additives and have launched safety criteria for their appropriate use. Their major objectives include the mentioned functional roles within food products; preserving the nutritional integrity of food products; recover the stability and shelf life for the resolution of food waste; increasing the sensory appeal of food for consumer reception; and enabling essential functions throughout food processing operations [3]. Owing to their reproducibility, speed and precision, e-nose and e-tongue technologies are highly favorable for fulfilling the requirements established by the European Food Safety Authority (EFSA) and the U.S. Food and Drug Administration (FDA). In the case of the EFSA, there is a condition of having observable data for food security valuation, while the FDA need a standard analytical tool to control the quality of pharmaceuticals [4]. Moreover, in the present decade, maintaining the quality and freshness of food is a major challenge for industry growth. Several tools are being used for the monitoring of food products, but accurate evaluation of food freshness is essential to minimize waste and to protect human health [4].

Chromatography, gas chromatography–mass spectrometry (GC-MS), Inductively Coupled Plasma Mass Spectrometry (ICP-MS), and liquid chromatography–mass spectrometry (LC-MS)-based methods are among the many technologies used in food security [5]. Eleni C. Mazarakioti et al. suggested an ICP-MS technique for testing the authenticity of food products [6]; Han Shim et al. employed gas chromatography–tandem mass spectrometry (GC-MS/MS) for the detection of the troublesome pesticide dimethipin in real samples of milk, eggs, chicken and pork [7]; Da-Young Yun et al. analyzed chlorothalonil in apples with the help of GC-MS/MS techniques [8]; Rabab A. Hakami et al. checked the performance of GC-MS for the detection of multi-residue pesticides in cereals [9]; while Santino Barreca et al. successfully explored the chemometric analysis of macro and micro elements in food samples of meal [10]. However, these techniques have tough working settings, the need for trained personnel, and a high cost of equipment [5]. Electrochemical sensors overcome these limitations due to their rapid analysis and sensitivity [11]. Electrochemical sensors convert the electrochemical reactions between the analyte and electrode into an applicable qualitative or quantitative signal. They provide a low-cost solution for the detection of variable analytes from agriculture and food industries to biomedical and environmental applications. Moreover, the techniques of electrochemical sensors employ sophisticated methods for food observation, including cyclic voltammetry (CV), differential pulse voltammetry (DPV), square wave voltammetry (SWV), linear seep

voltammetry (LSV), electrochemical impedance spectroscopy (EIS), and potentiometry which enable precise monitoring of electron transfer mechanisms during electrochemical reactions [12,13]. The electrochemical biosensor market, including healthcare diagnostics, environmental monitoring, and food quality testing, was valued at USD 16.9 billion in 2023. It is projected to grow from USD 18.02 billion in 2024 to USD 28.3 billion by 2032, with a CAGR of 5.80% [14]. In 2024 Sun et al. explored the performance of electrochemical sensors in combination with machine learning technology for the detection of food contaminants to improve food safety [15].

Smart electrochemical sensors such as the electronic nose (e-nose) and electronic tongue (e-tongue) are promising, effective, and rapid devices. They have been successfully used in many food businesses [16]. The e-system has the advantages of simplicity, rapid detection, and versatility, and has the potential to be used for both at-line and online platforms. The first introduced e-nose sensory array was based on a Metal Oxide Semiconductor (MOS) and has the ability to detect 20 different odors. After this, technological advancements have permitted the development of sensor arrays, ranging from 6 to 32 sensors, and have accomplished the processing of thousands of different odors. E-noses use sophisticated sensor arrays and advanced pattern recognition algorithms to simulate human olfaction, enabling precise detection and analysis of volatile compounds. This technology facilitates innovative applications in quality assurance, environmental monitoring, and medical diagnostics [17]. This system includes various sensors for volatile detection: Quartz Crystal Microbalances (QCMs), optical fiber bundles, Conducting Organic Polymers (COPs), Metal Oxide Semiconductor Field Effect Transistors (MOSFETs), etc. [18]. Generally, the e-nose is increasingly used for analyzing the aromatic profiles of samples without the need to separate the volatile fractions into their individual components beforehand [19]. The essential components of an e-nose include a sample chamber which is used to collect gas samples, a sensor chamber housing multiple gas sensors, and the software system to deal with the analysis and acquisition [20]. During processing, the sensor films present inside the system undergo chemical reactions when exposed to target odor molecules, which leads to an electron transfer process, and as a result, the sensor detects it and converts it into an electrical signal [21]. The basic principal behind the function of the e-nose is that an electrical signal is produced after the interaction of a specific smell with the active materials present in the system; in order to successfully discriminate between various odors, the reaction of several sensors will form the sensor array's response spectrum to the odor. A mixed odor can be analyzed quantitatively or qualitatively due to the interaction of several chemicals present in the odor with the sensitive materials of the e-nose [2]. According to reports, the human nose can identify at least one trillion odors thanks to its around-400 scent receptors [22]. In addition to this, the human nose could face several limits, like in the detection of toxic gases and the limit sensing of different gases [22]. Hence, to cover this research gap, there is a serious demand for the e-nose on an industrial scale. Moreover, it offers different advantages across diverse sectors like healthcare, commerce, pharmaceuticals, cosmetics, etc., while also playing a critical part in advancing scientific roles and discoveries [23].

The performance of the e-nose technology in the fields of food engineering, medical diagnosis and environmental monitoring for both qualitative and quantitative odor analysis was further improved by using machine learning techniques. Modeling, feature extraction and drift correction are the most common machine learning workflows for e-nose applications. Analyzing their performance, the results of the e-nose technology for targeted gases suffered from redundant data and noise. Feature extraction holds only the distinctive information defining an odor signal's pattern. Extracted features permit qualitative aroma analysis for odor differentiation while quantitative analysis is used for predicting target-odor properties through suitable modeling techniques. However, many

gas sensors are faced with the issue of drifting, which can be alleviated using machine learning-based drift compensation algorithms rather than upgrading modules with new data [24–26]. Currently in food processing industries, the involvement of machine learning and artificial intelligence technologies is significantly improving the optimization of quality control and operational efficiency. The application of intelligent systems is involved in automated product sorting, sanitation processes of equipment, the monitoring of food quality, and food product formulation [27]. During the analysis of food products, the e-nose signal, analyzed by means of pattern-recognition algorithms such as PCA and SVM and other machine learning classifiers, allows for sample identification by gathering similar volatile emissions from related food compounds [23,28].

The human tongue has 10,000 taste buds, each with 50–100 cells for detecting sweet, sour, bitter, salty, and umami flavors. The e-tongue mimics this by using sensors to detect various compounds and transmitting signals to a computer for interpretation [29]. The e-tongue consists of three main parts and is considered a liquid analysis instrument, featuring the following: (a) a sensor for detecting chemical properties, (b) a signal acquisition system for capturing and processing data, and (c) a pattern-recognition system interpreting the results [30]. The principal of the e-tongue system may be different; however, the first e-tongue was based on a biological taste-cell detecting mechanism. Using PVC and other materials, several lipid compounds, including n-decanol and oleic acid, were applied on the sensor surface. Taste characteristics and overall sample quality were evaluated by altering interactions among lipids and available taste compounds into membrane potentials, employing the use of an ion-selective electrode, followed by a pattern recognition investigation [2]. Moreover, to capture varying potential responses, in the case of voltammetry measurements, six different metallic electrodes were employed as working electrodes. The resulting data were subjected to principal component analysis (PCA) to evaluate the variation and effectively differentiate between the food samples [29]. Some useful sensors employed in the e-tongue include pH-related sensors and ionic selective electrodes. However, their selection depends on the behaviors of the tested analyte and precise applications [30]. Generally, the human tongue can feel five various tastes, bitterness, umami, sweetness, saltiness, and sourness. The different food products have been evaluated by skilled and unskilled teams. However, the process features a high cost and a long time. In some cases, if the panelists were not properly trained, sensory panels could induce biases. Hence, to overcome the aforementioned research issue, the researchers have successfully employed the e-tongue, which has a quick sensing ability and has a balanced function [31,32]. Additionally, there is a significant gap in the applications of sensors at a laboratory and industrial level. Labor and time are critical for production in the real-world, but are often despised in the laboratory setting, but on an industrial scale, time, cost and labor have significant importance. Hence, sensor analysis techniques are advancing to become more effective, quicker and also less prone to particular bias. This highlights the necessity for intelligent instruments that can autonomously conduct sensory analysis [33]. Thus, technologies of intelligent sensors emulating human senses are increasingly attracting more attention. Furthermore, the Internet of Things (IoT) enables real-time data collection and monitoring by communicating devices through a shared infrastructure. The IoT enables smart home sensors, environmental monitoring systems and wearable devices to provide continuous and physiological responses [34].

In e-tongue data analysis, machine learning methods, particularly support vector machines (SVMs), owing to their strong performance in high-dimensional spaces, are commonly applied for classification, regression and signal datasets [35]. Current developed machine learning techniques have the abilities to process MLAPV signals to classify samples with liquid substances. In 2020, a machine learning approach achieved a 96.83% accuracy in

distinguishing among seven various aqueous matrices, while a 94% accuracy was attained by using the other methodology for the cataloguing of 13 various liquid substances [36].

As shown in Figure 1, e-noses and -tongues have shown broad applications in the monitoring of food and beverages, analysis of volatile organic compounds, shelf life in foods, shelf-life monitoring in food, analysis of liquid compounds, food safety and food contamination detection.

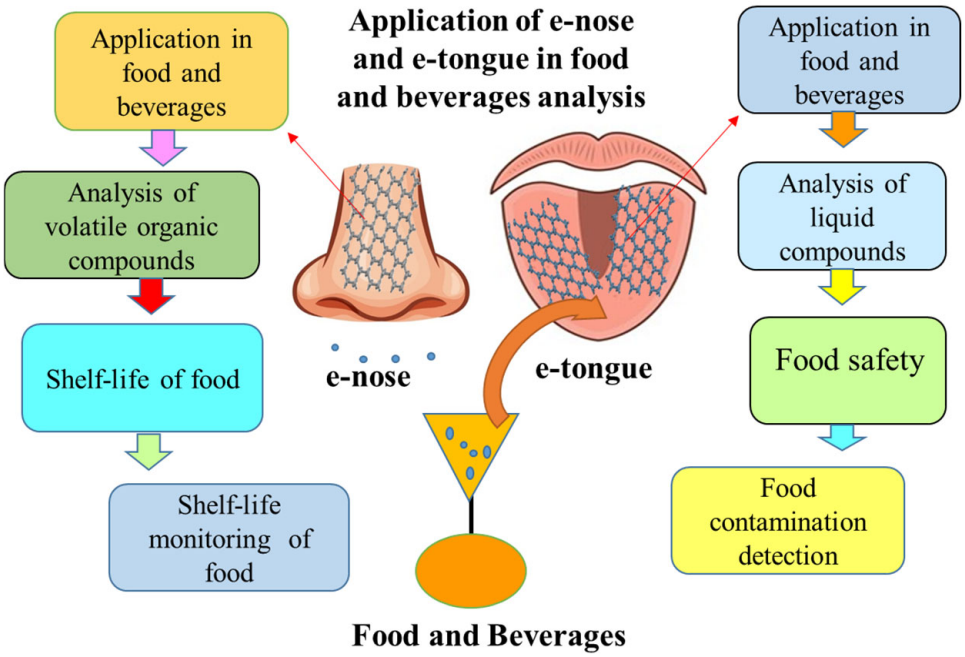


Figure 1. Application of e-nose and e-tongue in food and beverages.

E-nose devices are particularly useful for foods that release high concentrations of volatiles during storage due to rapid degradation. The setup of the e-nose system consists of multisensory devices for use during the detection of complex VOCs mixtures with the help of Al algorithms and pattern recognition [37]. The sensory arrays whose selection is considered a major challenge have been established to improve selectivity and sensitivity for the detection of various interesting analytes [38]. With technological advancements, e-noses and e-tongues are gaining a serious reputation across several industries. These devices precisely analyze chemical composition to detect and identify various substances and gases [29]. Nanostructured materials such as carbon nanotubes have the potential to enable gas sensing at lower concentrations [39]. A notable example is the portable e-nose by FoodSniffer (Redwood City, CA, USA), which evaluates meat, poultry, and fish freshness by wirelessly connecting to a smartphone app. It provides real-time feedback via a traffic light system: green (fresh), yellow (partially spoiled), and red (spoiled) [40]. Despite these advancements, a major research gap remains—industries are yet to fully recognize the potential of e-noses for food contamination detection and quality enhancement. Existing reviews [16,41,42] focus on compiling data from numerous studies but lack comprehensive analysis and insights.

To address this gap, the current review evaluates the performance of e-noses and e-tongues in food assessment, including shelf-life monitoring, food safety and contamination detection, the role of e-noses and e-tongues in food safety and security, and the use of electrochemical sensor techniques in the safety and security of food.

2. Research Method

This systematic review was conducted in accordance with the Preferred Reporting Items for Systematic reviews and Meta-Analysis (PRISMA) 2020 guidelines. A completed PRISMA checklist (Supplementary Materials) is provided.

2.1. Databases and Keywords

To reduce the risk of missing the relevant literature, databases including Google Scholar and ScienceDirect, which are strong for food science, material science and analytical chemistry, were used for the collection of information from 112 research articles by following the following keywords, employing the Boolean operators (AND, OR), phrase searching (" ") and truncation (*).

Keywords are listed as follows: ("electronic nose" OR "e-nose" OR "electronic tongue" OR "e-tongue") AND ("food adulteration" OR "food contaminants*" OR "food safety" OR "food spoilage" OR "food quality") AND ("analysis" OR "identification" OR "monitoring" OR "detection").

2.2. Inclusion and Exclusion Criteria

The inclusion criteria include the following:

- Articles published in English language only;
- Peer-reviewed articles;
- Studies which focused on the e-nose and e-tongue or a combination of both for food contaminant monitoring.

The exclusion criteria include the following:

- Articles published in languages other than English;
- Studies devoid of experimental data;
- Articles not available in full text.

2.3. The Following Food Safety Contests Were Discussed

(1) Shelf-life monitoring;

(2) Food safety and contamination detection;

(3) The role of the e-nose and e-tongue in food safety and security;

(4) The use of electrochemical sensor techniques in the safety and security of food; Figure 2 shows the preferred reporting items for the current systematic review and meta-analysis (PRISMA) diagram for the methodology section.

Assessing the risk of bias in included studies is crucial for ensuring the reliability and validity of a systematic review. Hence, in the current review, Microsoft Excel was used to create a variety of charts that reflected the data. Microsoft Word (MS Word 365) was used for the article, PowerPoint (version 2016) was helpful for generating figures, while EndNote (X8 version 2021) formatted the references of the current systematic review. Two reviewers independently screened the titles and abstracts of all retrieved records to assess their eligibility based on the predefined inclusion and exclusion criteria. Moreover, for each outcome, the measure of the effect used in the results was specified based on the type of data and study design. Confidence intervals, mean differences or standardized mean differences were used, depending on whether the same or different measurement scales were applied across studies.

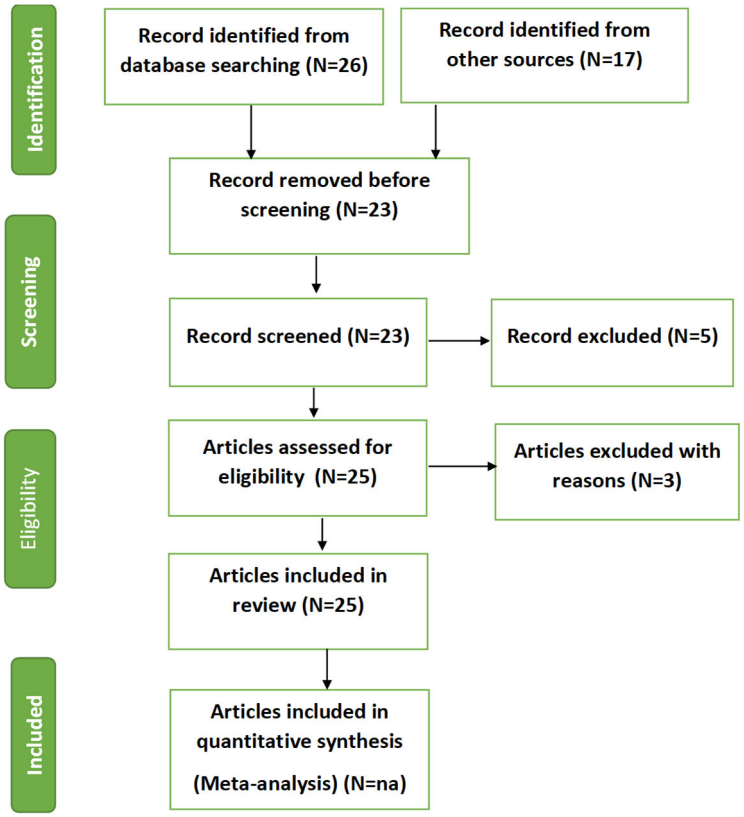


Figure 2. PRISMA diagram for the methodology; na = not applicable.

3. Results and Discussion

3.1. Application of E-Nose and E-Tongue in Food Quality Assessment

Table 1 provides a literature review on the performance of e-nose and e-tongue systems in food contamination detection, including the number of citations, countries of the authors, and publication years related to different food products. The diverse configuration of e-noses is successfully used for the profiling of a wide range of food products, such as oil, honey, fish, meat, and alcoholic and non-alcoholic beverages. Various food samples commonly consumed in daily life (fruits, vegetables, meat, water, and milk) were analyzed for key contaminants such as chitosan, soft-rot, pathogens, sugar, phenols, and bacteria. In the case of e-nose applications in food quality, safety and storage, the highest sensitivity was reported for soft-rot detection for potatoes (100%) using PCA analysis in the UK (2018); in the category of e-nose applications in food security, researchers of Thailand researching garlic achieved the highest sensitivity, of 99.0%, by using PCA (2015). In the same way, in Indonesia, during the performance of e-nose applications in the shelf monitoring of food, the desired sensitivity was achieved for *E. coli* detection in chicken meat (95.7%) by using PCA (2021). Regarding e-tongue applications in food assessment, the highest sensitivity of 100% was obtained in the case of adulteration check detection in red meat and poultry using LDA in Hungary (2021) and in beer quality assessment (100%) using PCA and LDA in Spain (2012). Additionally, Enterococcus faecalis, Staphylococcus aureus, Escherichia coli, and Pseudomonas aeruginosa identification in water using LDA-SA reached 100% sensitivity in Portugal (2021).

Table 1. Overview on the performance of e-nose and e-tongue technologies towards the detection of food contaminants. (Samples of food, interested analytes, type of analysis, accuracy and sensitivity, number of citations, countries of the authors, and publication years).

Food Samples	Analyte	Analysis	Accuracy/Sensitivity (%)	Citations (Jan-2025)	Countries	Publication Year	Ref.
e-nose in food quality, safety and storage							
Olive oil	-	-	-	6	Ireland	2015	[43]
Citrus fruits	Chitosan	LDA	97.5	178	China	2017	[44]
-	-	-	(Original groups)	-	-	-	-
Potatoes	Soft-rot	PCA	100	50	UK	2018	[45]
Apple	Pathogen	PCA	<90.5	65	India	2018	[46]
Apple	Pathogens	BPNN	96.3 (Group A)	112	China	2019	[47]
Meat, vegetables, fruits	Gases	-	96.2	54	China -	2018	[48]
Soybean	Gases	LDA/PCA	94.4	2	Brazil	2024	[49]
Strawberry	VOCs	LS-SVM	99.2	14	China	2020	[50]
e-nose in food security							
Garlic	-	PCA	99	203	Thailand	2015	[51]
Cucumber	Urea	LDA-QDA	98.7	41	Iran	2022	[52]
e-nose in shelf monitoring of food							
Chicken meat	E-coli	PCA	95.7	41	Indonesia	2021	[53]
Fish	Microorganisms	PCA	93.4	-	Spain	2020	[54]
Barattiere	VOCs	PLS	-	3	Italy	2024	[55]
Lemon, Apple,	Climacteric-fruits	CNN	94.6	4	India	2021	[56]
Banana, Pear	-	-	-	-	-		-
Potatoes	Sugar, Carbohydrates	QDA/MDA	<90.0	12	Iran	2023	[57]
e-tongue in food quality assessment							
Beers	-	PCA, LDA	100	130	Spain	2012	[58]
Grapes	Sugar, Phenol	PCA	-	23	Spain	2016	[59]
Olive oil	Bitterness	PCA, PLS-DA	97.4	39	Spain	2019	[60]
Plum juice	M. fructigena	LDA	-	20	Hungary	2021	[61]
Red meat, Poultry	Adulteration check	LDA	100	32	Hungary	2021	[62]
	-	-	-	-	-	-	-
e-tongue in food contamination							
Water	[1] E. f, S.a, E. C,	LDA-SA	100	19	Portugal	2021	[63]
-	P. A,	-	-	-	-	-	-
Water	E. Coli	PCA	97.6	8	Colombia	2019	[64]
Water	2-MethylIsoborneol	PCA	86	7	R. Korea	2023	[65]
Milk	E. Coli	PCA	98.7	21	Colombia	2021	[66]
Water	Cyanobacteria	-	10^{-6} mol/L(LOD)	51	Italy	2016	[67]

List of abbreviations for mentioned analysis with comparison of their advantages and possible disadvantages

LDA	Linear discriminant analysis	The advantage of using LDA for the analysis of text is to represent a large amount of data [68] in short descriptions to represent various topics with speed. The major disadvantage of standardized LDA is that multiple tuning parameter [69] sets can yield the same cross-validation error, yet result in significantly different test errors, making the selection of optimal parameters challenging.
PCA	Principal component analysis	The objective of PCA is to characterize the data in as [70] limited an extent as possible and to obtain consistent results for the analysis. The disadvantages include the requirement of the suitability of 2D face image with [71] a 1D vector.
BPN-N	Backpropagation neural network	Used for educating the accuracies in different functioning environments [72]
LS-SVM	Least squares support vector machine	Helpful to improve training efficiency and to solve linear equations [73]. Limitation includes time consumption and demanding for huge space [74]
QDA	Quadratic discriminant analysis	Have the advantage to use for binary cataloguing problems [75].

Table 1. *Cont.*

List of abbreviations for mentioned analysis with comparison of their advantages and possible disadvantages		
CNN	Convolutional neural network	CNN is helpful for such problem having object detection, image segmentation and classification [76] The limitation may include the requirement for large, expertly annotated [77] datasets, which demand domain-specific expertise and need large time.
PLS	Partial least square	Use for the investigation of valuable information to extracts array of activity [78] and to support a concern among enterprise elements.
PLSR	Partial least squares regression	Combine the advantages of PCA and canonical correlation analysis to remove [79] batch affects.
PLS-DA	Partial least square-discriminant analysis	-
LRA	Linear regression analysis	-
MDA	Multivariate discrimination analysis	-

[1] E.f: Enterococcus faecalis; S.a: Staphylococcus aureus; E. C: Escherichia coli; P. A: Pseudomonas aeruginosa.

By plotting the data of Table 1, the results (Figure 3) show that the mostly widely used analysis has been reported for PCA (9) analysis for both e-nose and e-tongue technologies. The maximum sensitivity of 100% was attained by the e-nose with the help of PCA analysis while a value of 100% sensitivity was obtained by the e-tongue system through PCA, LDA, LDA, and LDA-SA analysis, respectively, in different food samples.

By further exploring the results, it has been confirmed that the highest number of research articles (6) on the e-nose and e-tongue technologies were published in the year 2021 (Figure 4). With respect to percentage, in the case of the e-nose, it was reported as 99.0% in 2015, and as 100% in 2012 for the e-tongue.

Plotting the data of Table 1, with respect to the performance of countries, it has been confirmed (Figure 5) that in the case of e-nose technology, the best figure, of 26.7%, was obtained by China, while a value of 26.7% for use of e-tongue technology was achieved by Spain. With respect to the sensitivity, a 100% sensitivity was achieved by the UK by using the e-nose system, while in the case of e-tongue, a 100% sensitivity was achieved by Spain, Hungary and Portugal, separately, calculated using various food samples.

In terms of various food samples (Figure 6), a maximum percentage of 15% was obtained by using apple samples with the help of an e-nose while a value of 40.5% was achieved by using water samples through e-tongue technology. By comparing both technologies in terms of the achieved citations, it has been concluded that highest number of citations (203) were achieved by e-nose technology by using garlic samples and a total of 51 citations were reported for e-tongue by monitoring water samples.

To further increase the worth of the current systematic review, all the results have been deeply explained with respect to every figure.

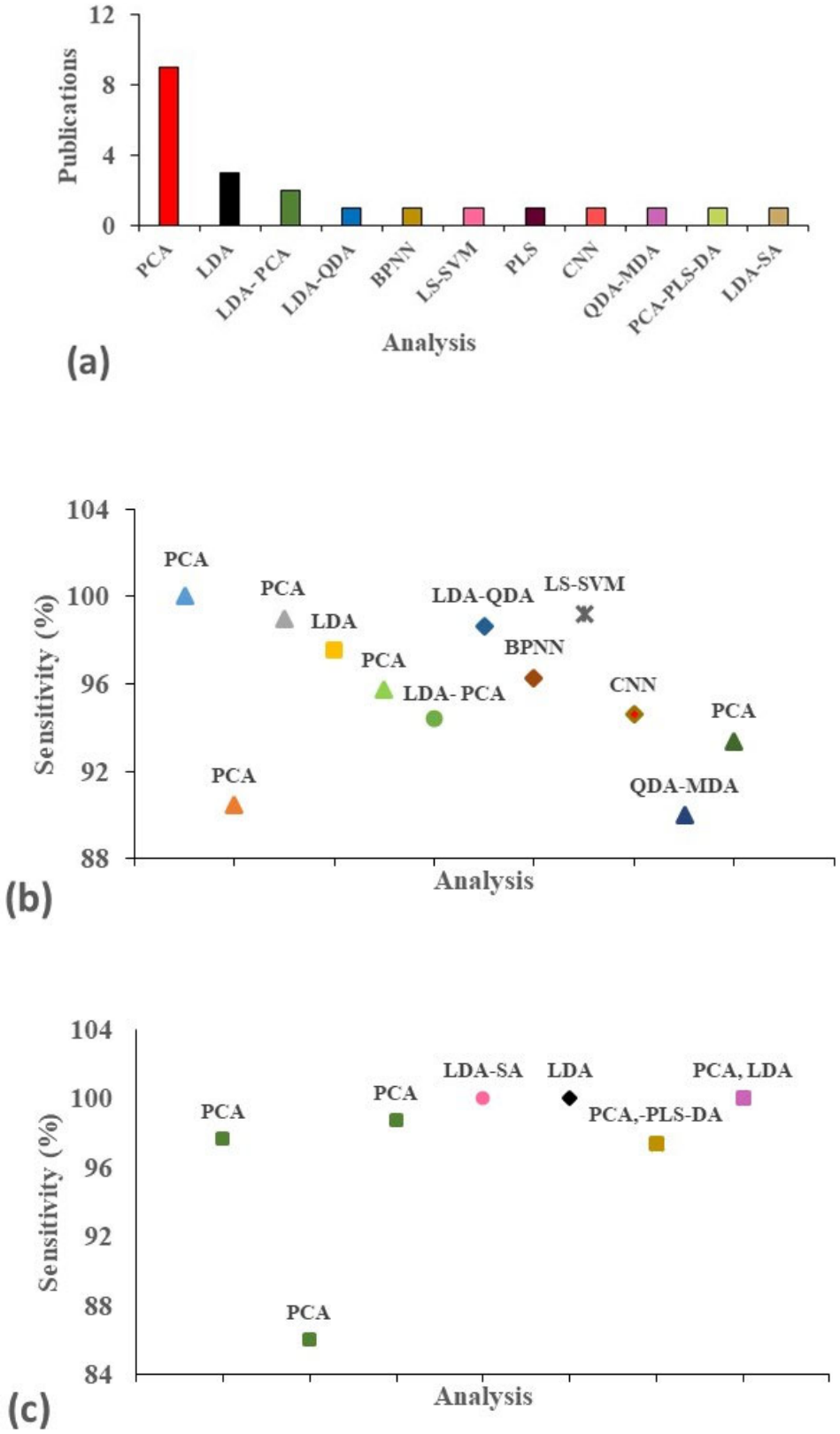


Figure 3. (**a**) Number of simultaneous publications for e-nose and e-tongue with respect to various analyses; (**b**) obtained sensitivity of e-nose by different analyses; (**c**) obtained sensitivity of e-tongue by different analyses.

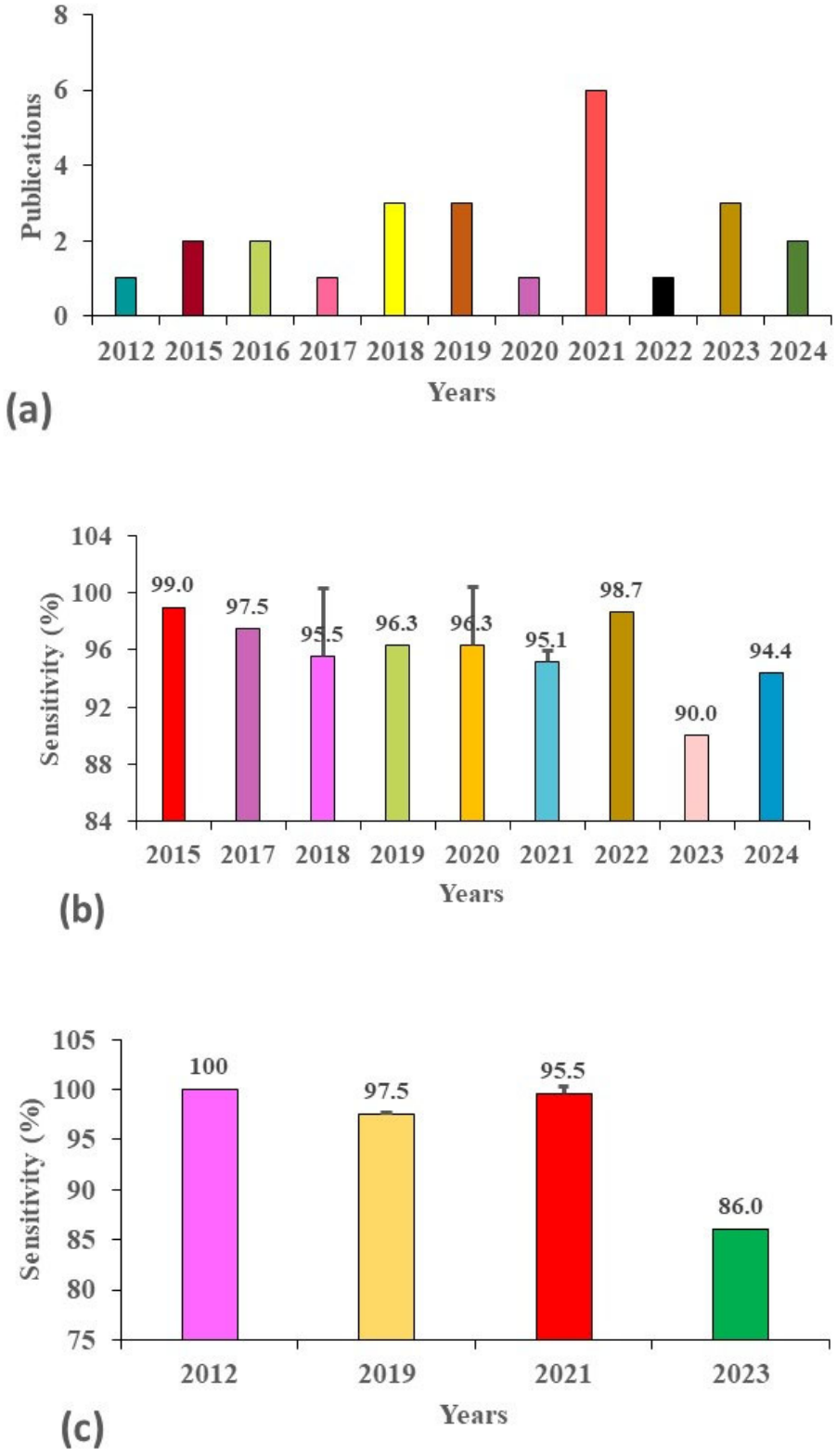
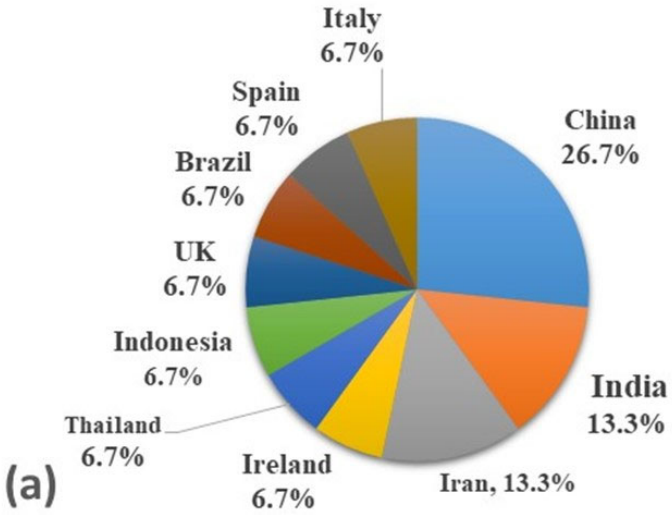
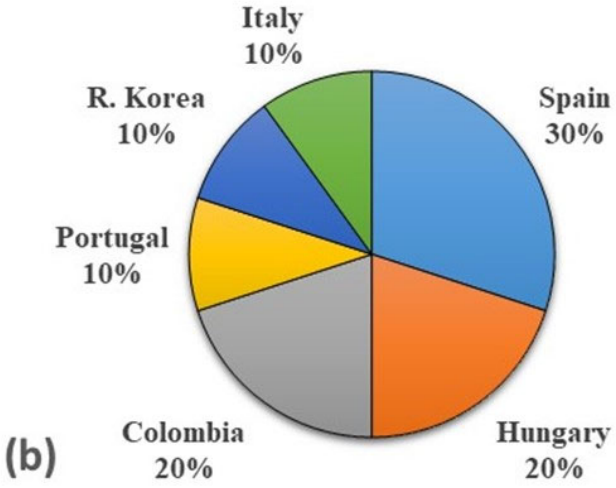


Figure 4. (**a**) Number of published research articles for both e-nose and tongue during the time period from 2012 to 2024. (**b**) Performance of e-nose in food monitoring in terms of obtained sensitivity and year-average values for 2018, 2021 and 2024. (**c**) Performance of e-tongue in food monitoring in terms of obtained sensitivity and year-average values for 2019 and 2021.





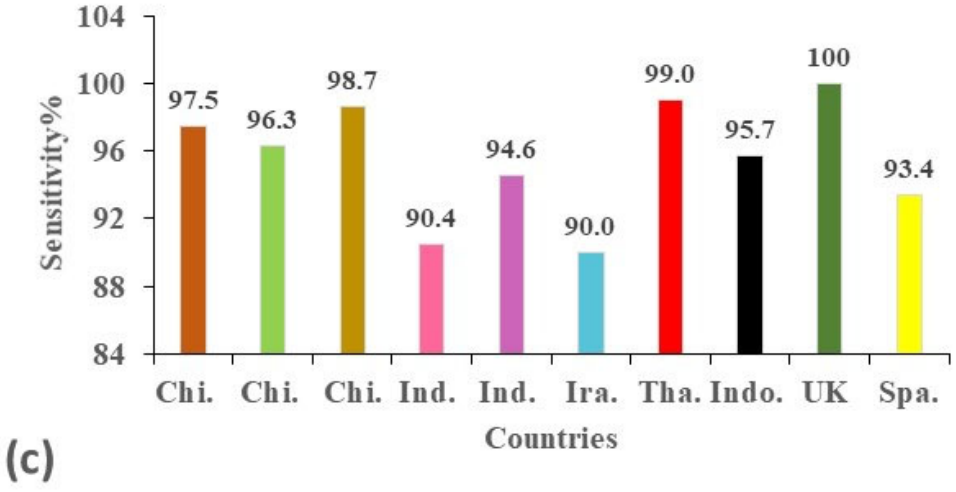


Figure 5. *Cont.*

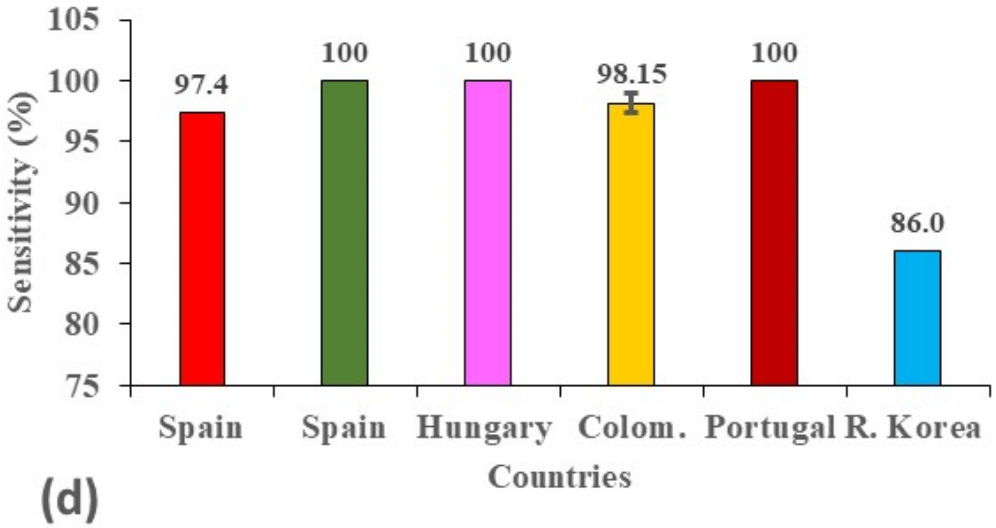


Figure 5. (**a**) Percentage of published research articles for e-nose for different countries. (**b**) Percentage of published research articles for e-tongue for different countries. (**c**) Interest of various countries in e-nose technology in terms of obtained sensitivity: Chi: China; Ind: India; Ira: Iran; Tha: Thailand; Indo: Indonisia; Spa: Spain. (**d**) Interest of various countries in e-tongue technology in terms of obtained average-sensitivity values for Colom (Columbia).

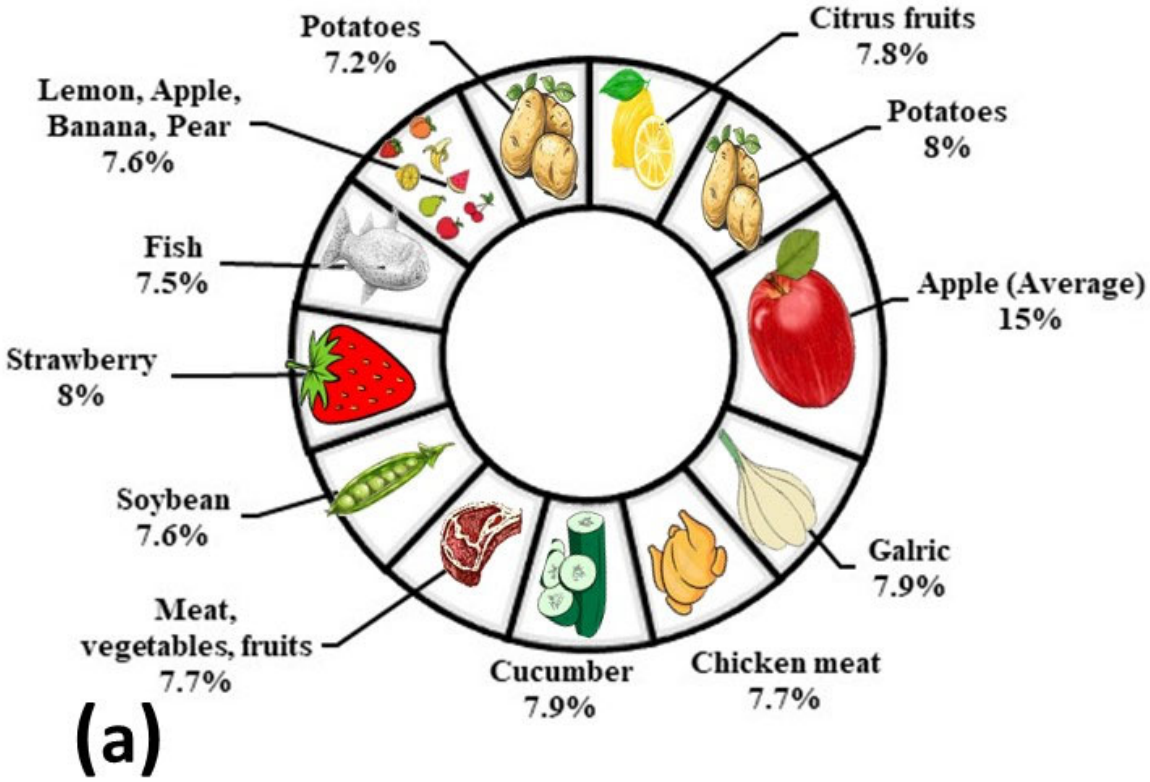


Figure 6. *Cont.*

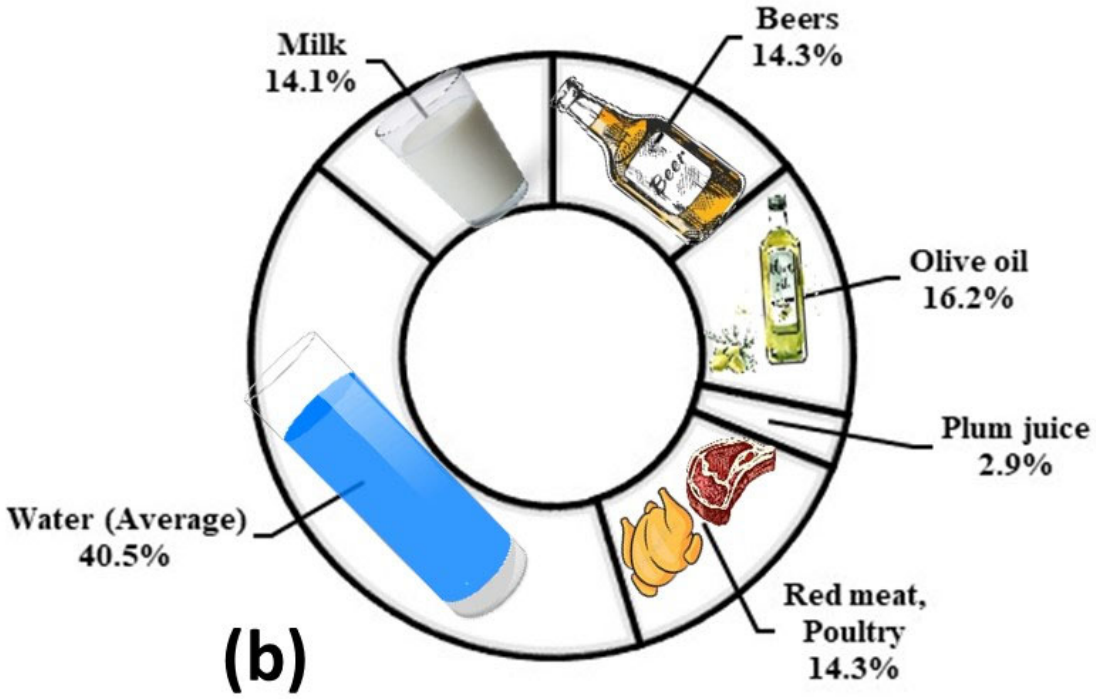


Figure 6. Performance of e-noses for food products: (**a**) performance percentages of e-nose and (**b**) e-tongue for food products.

3.2. E-Nose Performance in Food Safety and Storage

The use of an e-nose offers a rapid and precise method for detecting food contaminants of microbiological, chemical, and physical origins, requiring minimal or no sample preparation.

(i) Soft-rot Disease Detection

The on-time detection of soft-rot caused by *Pectobacterium carotovorum* is very crucial for the safety of crops. Several methods like Gas Chromatography (GC) and Gas Chromatography–Mass Chromatography (GCMS) have been employed; however, finding the responsible biomarker for such a disease is still a serious challenge. The limitations of such techniques include the requirement of using a trained person and the need for specialized equipment. Changlong Chen et al. proposed a PCR-based detection method for *Pectobacterium carotovorum* [80], Se-Wook oh et al. isolated *Pectobacterium carotovorum* from affected agricultural products by using a carbon source and bromocresol green pH indicator [81], and M. Belen Suarez et al. developed a PCR-based assay by using a new pair of primers, Pcar1F/R, for the identification of *Pectobacterium carotovorum* [82]. However, there is still a need to develop a commercial technology for the rapid detection of *Pectobacterium carotovorum*. James A. Covington et al. developed an e-nose-based gas sensor which has the advantage of being low-cost (sub USD 50) and portable, with a highest value of 100% sensitivity in models for both the full sensor array and the selected subset (except for the C5 algorithm, which verified with a slightly lower sensitivity in the subset) [45]. The results showed that the sensor used for carbon monoxide, nitric oxide and ethylene oxide is a promising tool for their early detection. Unfortunately, the limitation of this study was the requirement of harsh experimental conditions, i.e., lower humidity, a high temperature and the need for a higher amount of chemicals.

(ii) Chitosan Detection in fruits

Chitosan, derived from chitin in crustaceans, is a biodegradable, biocompatible aminopolysaccharide with growing commercial potential in agriculture, food, pharma-

ceuticals, and nutraceuticals. Its coating on fruits and vegetables helps reduce harmful microorganisms and extend shelf life. Various studies have explored the performance of several techniques for the detection of benzoic acid and chitosan, such as high-performance liquid chromatography (HPLC) (benzoic and sorbic acid) and the process of acid hydrolysis modified with HPLC (chitosan). However, these methods have the drawbacks of the requirement of skilled staff, their time consumption and the multi-step sample preparation process. Hence, Shanshan Qiu and Jun Wang [44] developed a method as an alternative to traditional monitoring technologies which has the advantage of being quick and simple for determining benzoic acid and chitosan. Chitosan detection in citrus fruits achieved a 97.5% sensitivity using linear discriminant analysis. The experimental setup of the study was to check the performance of ten e-nose metal oxide semiconductor (MOS)-based sensors (S1–S10) for the targeted analytes (benzoic acid and chitosan). After 60 s, the performance of each sensor was examined, and the S2 sensor was favored in terms of achieving the highest sensitivity. The sensors S4, S7 and S10 did not show any change, while the S1, S3, S5, S6, S7 and S9 sensors showed a very negligible change.

(iii) Pathogen Detection in fruits

Foodborne pathogens are considered a significant issue which has a key role in the economy of a country. Owing to it being a significant source of water, fiber and vitamins, apples are widely consumed around the world. Several methods like HPLC, spectroscopic techniques, and various biological culture-based techniques are being used for freshness, but these have the limitations of being expensive, non-portable, requiring chemicals and being time consuming. Hence, to overcome these challenges, John Bosco Balaguru Rayaappan et al. [46] and Gang Liang et al. [47] developed an e-nose-based sensor which has the advantages of portability and non-destructiveness in the pathogen (*Staphylococcus*, *Salmonella*, *Shigella* bacteria and *Penicillium expansum* and *Aspergillus niger*) detection, with sensitivities of <90.5% and 96.3%, by using principal component analysis and a backpropagation neural network, respectively. Moreover, the experiment [46] consists of comparing fresh, half and fully contaminated apples. The result revealed a 0.5 V swing in the original voltage in the case of fully contaminated samples and hence made it suitable for their monitoring.

(iv) Evaporated gas monitoring in fruits and vegetables

The freshness of fruits and vegetables has attracted much attention from researchers due to their direct concern with human health. Several appropriate techniques, including gas chromatography–mass spectrometry (GC-MS), capillary electrochromatography, and texture analysis, have been applied for the maintenance of food freshness, but these have the problem of being time consuming, difficult to handle, and having harsh environmental requirements. Hence, Wang et al. [48] and Herrmann et al. [49] proposed an e-nose system, which is considered a reasonable device for gas monitoring on a worldwide basis for fruits and vegetables, with achieved sensitivities of 96.2% and 94.4%, respectively, by performing linear discriminant analysis/principal component analysis. In the case of reference [48], the proposed system consists of an MOS-based sensory array which has the capability to work in a refrigerator to monitor the odor and leads to the identification of the freshness, while reference [49] showed potential to analyze the gases in soybeans under water stress.

(v) Volatile Organic Compound (VOC) Monitoring

Strawberries are famous for their color, taste and pleasant aroma, and are considered a low-sugar and -calorie fruit. Moreover, they are used in diets to fulfil the need for vitamin C, carotene, folates, etc. To enhance their quality, different methods based on their shape and size have been used to measure damage [83], but these are destructive and labor-intensive.

Di Wu et al. [50] suggested an e-nose system and GC-MS for the monitoring of VOCs in strawberries to achieve a 99.2% sensitivity using least-squares support-vector machine analysis. The advantages of the proposed system were the detection of the vibrational damage (the damage which occurred day after day) via a non-destructive route. Before the experiment, samples were placed for some time in a closed beaker to produce VOCs. After this, the chamber of the e-nose system evaluated the freshness of the samples by detecting the released VOCs.

3.3. E-Nose Applications in Food Security

Food security concerns the global challenge to advance technological solutions to provide food sustainability. Hence, to cover such problems, the e-nose system has the potential to play a key role in the distribution, production and processing of foods.

(i) Classifying garlic cultivars

Classifying garlic cultivars is essential for sustainable production and resource conservation, but their similar morphology makes differentiation challenging. Traditional methods, including oil content analysis, metal profiling, DNA fingerprinting, High-Performance Liquid Chromatography (HPLC), and gas chromatography–mass spectrometry (GC-MS), have been employed but are time-consuming and costly. A simpler, more efficient classification method is needed. Trirongjitmoah et al. [51] developed an e-nose method which has the advantages of differentiating among the multiple and complex odors for classifying garlic cultivars. Four Thai garlic cultivars were characterized and grouped into three categories using the e-nose method and compared to Amplified Fragment Length Polymorphism (AFLP) and GC-MS methods. The e-nose method achieved a 99.0% accuracy using PCA analysis for garlic quality assessment. The applied e-nose sensor functioned based on the concentration of the garlic odor, which altered the output voltage of the sensor. A representative response time of 600 sec was selected for the sensor system to classify the samples.

(ii) Urea detection in plants

Several vegetables are affected due to the continuous application of nitrogen fertilizers to crops. As a result, their direct consumption is harmful for human health. Different techniques, including mass spectroscopy and gas chromatography, are widely applied for their detection, but these are faced with the problem of the requirement of a high analyte concentration and a long analysis time [25,84]. Hence, Alphus dan Wilson et al. [53] proposed an MOS-based e-nose-device system, which has the ability to analyze VOCs owing to its excellent sensitivity and the cross-reactivity of multisensory arrays, and was used for the examination of the concentration of urea in cucumber, with an achieved sensitivity of 98.7%, using linear discriminant analysis–quadratic discriminant analysis.

3.4. E-Nose Applications in Shelf-Life Monitoring

The technology of the e-nose system has attracted much attention from researchers in the field of the shelf-life monitoring of food, checking its performance for early spoilage detection, microbial contamination and oxidation to provide a rapid, non-destructive and alternative approach to the traditional techniques.

(i) Bacteria detection in meat

The demand for chicken meat is increasing day by day because of its consumption in daily diets. Unfortunately, bacteria, especially E. coli, can easily attack it, which can cause haemorrhagic enteritis in human beings [53]. Conventional methods like the Eber test are widely used for the testing of affected meat but its applications are limited owing to the additional requirement of HCl. Hence, to handle this challenge, a practical analyzing

system is need for the rapid generation of data analysis. Astuti at al [53] proposed a digital system based on an e-nose for the rapid detection of E-coli in chicken meat. A sensitivity of 95.7% was achieved with the help of principal component analysis; the experimental setup consisted of six varieties of sensors, which were responsible for a specific gas type. Moreover, the study enabled the comparison of fresh and E-coli-affected chicken meat by following the mechanism of changing the sensor output voltage.

(ii) Monitoring of Barattiere and climacteric fruits

Barattiere are a valuable food product, with a negligible amount of sodium and sugar while having a sufficient concentration of potassium, and they are used to treat digestive problems. Unfortunately, the release of active enzymes and substrates and intense metabolic activity decreases their shelf life. Various conventional techniques like GC-MS have been used to monitor the VOCs released, but these methods have the limitations of having a high cost and requiring of a long analysis time. Hence, an alternative tool to these conventional techniques with the advantages of being easy to operate, fast and with promising behaviors is still required. Rosaria Cozzolino et al. [55] developed an advanced e-nose and ATR-FTIR system for the monitoring of VOCs in barattiere by using partial least-square analysis. Firstly, these were cut and stored at 7 °C for 11 days. It was concluded that the S5 sensor was favored for testing the freshness of the sample by detecting hydrocarbons and VOCs (1-nonanol and *cis*-6-nonenol) in it. The storage days of the cut barattiere were estimated from the analysis of partial least-square analysis with an R^2 value of 0.84. To reduce the food wastage and to enhance the shelf life, Sunil Karamchandani et al. [56] used an e-nose gas-sensor system for the monitoring of climacteric fruits (apple, banana, lemon, and pear), with a sensitivity of 94.6%, by using convolutional neural network analysis. The mechanism of the process was based on the recording of released-gas concentrations of the samples through the e-nose chamber.

(iii) Microorganism detection in fish

Maintaining the freshness of fish to enhance their shelf life and quality is considered a challenge to the fishing industry. Traditional techniques like chromatography and the analysis of microbes by sensory array have been widely used, but these are costly and slow. Hence, reference [54] highlighted the performance of an e-nose gas sensor based on MOS for the monitoring of microorganisms (aerobic mesophilic bacteria) in Tench fish samples, with a sensitivity of 93.4%, by using principal component analysis. The proposed system has the benefits over the used techniques of an improved efficiency and precision. Firstly, river fish were classified based on their freshness conditions and the presence of microorganisms was then observed. The presence of aerobic mesophilic bacteria allows the sensory analysis to detect their quality and shelf life.

(iv) Sugar and carbohydrate detection

Potatoes are a food product consumed worldwide due to their unique properties, such as their proteins, minerals, and vitamins. Hence, they are widely used for protection from cancer and to strengthen the immune system. To maintain their quality, their storage in houses is one of the most effective and common methods. However, maintaining their sweetness and freshness is a challenging task. Conventional methods, including spectroscopy, acoustics and thermography, are being effectively used to check their quality, but these have the issue of being inefficient, boring, lacking automatic control, and being hard and destructive. Hence, to cover these limitations, Mansour Rasekh et al. [57] forwarded an MOS-based e-nose sensor technology for the detection of sugar and carbohydrate levels, which have a direct relation with shelf life, affecting physiological changes and their susceptibility to spoilage, with over 90.0% accuracy, using quadratic discriminant analysis/multivariate discrimination analysis in potato samples. The VOCs released

from various samples detected by the e-nose system were used to categorize both their quality and shelf life. Moreover, decomposed food emits VOCs and undergoes specific chemical transformations, which can be identified and analyzed using advanced sensing technologies [85].

3.5. E-Tongue Performance in Food Quality Assessment

E-tongue technology is a unique sensing technology which mimics human taste perception for the monitoring of complex liquid samples. This system has being widely used in food industries owing to its accuracy and quick analysis time.

(i) Monitoring beer

Despite the use of conventional techniques like FTIR and GC, the determination of beer flavor profiles for improving its quality remains a major challenge in brewing industries. Hence, to further improve sensitivity and selectivity, Mahdi Ghasemi-Varnamkhasti et al. developed, for the first time, an e-tongue system based on voltametric studies with the modification of phthalocyanines chemicals, which have the role of being electron mediators, for the monitoring of beer flavor, with a 100% sensitivity, employing principal component analysis and linear discriminant analysis [58]. The mechanism of the proposed system worked by using tyrosinase and phthalocyanines as electron mediators to produce various electrochemical signals which were responsible for the differentiation of the aging of various beer samples.

Meat (red and poultry) is a rich source of proteins and hence an essential part of the human diet. To control its side effects on human health, its quality is considered a challenging task for industries. To date, various techniques, including enzyme-linked immunosorbent assay (ELISA) [86] and mass spectrometry [87], have been employed, but these are faced with the limitations of a high cost and lower reliability and accuracy. Hence, to improve quality, John-Lewis Zinia Zaukuu et al. forwarded a potentiometric e-tongue sensor array, which has the advantages of detection of low levels with a 100% sensitivity, using linear discriminant analysis to check for the adulteration of the meat [62]. A three-extraction method—including raw meat extraction with distilled water, meat extraction by cooking with distilled water, and frozen meat extraction with distilled water—was employed.

(ii) Bitterness detection in olive oil

Plants oil have a significant amount of redox-active compounds, such as tocopherols, sterols, and polyphenols, which are famous for their quality and bitterness and have a key role in providing antioxidant properties. Several techniques have been applied for the investigation of these compounds in vegetable oil. In 2012, Constantin Apetrei proposed an e-tongue system, showing significantly higher selectivity over the other conventional methods based on voltametric electrodes; it achieved this by using polypyrrole to perform a bitterness detection in olive oil with a 97.4% sensitivity through principal component analysis and partial least-square discriminant analysis [60]. Moreover, the cyclic voltammetry technique was used, and the various olive oils were differentiated based on the created signal peaks.

3.6. E-Tongue Applications in Food Contaminant Detection

The e-tongue has a wide range of applications in the analysis of bitterness, sourness, umami, and sweetness in food products. Rather than traditional techniques, it offers a successful alternative tool for food industries.

(i) Pathogenic microorganisms present in foodstuffs are considered a serious risk for causing various diseases in human beings. Their rapid detection due to low analyte concentrations has caused a technical challenge. Conventional techniques,

including polymerase chain reaction [88] and conventional cultural methods [89], have been employed, but these are laborious and costly and have required a large amount of time. Hiba Ghrissi et al. proposed a potentiometric e-tongue lipid-sensor membrane system to investigate four types of bacteria (*E. faecalis, S. aureus, E. coli*, and *P. aeruginosa*—abbreviated at the endnotes of Table 1) in water samples, with a sensitivity of 100%, by using linear discriminant analysis–simulated annealing algorithm analysis [63]. The advantages of the proposed system over the other used techniques were its quick analysis and economical behaviors. The mechanism of such a system includes the differentiation of four samples from each other by following hydrogen bonding or electrostatic interactions among the various compounds and lipid-membrane polar and non-polar sites.

(ii) Foodborne diseases caused by *E. coli* which affect human health are a serious problem nowadays. Different methods based on the growth of bacteria strains are being used by industries for its detection, but these require special infrastructure and have high time requirements. Jeniffer Katerine Carrilo-Gomex et al. proposed an e-tongue system owing to its efficient sensitivity, stability and multivariate analysis behaviors to determine the various *E-coli* concentrations in milk samples, with a 98.7% sensitivity, by using principal component analysis to separate the different voltametric signals which were obtained from diverse samples [66]. The best performance of the e-tongue was shown by using gold instead of a carbon electrode. Additionally, Jeniffer Katerine Carrillo Gomez et al. [64] developed a membrane filter-based e-tongue-and-e-nose-based technique for E-coli detection in water samples with a 97.6% sensitivity by using principal component analysis (only for e-tongue).

(iii) Nowadays, the supply of clean and pure water to living organisms is a major issue. Different poisonous compounds have dissolved in water, disturbing its taste and odor. Various methods, such as headspace solid-phase micro extraction with gas chromatography–mass spectrometry (HS-SPME), have been widely used [90], but they need a trained person, have a long analysis time (1 h), and feature expensive equipment's. Tae-Mun Hwang et al. [65] proposed an e-tongue-based system which has the properties of providing a rapid analysis (3 min) and being economical for the monitoring of 2-methylisoborneol compound, which is mostly produced by algae in water, with a sensitivity of 86.0%. The signal data was interpreted by using principal component analysis with a large variance. L. Lvova et al. developed a potentiometric e-tongue system for the detection of cyanobacteria in water, which achieved a limit of detection (LOD) of 10^{-6} mol/L. The obtained results were compared with colorimetric enzymatic analysis and a chromatographic technique. The performance of the e-tongue was considered highly effective for future use in the treatment of water.

Figure 3a (data has being used from Table 1) reveals the total number of published research articles and the applied analysis types which are being used by the e-nose and the e-tongue system for the monitoring of food products. The highest number of research articles (9) published in the case of both the e-nose and the e-tongue used principal component analysis because it is conserves crucial variance and successfully shrinks the dimensionality of complex sensor data. Moreover, principal component analysis helps to simplify and visualize the data by highlighting the important variations in the data set. After this, followed by linear discriminant analysis, publishing in a total of three research articles, other methods of analysis—like linear discriminant analysis–principal component analysis, linear discriminant analysis–quadratic discriminant analysis, backpropagation neural network, least squares support square machine—have been used by a very limited number of research articles in the area of e-nose and e-tongue technology systems.

Figure 3b displays the various analysis types which were used by e-nose technology. The highest sensitivity of 100% was achieved by the principal component analysis, which was used for the detection of soft-rot [45], followed by 99.2% for least-squares support square machine analysis to detect VOCs [50]; by principal component analysis for garlic, with a 99.0% sensitivity [51]; by linear discriminant analysis–quadratic discriminant analysis, with a 98.7% sensitivity in urea detection [52]; by linear discriminant analysis, with a 97.5% sensitivity for chitosan [45]; by using backpropagation neural network analysis, with a sensitivity of 96.3% in pathogens [47]; by principal component analysis, with a 95.7% sensitivity, which was employed for E-coli [53]; by use of a convolutional neural network, with a sensitivity of 94.6% for climacteric fruits [56]; by linear discriminant analysis–principal component analysis, with a sensitivity of 94.4% for gases [49]; by principal component analysis, with a sensitivity of 93.4% for microorganisms [54]; and by using principal component analysis and quadratic discriminant analysis–multivariate discrimination analysis, with sensitivities of 90.4% and 90% for pathogens, sugar and carbohydrates [46,57].

Figure 3c shows an interesting trend for the various employed analyses for the e-tongue technology with respect to their achieved sensitivity. The highest sensitivity of 100% was obtained by using principal component analysis, linear discriminant analysis, linear discriminant analysis, and linear discriminant analysis–simulated annealing algorithms in samples of beers [58], adulteration checks [62], and checks for Escherichia faecalis, Staphylococcus aureus, E. coli and Pseudomonas Aeruginosa [64], respectively. The principal component analysis in E-coli detection obtained a sensitivity of 98.7% [66], while in the case of principal component analysis (E-coli), principal component analysis, partial least square–discriminant analysis (bitterness) and principal component analysis (2-MethylIsoborneol), the values are 97.6% [64], 97.4% [60], and 86.0% [65], respectively.

Figure 4a shows the number of published research articles on the e-nose and the e-tongue for different years. The highest number of articles (six) published on both the e-nose and the e-tongue were published in the year 2021, followed by 2018, 2019, and 2023, and 2024, 2016, and 2015, in which were published three, three, and three, and two, two, and two research articles, respectively. A low number of research articles were also published in the years of 2012 (one), 2017 (one), 2020 (one), and 2022 (one).

Figure 4b shows the performance of the e-nose system with respect to different years. The highest sensitivity of 99.0% was obtained in the year of 2015, followed by 98.7% in the year of 2022, than 97.5% in 2017, and 96.3% in 2019 and 2020 (average values [50,54]); values of 95.5%, 95.1%, 94.4%, and 90.0% were achieved in 2018 (average values [45–47]), 2021 (average values [53,55]), 2024 and 2023, respectively.

Figure 4c highlights e-tongue performance for achieved sensitivity with respect to different years. The highest sensitivity of 100% was obtained in the year of 2012, with average values of 97.5% and 95.5% in 2019 and 2021, respectively, with a value of only 86.0% in 2023.

Figure 5a displays the performance of different countries in terms of percentage for the e-nose technology for food analysis; the highest percentage of 26.7% was shown by China, followed by Iran (13.3%) and India (13.3%), while Italy, Spain, Brazil, the UK, Thailand and Ireland achieved only 6.7%, respectively.

Figure 5b shows the performance of several countries for the use of e-tongue technology being used for food product monitoring; the highest performance of 30% was shown by Spain, followed by Hungary and Columbia with 20%, respectively, and then by Portugal, Italy and Korea with only 10%, respectively.

Figure 5c highlights the interest of different countries with respect to the achieved sensitivity of the e-nose system. The maximum sensitivity of 100% was obtained by the researchers of UK, followed by Thailand with 99%, then by China with 98.7%, 97.5%, and

96.3%, respectively, and 95.7%, 94.6%, and 93.4% by the researchers of Indonesia, India, Spain; 90.6% and 90.0% were achieved by India and Iran, respectively.

Figure 5d shows the performance of the e-tongue technology in terms of the achieved sensitivity with respect to various countries; the highest average sensitivity of 100% was achieved by Spain, Hungary and Portugal, respectively [58,62,63], followed by the researchers of Columbia, with an average sensitivity of 98.15% [64,66], while sensitivity values of 97.4% and 86.0% were also obtained by the researchers of Spain and the Republic of Korea [60,65].

Calibration and interpretation is considered a major barrier in the performance of e-nose and e-tongue technologies. In the case of individual sensors, consistent re-calibration phenomena with the help of a standard is a recognized process, like for pH glass electrode calibration in a sequence of buffer solutions, but in the case of a multisensory system, it is considered a serious challenge. The partially selective sensors of the e-nose and e-tongue can generate non-specific signals in complex media including real-world samples and, hence, they use multivariate calibration models to understand responses and compare them with the concentration or property of interest. A substantial number of standard samples may be required for multivariate calibration, and some of them may be very difficult to obtain. Owing to standard sample and labor necessities and time consumption, regular recalibration of sensor arrays is highly expensive [91].

Figure 6a shows the performance of the e-nose for different food samples with respect to its sensitivity (Table 1). The maximum sensitivity of 15% was obtained in the case of apples for the monitoring of pathogens, followed by strawberry (VOCs) and potatoes (soft-rot) with a sensitivity of 8%, 7.9% for garlic and cucumber (urea); citrus fruits (chitosan) obtained a value of 7.8%; chicken meat (E-coli), meat, vegetables and fruits (gases) achieved a sensitivity of 7.7%; soybean (gases), lemon, apple, bananas and pears (climacteric fruits) achieved a value of 7.6%, respectively; and fish (microorganisms) and potatoes (sugar and carbohydrates) obtained a value of only 7.2%, respectively.

Figure 6b highlights the performance of the e-tongue for various food samples. The highest average percentage sensitivity of 40.5% was achieved in the case of water, followed by olive oils (bitterness) with a sensitivity of 16.2%, then by beer, red meat and poultry (adulteration check) with 14.3%, milk with 14.1% (E-coli), and only 2.9% for plum juices (*M. fructigena*).

3.7. A Comparison of the Strengths and Weaknesses of E-Nose and E-Tongue Technologies in Different Food Matrices

The e-nose technology employs multiple pattern and sensor techniques to monitor volatile compounds with high precision, sensitivity and consistency [44]. Due to its extreme sensitivity and selectivity, it is mostly employed in the case of volatile compounds. The technology of the e-tongue has sensors and electronic components, simulates human taste perception and facilitates a rapid, non-destructive and real-time analysis [92]. The e-tongue has the potential to be applied for different beverages and food products in various ways, like coffee differentiation [93], in yogurt and milk [94], in cheese [95], for storage conditions of melon [96], and for dry-aged beef [97]. Among them, coffee is the most extensively consumed beverage worldwide and constitutes a major segment of the global commodity market, ranking second only to crude oil in terms of economic significance [98]. Quality plays a crucial role in the modern coffee industry, as delivering a high-quality product at a competitive price is a fundamental requirement for success in today's highly competitive market [99]. However, the e-nose and models are validated with robust technology, like GC/MS, verifying its high accuracy and objective results. The fact that the e-nose is portable and fully wireless makes it more convenient for transporting the device and measuring samples in any location, with the potential for it to be used in the field to mainly assess

coffee beans [100]. The major limitations and challenges in e-nose technology include the sampling and preparation of samples in which volatile concentrations of analyzed foods are linked with pressure, humidity and temperature. Moreover, the gas sensor is highly sensitive to temperature, gas velocity, and the concentration of vapors, humidity and pressure. The strict control of sampling and the preparation of samples is essential for the desired precision and repeatability [21]. In the case of the e-nose, for effective validation, a large sample size is typically needed, requiring energy for the establishment of equilibrium before measuring. It is a confusing task to compare the performance of the e-nose from the literature due to pattern recognition algorithms, the preparation of samples and approach to sampling, and the resulting pool of training data [101]. At the same time, the limitations in the technology of the e-tongue include matrix effects in the case of food samples [102], multiple analysis steps, it being time-consuming and it having a short lifetime [103].

Figure 7 summarizes a trend in the obtained citations of the used research articles in Table 1, in both e-nose and e-tongue technologies. A total of 203 citations were obtained by the monitoring of garlic samples using the e-nose technology [52]; followed by 54 citations, which was achieved by the e-nose technology in the sensing of gases in fruit samples [49]; then by cyanobacteria, which was detected in water by using the e-tongue technology to obtain a total of 51 citations [69]; the monitoring of urea and chicken meat with the help of the e-nose achieved a total of 82 citations (41 + 41) [53,54]; 19 were achieved for the monitoring of water; and 21 were achieved for E-coli detection in milk samples by using the e-tongue [65,67]. A smaller number of citations like detection of E.f, S.a, E.C, P.A, [64] and 2-MethylIsoborenol [66] in water (7 and 8) has achieved citations respectively, were also noted for the other research articles mentioned.



Figure 7. Number of citations obtained by various food-related research publications.

Table 2 summarizes the application of the e-nose and e-tongue in the analysis of various samples of daily used foods, along with the algorithms like PCA, LDA, GANN, BPNN, LDA, used for data analysis. The table highlights the diversity of food products assessed and the types of analysis performed, like freshness, adulteration, and contaminant identification. Moreover, the year of study and the relevant references have also been included.

Table 2. Summary of the applications of the e-nose and e-tongue in analysis of food samples with their algorithms.

Food Samples	Purpose	Algorithms Used (Analysis)	Year	Ref.
E-nose				
Sardines	Freshness	PCA	2007	[104]
Milk	Adulteration	PCA/LDA	2007	[105]
Egg	Storage time and quality	[1] GANN/BPNN (better result)	2009	[106]
Sesame oil	Adulteration	PCA/LDA	2023	[107]
Almonds	Detection of contaminants chemical process	PCA	2023	[108]
Beef and pork	Adulteration	LDA	2020	[109]
Coffee	Volatile compounds	PCA	2022	[110]
Coffee	Coffee aroma	PCA	2022	[111]
Potatoes	VOCs	SVR	2022	[99]
Wheat bread	VOCs	-	2021	[112]
Wheat bread	VOCs	-	2020	[113]
Rapeseed oil	VOCs	PCA	2019	[114]
E-tongue				
Water	Differentiation of bacteria	LDA-SA	2021	[63]
Milk	Adulteration	PCA/PLA	2024	[115]
Water	Pesticides	PCA/LDA	2023	[116]
Melipona scutellaris honey	Characterization	PCA	2022	[117]
Fat and milk	Tetracycline	PCA	2016	[118]

[1] Genetic-algorithm neural network/back-propagation neural network.

As displayed in Table 2, both e-nose and e-tongue technologies have a lot of applications in food analysis. PCA is an adopted algorithm across various studies in the case of both the e-nose and e-tongue, owing to its efficacy in data-dimensionality reduction and pattern recognition, including for sardine freshness [104], milk adulteration [105], the detection of contaminants in almonds [108], sesame and rapeseed oil adulteration checking and VOC detection [107,114], and VOCs detection and aroma in coffee [110]. Moreover, other methods of analysis, like GANN/BPNN, LDA, LDA-SA, and SVR, have been used for the monitoring of egg [106], beef and pork [109], water [63], and potatoes [99].

Table 3 presents a detailed comparison of the advantages and limitations of both e-nose and e-tongue technologies. In addition to their significant importance, these techniques also face several serious limitations that may affect their performance depending on the applications and conditions. Hence, the table below summarizes the key characteristics along with the [22,119–125].

As summarized in Table 3, the techniques of both the e-nose and e-tongue present notable advantages in terms of real-time analysis, portability and operational simplicity. The technology of the e-nose is considered as invasive, providing fast detection with minimal sample preparation, and as having an operational simplicity [119–121]. At the same time, the e-tongue offers versatility through membrane selection and has the ability to respond to a wide range of analytes [22,124]. However, both systems also suffer from several limitations. In the case of the e-nose, it has the issue of selectivity, the need for frequent recalibration, and demonstrates a limited scope for certain complex analytes [120,122,123]. The e-tongue system is cost effective, sensitive to temperature and requires a skilled person [22,124,125].

Table 3. Summary for the comparison of the advantages and limitations of e-nose and e-tongue technologies.

Techniques	Advantages	Ref.
E-nose	Greater precision and reliability.	[119]
	Robust to various environmental conditions and accurate interpretation of data.	[119]
	Fast and noninvasive technique; needs little or no sample preparation.	[120]
	Provides real-time and automated measurements; advantages of portability and ease of use.	[120]
	Flexibility and time-saving technique.	[121]
	Limitations	
	Hardware friendliness and anti-noise capability.	[122]
	Poor selectivity and susceptibility.	[123]
	Requires periodic recalibration; susceptible to interfering gases and environmental factors; limited range of applications and sensor limitations.	[120]
E-Tongue	**Advantages**	
	It can select many different (both specific and less specific) membranes for its electrodes.	[22]
	Low cost; simple manufacturing and assembly; long-term stability and ability to taste toxic compounds.	[124]
	Limitations	
	Sensitive to temperature.	[22]
	Adsorption of components and influence of changes in solution composition;	[124]
	pretreatment of samples and short lifetime of components; needs skilled person.	[125]

4. Challenges and Future Aspects

In the present decade, food safety is a major problem around the world, owing to several challenges [126]. These challenges include sensor stability and calibration, which are affected by environmental factors and sensor degradation; the complexity of the food matrix, which makes the e-nose and e-tongue unreliable at differentiating specific components and at targeting components; and data analysis and interpretation, standardization, and validation, which affects the standardization of protocols and calibration methods across laboratories and devices. The mechanism of degradation in the case of material fatigue is considered a common cause in which materials are affected by environmental conditions like temperature, and leads to irreparable changes including nanoparticle sintering, which affects the sensor performance. Surface contamination, in which the surface of the sensor is covered by other annoying substances, shrinks the binding sites and affects their performance. Other causes for the degradation of the e-nose and e-tongue may include physical damage, ageing, use, and harsh environmental conditions like temperature, humidity, wind [127,128]. Another challenge which affects the performance of the sensor is exposure to humidity, which causes water poisoning, blocking of active sites and produces electrons, which leads to the inhibition of oxide semiconductor sensors and affects the sensitivity [129]. During the monitoring of sugar- and fat-containing food products, the performance of the sensors is significantly affected. In the case of the e-nose, the viscosity of the matrix is increased, suppressing the volatility of aroma compounds and interfering

with the signal stability, while in the e-tongue, the deposition of sugar contents can decrease its lifetime and affect its surface.

To cover the aforementioned challenges, future prospects include the following:

(i) Combination/integration of other analytical instruments: Future advancements in the evaluation of food quality will probably entail combining e-nose and e-tongue systems with additional analytical methods, including spectroscopy, chromatography, and sophisticated imaging techniques. This multi-modal method can improve the detection of pollutants and the entire quality-assurance process by offering more thorough data on food safety.

(ii) Artificial Intelligence Developments: The capabilities of e-nose and e-tongue systems are set to be improved by the integration of artificial intelligence (AI) and machine learning. AI can enhance sensor data interpretation, facilitate real-time analysis, and boost system accuracy and selectivity by using big datasets and complex algorithms [130]. This may result in automated and more user-friendly food quality monitoring systems that are simple to implement in a range of food processing and production settings.

(iii) Consistency and Regulatory Acceptance: Standardized procedures for calibration, testing, and performance evaluation are required if e-nose and e-tongue systems are to be widely used in the food business. In order to guarantee the accuracy and dependability of new technologies, regulatory agencies like the food and drug administration (FDA) and European food safety authority (EFSA) will also need to set rules for their usage in food safety monitoring.

(iv) Miniaturization and portability:

Real-time food quality monitoring and the development of multi-analyte sensors will enhance reliability and decrease analysis time; application in personalized nutrition will improve health and consumer satisfaction; the quality of the applied nanomaterials will be enhanced.

(v) Advances in sensor calibration:

- Baseline alteration and standardization will be performed before pattern recognition to eliminate environmental noise and baseline drift for the regulation of raw signals.
- During operation, machine learning algorithms vigorously recalibrate sensor performance.
- Reusing formerly calibrated progressions and regulating them to diverse sensor environments.

(vi) Rapid detection of emerging foodborne pathogens:

Current techniques will be used for the control of foodborne pathogens by training safety officers in the application of these techniques. Moreover, further research is required to explore the progress of more well-organized policies like leveraging bacteriophages for the targeted control and extinction of foodborne pathogens [131].

(vii) Personalized nutrition:

Personalized nutrition is becoming increasingly important for the safety of food products. This could be seen in the incorporation of apps on smartphones to rapidly detect the freshness, additives and adulteration of food products, using the development of mobile chemical sensors and wearable devices to support dietary behaviors [131].

5. Conclusions

This review highlights the role of e-nose and e-tongue technologies in food safety, summarizing key findings in various tables and discussing them based on different parameters. Commonly consumed foods, including fruits, vegetables, meat, water, and milk, were analyzed for contaminants such as chitosan, soft-rot, pathogens, sugar, phenols, and bacteria. The application of e-nose and e-tongue technology in the food industry was briefly reviewed with comparative graphs, showing trends in sensitivity, publication years, countries, and citation rates. Among food safety, quality and storage applications, the

e-nose demonstrated the highest sensitivity for soft-rot detection in potatoes (100%) using PCA analysis in the UK (2018), showing a value of 99.0% in the case of food security for garlic monitoring by using PCA analysis in Thailand (2015), while in the shelf monitoring of food, a sensitivity of 95.7% was obtained for the detection of *E. coli* in chicken meat by researchers in Indonesia (2021). Regarding e-tongue applications in food quality assessment, adulteration checks in red meat, poultry and beer using LDA, PCA and LDA exhibited 100% sensitivity in Hungary (2021) and Spain (2012). Moreover, the e-tongue achieved 100% sensitivity in the monitoring of water in Portugal (2021). PCA analysis was particularly favored in 2021 for achieving a high accuracy. The worldwide research contributions showed China at the forefront of e-nose studies (26.7%) and Spain leading in e-tongue research (30%). The highest sensitivity values were 99.0% for the e-nose in 2015 and 100% for the e-tongue in 2012. In specific applications, the e-nose achieved a maximum average sensitivity of 15% in apple analysis, while the e-tongue achieved a maximum average sensitivity of 40.5% in water samples. Additionally, by analyzing country contributions and citation trends (Table 1), this review highlights opportunities for international collaboration among scientists in the field of food safety.

Supplementary Materials: The following supporting information can be downloaded at https://www.mdpi.com/article/10.3390/chemosensors13070262/s1. File S1, PRISMA 2020 Checklist. Reference [132] is cited in the supplementary materials.

Author Contributions: M.Z.U.H.: Writing—original-draft, data curation, investigation, design, formatting; B.S., X.F. and A.B.: conceptualization and writing—review and editing; F.T.: supervision, conceptualization, writing—review and editing. All authors have read and agreed to the published version of the manuscript.

Funding: This review article received no external funding.

Informed Consent Statement: Not applicable.

Data Availability Statement: Not applicable.

Acknowledgments: M.Z.U.H. thanks the support of F.T., X.F., A.B. & B.S.

Conflicts of Interest: The authors declare no conflicts of interest.

References

1. Garcia-Perez, P.; Becchi, P.P.; Zhang, L.; Rocchetti, G.; Lucini, L. Metabolomics and chemometrics: The next-generation analytical toolkit for the evaluation of food quality and authenticity. *Trends Food Sci. Technol.* **2024**, *147*, 104481. [CrossRef]
2. Lu, L.; Hu, Z.; Hu, X.; Li, D.; Tian, S. Electronic tongue and electronic nose for food quality and safety. *Food Res Int.* **2022**, *162*, 112214. [CrossRef] [PubMed]
3. Magnuson, B.; Munro, I.; Abbot, P.; Baldwin, N.; Lopez-Garcia, R.; Ly, K.; McGirr, L.; Roberts, A.; Socolovsky, S. Review of the regulation and safety assessment of food substances in various countries and jurisdictions. *Food Addit. Contam.* **2013**, *30*, 1147–1220. [CrossRef] [PubMed]
4. Committee, E.S.; Benford, D.; Halldorsson, T.; Jeger, M.J.; Knutsen, H.K.; More, S.; Naegeli, H.; Noteborn, H.; Ockleford, C.; Ricci, A. The principles and methods behind EFSA's guidance on uncertainty analysis in scientific assessment. *EFSA J.* **2018**, *16*, e05122. [CrossRef] [PubMed]
5. Ling, Z.; Yang, L.; Zhang, W.; Yao, T.; Xu, H. Detection of food contaminants: A review of established rapid analytical techniques and their applications and limitations. *Food Saf. Health* **2024**, *2*, 72–95. [CrossRef]
6. Mazarakioti, E.C.; Zotos, A.; Thomatou, A.-A.; Kontogeorgos, A.; Patakas, A.; Ladavos, A. Inductively coupled plasma-mass spectrometry (ICP-MS), a useful tool in authenticity of agricultural products' and foods' origin. *Foods* **2022**, *11*, 3705. [CrossRef] [PubMed]
7. Shim, J.-H.; Rahman, M.M.; Esatbeyoglu, T.; Oz, F.; El-Aty, A.A. Development of an enhanced analytical method utilizing pepper matrix as an analyte protectant for sensitive GC–MS/MS detection of dimethipin in animal-based food products. *PLoS ONE* **2023**, *18*, e0295968. [CrossRef] [PubMed]

8. Yun, D.-Y.; Bae, J.-Y.; Park, C.-W.; Jang, G.-H.; Choe, W.-J. Determination of Modified QuEChERS Method for Chlorothalonil Analysis in Agricultural Products Using Gas Chromatography–Mass Spectrometry (GC-MS/MS). *Foods* **2023**, *12*, 3793. [CrossRef] [PubMed]
9. Hakami, R.A.; Aqel, A.; Ghfar, A.A.; ALOthman, Z.A.; Badjah-Hadj-Ahmed, A.-Y. Development of QuEChERS extraction method for the determination of pesticide residues in cereals using DART-ToF-MS and GC-MS techniques. Correlation and quantification study. *J. Food Compos. Anal.* **2021**, *98*, 103822. [CrossRef]
10. Barreca, S.; Orecchio, S.; Orecchio, S.; Abbate, I.; Pellerito, C. Macro and micro elements in traditional meals of Mediterranean diet: Determination, estimated intake by population, risk assessment and chemometric analysis. *J. Food Compos. Anal.* **2023**, *123*, 105541. [CrossRef]
11. Hassan, M.H.; Khan, R.; Andreescu, S. Advances in electrochemical detection methods for measuring contaminants of emerging concerns. *Electrochem. Sci. Adv.* **2022**, *2*, e2100184. [CrossRef]
12. Sakthivel, K.; Balasubramanian, S.; Chang-Chien, G.-P.; Wang, S.-F.; Billey, W.; Platero, J.; Soundappan, T.; Sekhar, P. Editors' choice—Review—Advances in electrochemical sensors: Improving food safety, quality, and traceability. *ECS Sens. Plus* **2024**, *3*, 020605. [CrossRef]
13. Umapathi, R.; Ghoreishian, S.M.; Sonwal, S.; Rani, G.M.; Huh, Y.S. Portable electrochemical sensing methodologies for on-site detection of pesticide residues in fruits and vegetables. *Coord. Chem. Rev.* **2022**, *453*, 214305. [CrossRef]
14. Dey, K. Electrochemical Biosensors Market Research Report Information by Type (Diagnosis and Monitoring), by End User (Healthcare Diagnostics, Environmental Monitoring, and Food Quality Testing), And By Region (North America, Europe, Asia-Pacific, and the Rest of the World)–Market Forecast Till 2032. Available online: https://www.marketresearchfuture.com/reports/electrochemical-biosensors-market-2792 (accessed on 30 August 2019).
15. Sun, X.; Liu, F.; Xue, X. Machine learning combined with electrochemical sensor for rapid detection of Sudan Red I in food. *J. Food Meas. Charact.* **2024**, *18*, 95–104. [CrossRef]
16. Wang, M.; Chen, Y. Electronic nose and its application in the food industry: A review. *Eur. Food Res. Technol.* **2024**, *250*, 21–67. [CrossRef]
17. Casalinuovo, I.A.; Di Pierro, D.; Coletta, M.; Di Francesco, P. Application of electronic noses for disease diagnosis and food spoilage detection. *Sensors* **2006**, *6*, 1428–1439. [CrossRef]
18. Gliszczyńska-Świgło, A.; Chmielewski, J. Electronic nose as a tool for monitoring the authenticity of food. A review. *Food Anal. Methods* **2017**, *10*, 1800–1816. [CrossRef]
19. Mohamed, R.R.; Yaacob, R.; Mohamed, M.A.; Dir, T.A.T.; Rahim, F.A. Food freshness using electronic nose and its classification method: A review. *Int. J. Eng. Technol.* **2018**, *7*, 49–53. [CrossRef]
20. Arshak, K.; Moore, E.; Lyons, G.M.; Harris, J.; Clifford, S. A review of gas sensors employed in electronic nose applications. *Sens. Rev.* **2004**, *24*, 181–198. [CrossRef]
21. Tan, J.; Xu, J. Applications of electronic nose (e-nose) and electronic tongue (e-tongue) in food quality-related properties determination: A review. *Artif. Intell. Agric.* **2020**, *4*, 104–115. [CrossRef]
22. Baietto, M.; Wilson, A.D. Electronic-nose applications for fruit identification, ripeness and quality grading. *Sensors* **2015**, *15*, 899–931. [CrossRef] [PubMed]
23. Yan, K.; Zhang, D. Correcting instrumental variation and time-varying drift: A transfer learning approach with autoencoders. *IEEE Trans. Instrum. Meas.* **2016**, *65*, 2012–2022. [CrossRef]
24. Verma, M.; Asmita, S.; Shukla, K. A regularized ensemble of classifiers for sensor drift compensation. *IEEE Trans. Instrum.* **2015**, *16*, 1310–1318. [CrossRef]
25. Vanaraj, R.; IP, B.; Mayakrishnan, G.; Kim, I.S.; Kim, S.-C. A Systematic Review of the Applications of Electronic Nose and Electronic Tongue in Food Quality Assessment and Safety. *Chemosensors* **2025**, *13*, 161. [CrossRef]
26. Ye, Z.; Liu, Y.; Li, Q. Recent progress in smart electronic nose technologies enabled with machine learning methods. *Sensors* **2021**, *21*, 7620. [CrossRef] [PubMed]
27. Yadav, U.; Khurana, S.; Rawal, K.; Arora, B.; Yadav, A. Integrating AI with Electronic Tongue (E-Tongue) for Real-Time Detection in the Food Industry. In *Artificial Intelligence in the Food Industry*; CRC Press: Boca Raton, FL, USA, 2025; pp. 277–296.
28. Tahara, Y.; Toko, K. Electronic tongues–a review. *IEEE Sens. J.* **2013**, *13*, 3001–3011. [CrossRef]
29. Tibaduiza, D.; Anaya, M.; Gómez, J.; Sarmiento, J.; Perez, M.; Lara, C.; Ruiz, J.; Osorio, N.; Rodriguez, K.; Hernandez, I. Electronic tongues and noses: A general overview. *Biosensors* **2024**, *14*, 190. [CrossRef] [PubMed]
30. Jiang, H.; Zhang, M.; Bhandari, B.; Adhikari, B. Application of electronic tongue for fresh foods quality evaluation: A review. *Food Rev. Int.* **2018**, *34*, 746–769. [CrossRef]
31. Schlossareck, C.; Ross, C.F. Electronic tongue and consumer sensory evaluation of spicy paneer cheese. *J. Food Sci.* **2019**, *84*, 1563–1569. [CrossRef] [PubMed]
32. Suthaharan, S. Support vector machine. In *Machine Learning Models and Algorithms for Big Data Classification: Thinking with Examples for Effective Learning*; Springer: Berlin/Heidelberg, Germany, 2016; pp. 207–235.

33. Leon-Medina, J.X.; Anaya, M.; Pozo, F.; Tibaduiza, D. Nonlinear feature extraction through manifold learning in an electronic tongue classification task. *Sensors* **2020**, *20*, 4834. [CrossRef] [PubMed]
34. Leon-Medina, J.X.; Cardenas-Flechas, L.J.; Tibaduiza, D.A. A data-driven methodology for the classification of different liquids in artificial taste recognition applications with a pulse voltammetric electronic tongue. *Int. J. Distrib. Sens. Netw.* **2019**, *15*, 1550147719881601. [CrossRef]
35. Torrico, D.D.; Mehta, A.; Borssato, A.B. New methods to assess sensory responses: A brief review of innovative techniques in sensory evaluation. *Curr. Opin. Food Sci.* **2023**, *49*, 100978. [CrossRef]
36. Bouchouras, G.; Kotis, K. Integrating Artificial Intelligence, Internet of Things, and Sensor-Based Technologies: A Systematic Review of Methodologies in Autism Spectrum Disorder Detection. *Algorithms* **2025**, *18*, 34. [CrossRef]
37. Kuchmenko, T.; Umarkhanov, R.; Lvova, L. E-nose for the monitoring of plastics catalytic degradation through the released Volatile Organic Compounds (VOCs) detection. *Sens. Actuators B Chem.* **2020**, *322*, 128585. [CrossRef]
38. Okur, S.; Zhang, Z.; Sarheed, M.; Nick, P.; Lemmer, U.; Heinke, L. Towards a MOF e-Nose: A SURMOF sensor array for detection and discrimination of plant oil scents and their mixtures. *Sens. Actuators B Chem.* **2020**, *306*, 127502. [CrossRef]
39. Shooshtari, M.; Salehi, A. An electronic nose based on carbon nanotube-titanium dioxide hybrid nanostructures for detection and discrimination of volatile organic compounds. *Sens. Actuators B Chem.* **2022**, *357*, 131418. [CrossRef]
40. Grassi, S.; Benedetti, S.; Casiraghi, E.; Buratti, S. E-sensing systems for shelf life evaluation: A review on applications to fresh food of animal origin. *Food Packag. Shelf Life* **2023**, *40*, 101221. [CrossRef]
41. Gil, M.; Rudy, M.; Duma-Kocan, P.; Stanisławczyk, R. Electronic Sensing Technologies in Food Quality Assessment: A Comprehensive Literature Review. *Appl. Sci.* **2025**, *15*, 1530. [CrossRef]
42. Fayaz, U.; Srivastava, S.; Dar, A.H.; Bashir, I.; Manzoor, S.; Pandey, V.K.; Shams, R.; Dash, K.K. Recent insights into E-tongue interventions in food processing applications: An updated review. *Curr. Food Sci. Technol. Rep.* **2024**, *2*, 169–182. [CrossRef]
43. Ortega, J.B.; Garcia, J.G.; Ortega, J.G. Precision of volatile compound analysis in extra virgin olive oil: The influence of MOS electronic nose acquisition factors. In Proceedings of the 2015 IEEE International Conference on Industrial Technology (ICIT), Seville, Spain, 17–19 March 2015; pp. 1482–1487. [CrossRef]
44. Qiu, S.; Wang, J. The prediction of food additives in the fruit juice based on electronic nose with chemometrics. *Food Chem.* **2017**, *230*, 208–214. [CrossRef] [PubMed]
45. Rutolo, M.F.; Clarkson, J.P.; Covington, J.A. The use of an electronic nose to detect early signs of soft-rot infection in potatoes. *Biosyst. Eng.* **2018**, *167*, 137–143. [CrossRef]
46. Ezhilan, M.; Nesakumar, N.; Jayanth Babu, K.; Srinandan, C.S.; Rayappan, J.B.B. An Electronic Nose for Royal Delicious Apple Quality Assessment–A Tri-layer Approach. *Food Res. Int.* **2018**, *109*, 44–51. [CrossRef] [PubMed]
47. Jia, W.; Liang, G.; Tian, H.; Sun, J.; Wan, C. Electronic nose-based technique for rapid detection and recognition of moldy apples. *Sensors* **2019**, *19*, 1526. [CrossRef] [PubMed]
48. Wang, M.; Gao, F.; Wu, Q.; Zhang, J.; Xue, Y.; Wan, H.; Wang, P. Real-time assessment of food freshness in refrigerators based on a miniaturized electronic nose. *Anal. Methods* **2018**, *10*, 4741–4749. [CrossRef]
49. Herrmann, P.S.D.P.; Santos Luccas, M.D.; Ferreira, E.J.; Torre Neto, A. Application of electronic nose and machine learning used to detect soybean gases under water stress and variability throughout the daytime. *Front. Plant Sci.* **2024**, *15*, 1323296. [CrossRef] [PubMed]
50. Rao, J.; Zhang, Y.; Yang, Z.; Li, S.; Wu, D.; Sun, C.; Chen, K. Application of electronic nose and GC–MS for detection of strawberries with vibrational damage. *Food Qual. Saf.* **2020**, *4*, 181–192. [CrossRef]
51. Trirongjitmoah, S.; Juengmunkong, Z.; Srikulnath, K.; Somboon, P. Classification of garlic cultivars using an electronic nose. *Comput. Electron. Agric.* **2015**, *113*, 148–153. [CrossRef]
52. Tatli, S.; Mirzaee-Ghaleh, E.; Rabbani, H.; Karami, H.; Wilson, A.D. Rapid Detection of Urea Fertilizer Effects on VOC Emissions from Cucumber Fruits Using a MOS E-Nose Sensor Array. *Agronomy* **2022**, *12*, 35. [CrossRef]
53. Astuti, S.D.; Tamimi, M.H.; Pradhana, A.A.S.; Alamsyah, K.A.; Purnobasuki, H.; Khasanah, M.; Susilo, Y.; Triyana, K.; Kashif, M.; Syahrom, A. Gas sensor array to classify the chicken meat with E. coli contaminant by using random forest and support vector machine. *Biosens. Bioelectron. X* **2021**, *9*, 100083. [CrossRef]
54. Sanchez, R.; Alejo, M.; Escribano, P.; Arroyo, P.; Meléndez, F.; Lozano, J. Evaluation of the Shelf Life of Fresh Fish Using an Electronic Nose. *Chem. Eng. Trans.* **2024**, *112*, 115–120. [CrossRef]
55. Cozzolino, R.; Palumbo, M.; Cefola, M.; Laurino, C.; Siano, F.; De Giulio, B.; Pace, B. E-nose and Attenuated Total Reflectance-Fourier Transform Infrared data to estimate the shelf-life of fresh-cut Barattiere packaged in polypropylene or in biodegradable polylactic acid bags. *Food Packag. Shelf Life* **2023**, *38*, 101130. [CrossRef]
56. Karamchandani, S.; Sekhani, B.; Nair, K.; Shah, K. E-nose for shelf-life prediction of climacteric fruits. In Proceedings of the 2021 IEEE 4th International Conference on Computing, Power and Communication Technologies (GUCON), Kuala Lumpur, Malaysia, 24–26 September 2021. [CrossRef]

57. Khorramifar, A.; Rasekh, M.; Karami, H.; Lozano, J.; Gancarz, M.; Łazuka, E.; Łagód, G. Determining the shelf life and quality changes of potatoes (*Solanum tuberosum*) during storage using electronic nose and machine learning. *PLoS ONE* **2023**, *18*, e0284612. [CrossRef] [PubMed]
58. Ghasemi-Varnamkhasti, M.; Rodríguez-Méndez, M.L.; Mohtasebi, S.S.; Apetrei, C.; Lozano, J.; Ahmadi, H.; Razavi, S.H.; Antonio de Saja, J. Monitoring the aging of beers using a bioelectronic tongue. *Food Control* **2012**, *25*, 216–224. [CrossRef]
59. Medina-Plaza, C.; de Saja, J.A.; Fernández-Escudero, J.A.; Barajas, E.; Medrano, G.; Rodriguez-Mendez, M.L. Array of biosensors for discrimination of grapes according to grape variety, vintage and ripeness. *Anal. Chim. Acta.* **2016**, *947*, 16–22. [CrossRef] [PubMed]
60. Apetrei, C. Novel method based on polypyrrole-modified sensors and emulsions for the evaluation of bitterness in extra virgin olive oils. *Food Res. Int.* **2012**, *48*, 673–680. [CrossRef]
61. Vitalis, F.; Tjandra Nugraha, D.; Aouadi, B.; Aguinaga Bósquez, J.P.; Bodor, Z.; Zaukuu, J.L.Z.; Kocsis, T.; Zsom-Muha, V.; Gillay, Z.; Kovacs, Z. Detection of monilia contamination in plum and plum juice with NIR spectroscopy and electronic tongue. *Chemosensors* **2021**, *9*, 355. [CrossRef]
62. Zaukuu, J.L.Z.; Gillay, Z.; Kovacs, Z. Standardized extraction techniques for meat analysis with the electronic tongue: A case study of poultry and red meat adulteration. *Sensors* **2021**, *21*, 481. [CrossRef] [PubMed]
63. Ghrissi, H.; Veloso, A.C.; Marx, Í.M.; Dias, T.; Peres, A.M. A potentiometric electronic tongue as a discrimination tool of water-food indicator/contamination bacteria. *Chemosensors* **2021**, *9*, 143. [CrossRef]
64. Goméz, J.K.C.; Acevedo, C.M.D.; García, R.O. Application of an E-Tongue and E-nose for a rapid E. coli detection in a drinking water treatment plant. In Proceedings of the 2019 IEEE International Symposium on Olfaction and Electronic Nose (ISOEN), Fukuoka, Japan, 26–29 May 2019; pp. 1–4. [CrossRef]
65. Nam, S.-H.; Lee, J.; Kim, E.; Koo, J.-W.; Shin, Y.; Hwang, T.-M. Electronic tongue for the simple and rapid determination of taste and odor compounds in water. *Chemosphere* **2023**, *338*, 139511. [CrossRef] [PubMed]
66. Carrillo-Gómez, J.K.; Acevedo, C.M.D.; García-Rico, R.O. Detection of the bacteria concentration level in pasteurized milk by using two different artificial multisensory methods. *Sens. Bio-Sens. Res.* **2021**, *33*, 100428. [CrossRef]
67. Lvova, L.; Gonçalves, C.G.; Petropoulos, K.; Micheli, L.; Volpe, G.; Kirsanov, D.; Legin, A.; Viaggiu, E.; Congestri, R.; Guzzella, L. Electronic tongue for microcystin screening in waters. *Biosens. Bioelectron.* **2016**, *80*, 154–160. [CrossRef] [PubMed]
68. Wang, W.; Feng, Y.; Dai, W. Topic analysis of online reviews for two competitive products using latent Dirichlet allocation. *Electron. Commer. Res.* **2018**, *29*, 142–156. [CrossRef]
69. Xu, P.; Brock, G.N.; Parrish, R.S. Modified linear discriminant analysis approaches for classification of high-dimensional microarray data. *Comput. Stat. Data Anal.* **2009**, *53*, 1674–1687. [CrossRef]
70. Karamizadeh, S.; Abdullah, S.M.; Manaf, A.A.; Zamani, M.; Hooman, A. An overview of principal component analysis. *J. Signal Inf. Process.* **2013**, *4*, 173–175. [CrossRef]
71. Li, L.; Liu, S.; Peng, Y.; Sun, Z. Overview of principal component analysis algorithm. *Optik* **2016**, *127*, 3935–3944. [CrossRef]
72. Liu, J.; Ma, Z.; Tian, L.; Li, Q.; Bi, W. BPNN-assisted control algorithm application to a super large cable-net structure of active FAST reflector system. In *Structures*; Elsevier: Amsterdam, The Netherlands, 2025. [CrossRef]
73. Wang, M.; Liu, Z.; Yu, Y.; Yang, X.; Gao, W. Rate-Dependent Hysteresis Model Based on LS-SVM for Magnetic Shape Memory Alloy Actuator. In *Actuators*; MDPI: Basel, Switzerland, 2025. [CrossRef]
74. Guo, Z.; Bai, G. Application of least squares support vector machine for regression to reliability analysis. *Chin. J. Aeronaut.* **2009**, *22*, 160–166. [CrossRef]
75. Du, B.; Zheng, S.; Zhao, J. Quadratic discriminant analysis in distributed frameworks. *Statistics* **2025**, *3*, 735–761. [CrossRef]
76. Savino, P.; Graglia, F.; Scozza, G.; Pietra, V.D. Automated corrosion surface quantification in steel transmission towers using UAV photogrammetry and deep convolutional neural networks. *Comput. Aided Civ. Infrastruct. Eng.* **2025**, *40*, 2050–2070. [CrossRef]
77. Kamilaris, A.; Prenafeta-Boldú, F.X. A review of the use of convolutional neural networks in agriculture. *J. Agric. Sci.* **2018**, *156*, 312–322. [CrossRef]
78. Szostakiwskyj, J.M.H.; Cortese, F.; Abdul-Rhaman, R.; Anderson, S.J.; Warren, A.L.; Archer, R.; Read, E.; Hecker, K.G. The Problem with Time: Application of Partial Least Squares Analysis on Time-Frequency Plots to Account for Varying Time Intervals with Applied EEG Data. *Brain Sci.* **2025**, *15*, 135. [CrossRef] [PubMed]
79. Mo, Y.; Liu, J.; Zhang, L. Deconvolution of spatial transcriptomics data via graph contrastive learning and partial least square regression. *Brief. Bioinform.* **2025**, *26*, bbaf052. [CrossRef] [PubMed]
80. Chen, C.; Li, X.; Bo, Z.; Du, W.; Fu, L.; Tian, Y.; Cui, S.; Shi, Y.; Xie, H. Occurrence, characteristics, and PCR-based detection of Pectobacterium polaris causing soft rot of Chinese cabbage in China. *Plant Dis.* **2021**, *105*, 2880–2887. [CrossRef] [PubMed]
81. Baek, J.H.; Lee, S.-Y.; Bae, J.-Y.; Oh, S.-W. Development of a selective and differential medium for effective isolation of Pectobacterium carotovorum from soft rot-infected agricultural products. *Food Sci. Biotechnol.* **2025**, *34*, 1517–1524. [CrossRef] [PubMed]

82. Suárez, M.B.; Diego, M.; Feria, F.J.; Martín-Robles, M.J.; Moreno, S.; Palomo, J.L. New PCR-based assay for the identification of Pectobacterium carotovorum causing potato soft rot. *Plant Dis.* **2022**, *106*, 676–684. [CrossRef] [PubMed]
83. Li, Z.; Thomas, C. Quantitative evaluation of mechanical damage to fresh fruits. *Trends Food Sci. Technol.* **2014**, *35*, 138–150. [CrossRef]
84. Black, C.; Chevallier, O.P.; Elliott, C.T. The current and potential applications of ambient mass spectrometry in detecting food fraud. *TrAC Trends Anal. Chem.* **2016**, *82*, 268–278. [CrossRef]
85. Karami, H.; Rasekh, M.; Mirzaee-Ghaleh, E. Qualitative analysis of edible oil oxidation using an olfactory machine. *J. Food Meas. Charact.* **2020**, *14*, 2600–2610. [CrossRef]
86. Thienes, C.P.; Masiri, J.; Benoit, L.A.; Barrios-Lopez, B.; Samuel, S.A.; Krebs, R.A.; Samadpour, M. Quantitative detection of beef contamination in cooked meat products by ELISA. *J. AOAC Int.* **2019**, *102*, 898–902. [CrossRef] [PubMed]
87. Jordana-Lluch, E.; Giménez, M.; Quesada, M.D.; Ausina, V.; Martró, E. Improving the diagnosis of bloodstream infections: PCR coupled with mass spectrometry. *Biomed. Res. Int.* **2014**, *2014*, 501214. [CrossRef] [PubMed]
88. Lin, C.C.; Fung, L.L.; Chan, P.K.; Lee, C.M.; Chow, K.F.; Cheng, S.H. A rapid low-cost high-density DNA-based multi-detection test for routine inspection of meat species. *Meat Sci.* **2014**, *96*, 922–929. [CrossRef] [PubMed]
89. Gracias, K.S.; McKillip, J.L. A review of conventional detection and enumeration methods for pathogenic bacteria in food. *Can. J. Microbiol.* **2004**, *50*, 883–890. [CrossRef] [PubMed]
90. Ruan, E.D.; Aalhus, J.L.; Summerfelt, S.T.; Davidson, J.; Swift, B.; Juárez, M. Determination of off-flavor compounds, 2-methylisoborneol and geosmin, in salmon fillets using stir bar sorptive extraction–thermal desorption coupled with gas chromatography–mass spectrometry. *J. Chromatogr. A.* **2013**, *1321*, 133–136. [CrossRef] [PubMed]
91. Rudnitskaya, A. Calibration update and drift correction for electronic noses and tongues. *Front. Chem.* **2018**, *6*, 433. [CrossRef] [PubMed]
92. Yang, B.; Wang, H.; Cao, Z.; Yan, J.; Dong, Z.; Ren, F.; Zhang, W.; Chen, L. The Aroma, Taste Contributions, and Flavor Evaluation Based on GC-IMS, E-Nose, and E-Tongue in Soybean Pastes: A Comparative Study. *Foods* **2025**, *14*, 1178. [CrossRef] [PubMed]
93. Dong, W.; Zhao, J.; Hu, R.; Dong, Y.; Tan, L. Differentiation of Chinese robusta coffees according to species, using a combined electronic nose and tongue, with the aid of chemometrics. *Food Chem.* **2017**, *229*, 743–751. [CrossRef] [PubMed]
94. Hruškar, M.; Major, N.; Krpan, M.; Panjkota Krbavčić, I.; Šarić, G.; Marković, K.; Vahčić, N. Evaluation of milk and dairy products by electronic tongue. *Mljekarstvo Časopis Za Unaprjeđenje Proizv. I Prerade Mlijeka* **2009**, *59*, 193–200.
95. Lipkowitz, J.B.; Ross, C.F.; Diako, C.; Smith, D.M. Discriminating aging and protein-to-fat ratio in Cheddar cheese using sensory analysis and a potentiometric electronic tongue. *J. Dairy. Sci.* **2018**, *101*, 1990–2004. [CrossRef] [PubMed]
96. Németh, D.; Balázs, G.; Daood, H.G.; Kovács, Z.; Bodor, Z.; Zinia Zaukuu, J.-L.; Szentpéteri, V.; Kókai, Z.; Kappel, N. Standard analytical methods, sensory evaluation, NIRS and electronic tongue for sensing taste attributes of different melon varieties. *Sensors* **2019**, *19*, 5010. [CrossRef] [PubMed]
97. Lee, H.J.; Yoon, J.W.; Kim, M.; Oh, H.; Yoon, Y.; Jo, C. Changes in microbial composition on the crust by different air flow velocities and their effect on sensory properties of dry-aged beef. *Meat Sci.* **2019**, *153*, 152–158. [CrossRef] [PubMed]
98. Lee, C.H.; Chen, I.-T.; Yang, H.C.; Chen, Y.J. An AI-powered electronic nose system with fingerprint extraction for aroma recognition of coffee beans. *Micromachines* **2022**, *13*, 1313. [CrossRef] [PubMed]
99. Aunsa-Ard, W.; Kerdcharoen, T. Electronic nose for analysis of coffee beans obtained from different altitudes and origin. In Proceedings of the 2022 14th International Conference on Knowledge and Smart Technology (KST), Saen Suk, Thailand, 26–29 June 2022; pp. 147–151. [CrossRef]
100. Khorramifar, A.; Sharabiani, V.R.; Karami, H.; Kisalaei, A.; Lozano, J.; Rusinek, R.; Gancarz, M. Investigating changes in pH and soluble solids content of potato during the storage by electronic nose and Vis/NIR spectroscopy. *Foods* **2022**, *11*, 4077. [CrossRef] [PubMed]
101. Kiselev, I.; Sysoev, V.; Kaikov, I.; Koronczi, I.; Adil Akai Tegin, R.; Smanalieva, J.; Sommer, M.; Ilicali, C.; Hauptmannl, M. On the temporal stability of analyte recognition with an e-nose based on a metal oxide sensor array in practical applications. *Sensors* **2018**, *18*, 550. [CrossRef] [PubMed]
102. Cetó, X.; Voelcker, N.H.; Prieto-Simón, B. Bioelectronic tongues: New trends and applications in water and food analysis. *Biosens. Bioelectron.* **2016**, *79*, 608–626. [CrossRef] [PubMed]
103. Mahanti, N.K.; Shivashankar, S.; Chhetri, K.B.; Kumar, A.; Rao, B.B.; Aravind, J.; Swami, D. Enhancing food authentication through E-nose and E-tongue technologies: Current trends and future directions. *Trends Food Sci. Technol.* **2024**, *150*, 104574. [CrossRef]
104. El Barbri, N.; Amari, A.; Vinaixa, M.; Bouchikhi, B.; Correig, X.; Llobet, E. Building of a metal oxide gas sensor-based electronic nose to assess the freshness of sardines under cold storage. *Sensors Actuators B Chem.* **2007**, *128*, 235–244. [CrossRef]
105. Yu, H.; Wang, J.; Xu, Y. Identification of adulterated milk using electronic nose. *Sens. Mater.* **2007**, *19*, 275–285.
106. Yongwei, W.; Wang, J.; Zhou, B.; Lu, Q. Monitoring storage time and quality attribute of egg based on electronic nose. *Anal. Chim. Acta* **2009**, *650*, 183–188. [CrossRef] [PubMed]

107. Aghili, N.S.; Rasekh, M.; Karami, H.; Edriss, O.; Wilson, A.D.; Ramos, J. Aromatic fingerprints: VOC analysis with E-nose and GC-MS for rapid detection of adulteration in sesame oil. *Sensors* **2023**, *23*, 6294. [CrossRef] [PubMed]
108. Mesías, M.; Barea-Ramos, J.D.; Lozano, J.; Morales, F.J.; Martín-Vertedor, D. Application of an electronic nose technology for the prediction of chemical process contaminants in roasted almonds. *Chemosensors* **2023**, *11*, 287. [CrossRef]
109. Han, F.; Huang, X.H.; Aheto, J.; Zhang, D.; Feng, F. Detection of beef adulterated with pork using a low-cost electronic nose based on colorimetric sensors. *Foods* **2020**, *9*, 193. [CrossRef] [PubMed]
110. Aghdamifar, E.; Sharabiani, V.R.; Taghinezhad, E.; Szymanek, M.; Dziwulska-Hunek, A. E-nose as a non-destructive and fast method for identification and classification of coffee beans based on soft computing models. *Sens. Actuators B. Chem.* **2023**, *393*, 134229. [CrossRef]
111. Gonzalez Viejo, C.; Tongson, E.; Fuentes, S. Integrating a low-cost electronic nose and machine learning modelling to assess coffee aroma profile and intensity. *Sensors* **2021**, *21*, 2016. [CrossRef] [PubMed]
112. Gancarz, M.; Malaga-Toboła, U.; Oniszczuk, A.; Tabor, S.; Oniszczuk, T.; Gawrysiak-Witulska, M.; Rusinek, R. Detection and measurement of aroma compounds with the electronic nose and a novel method for MOS sensor signal analysis during the wheat bread making process. *Food Bioprod. Process* **2021**, *127*, 90–98. [CrossRef]
113. Rusinek, R.; Gancarz, M.; Nawrocka, A. Application of an electronic nose with novel method for generation of smellprints for testing the suitability for consumption of wheat bread during 4-day storage. *LWT* **2020**, *117*, 108665. [CrossRef]
114. Rusinek, R.; Siger, A.; Gawrysiak-Witulska, M.; Rokosik, E.; Malaga-Toboła, U.; Gancarz, M. Application of an electronic nose for determination of pre-pressing treatment of rapeseed based on the analysis of volatile compounds contained in pressed oil. *Int. J. Food Sci. Technol.* **2019**, *55*, 2161–2170. [CrossRef]
115. Perez-Gonzalez, C.; Garcia-Hernandez, C.; Garcia-Cabezon, C.; Rodriguez-Mendez, M.L.; Dias, L.; Martin-Pedrosa, F. Analysis of milk adulteration by means of a potentiometric electronic tongue. *J. Dairy. Sci.* **2024**, *107*, 9135–9144. [CrossRef] [PubMed]
116. Gómez, J.K.C.; Puentes, Y.A.N.; Niño, D.D.C.; Acevedo, C.M.D. Detection of pesticides in water through an electronic tongue and data processing methods. *Water* **2023**, *15*, 624. [CrossRef]
117. do Nascimento, A.S.; Silva, F.d.L.; Machado, C.S.; Cavalcante da Silva, S.M.P.; Estevinho, L.M.; Dias, L.G.; Carvalho, C.A.L.d. Use of the electronic tongue as a tool for the characterization of Melipona scutellaris Latreille honey. *J. Apic. Res.* **2022**, *61*, 79–90. [CrossRef]
118. Scagion, V.P.; Mercante, L.A.; Sakamoto, K.Y.; Oliveira, J.E.; Fonseca, F.J.; Mattoso, L.H.; Ferreira, M.D.; Correa, D.S. An electronic tongue based on conducting electrospun nanofibers for detecting tetracycline in milk samples. *RSC Adv.* **2016**, *6*, 103740–103746. [CrossRef]
119. Munekata, P.E.; Finardi, S.; de Souza, C.K.; Meinert, C.; Pateiro, M.; Hoffmann, T.G.; Domínguez, R.; Bertoli, S.L.; Kumar, M.; Lorenzo, J.M. Applications of electronic nose, electronic eye and electronic tongue in quality, safety and shelf life of meat and meat products: A review. *Sensors* **2023**, *23*, 672. [CrossRef] [PubMed]
120. Alfieri, G.; Modesti, M.; Riggi, R.; Bellincontro, A. Recent advances and future perspectives in the E-nose technologies addressed to the wine industry. *Sensors* **2024**, *24*, 2293. [CrossRef] [PubMed]
121. Bonah, E.; Huang, X.; Aheto, J.H.; Osae, R. Application of electronic nose as a non-invasive technique for odor fingerprinting and detection of bacterial foodborne pathogens: A review. *J. Food Sci. Technol.* **2020**, *57*, 1977–1990. [CrossRef] [PubMed]
122. Moshayedi, A.J.; Sohail Khan, A.; Hu, J.; Nawaz, A.; Zhu, J. E-nose-driven advancements in ammonia gas detection: A comprehensive review from traditional to cutting-edge systems in indoor to outdoor agriculture. *Sustainability* **2023**, *15*, 11601. [CrossRef]
123. Li, Y.; Wang, Z.; Zhao, T.; Li, H.; Jiang, J.; Ye, J. Electronic nose for the detection and discrimination of volatile organic compounds: Application, challenges, and perspectives. *TrAC Trends Anal. Chem.* **2024**, *180*, 117958. [CrossRef]
124. Chen, H.; Huo, D.; Zhang, J. Gas recognition in E-nose system: A review. *IEEE Trans. Biomed. Circuits Syst.* **2022**, *16*, 169–184. [CrossRef] [PubMed]
125. Cho, S.; Moazzem, M.S. Recent applications of potentiometric electronic tongue and electronic nose in sensory evaluation. *Prev. Nutr. Food Sci.* **2022**, *27*, 354. [CrossRef] [PubMed]
126. Sadati, A.K.; Nayedar, M.; Nayedar, L.; Falakodin, Z. Challenges for food security and safety: A qualitative study in an agriculture supply chain company in Iran. *Agric. Food Secur.* **2021**, *10*, 41. [CrossRef] [PubMed]
127. Röck, F.; Barsan, N.; Weimar, U. Electronic nose: Current status and future trends. *Chem. Rev.* **2008**, *108*, 705–725. [CrossRef] [PubMed]
128. Aladhadh, M. A review of modern methods for the detection of foodborne pathogens. *Microorganisms* **2023**, *11*, 1111. [CrossRef] [PubMed]
129. Dhal, S.B.; Kar, D. Leveraging artificial intelligence and advanced food processing techniques for enhanced food safety, quality, and security: A comprehensive review. *Discov. Appl. Sci.* **2025**, *7*, 75. [CrossRef]

130. Ma, T.; Wang, H.; Wei, M.; Lan, T.; Wang, J.; Bao, S.; Ge, Q.; Fang, Y.; Sun, X. Application of smart-phone use in rapid food detection, food traceability systems, and personalized diet guidance, making our diet more health. *Food Res. Int.* **2022**, *152*, 110918. [CrossRef] [PubMed]
131. Sempionatto, J.R.; Montiel, V.R.-V.; Vargas, E.; Teymourian, H.; Wang, J. Wearable and mobile sensors for personalized nutrition. *ACS Sens.* **2021**, *6*, 1745–1760. [CrossRef] [PubMed]
132. Page, M.J.; McKenzie, J.E.; Bossuyt, P.M.; Boutron, I.; Hoffmann, T.C.; Mulrow, C.D.; Shamseer, L.; Tetzlaff, J.M.; Akl, E.A.; Brennan, S.E.; et al. The PRISMA 2020 statement: An updated guideline for reporting systematic reviews. *BMJ* **2021**, *372*, n71. [CrossRef] [PubMed]

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