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Review

Electronic Sensing Technologies in Food Quality Assessment: A Comprehensive Literature Review

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Abstract: This manuscript was prepared for the purpose of an in-depth analysis of the development of electronic sensors in food quality assessment. In this study, the following research question was asked: What are the arguments for the development of electronic sensors for food assessment? The aim of this work was to comprehensively review the current scientific literature presenting the discussed issues and their systematization, as well as to present the prospects, threats, and applications of electronic sensors in food quality testing. The greatest interest of researchers lies in the use of e-nose. In contrast, fewer publications concerned e-tongue applications, and the smallest number of works concerned e-eye application. The initial application of electronic sensors in the food industry progressed from research on the identification of single ingredients or properties to the creation of increasingly complex research instruments that comprehensively analyze areas of food characteristics. Specifically, e-sensor research has focused on individual e-nose, e-tongue, and e-eye devices and has not provided complete information about food. This is confirmed by the high accuracy of research results regarding the combined use of sensors in food quality assessment.

Keywords: e-nose; e-tongue; e-eye; food quality; electronic sensors

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1. Introduction

Food quality is a concept that encompasses many aspects, from sensory experience to safety and nutritional value, making it an important factor influencing consumer choices. The fundamental condition in this respect is food safety. Both elements are closely related and together create the criteria by which customers evaluate food. In most cases, food quality changes dynamically [1]. The development of the economy and the growth of prosperity have significantly increased the awareness of consumers of harmful substances in food and have led to an increase in the demand for high-quality food. The important problems that are currently emerging in the food industry are the authenticity and safety of food, real-time monitoring during food processing, evaluation of organoleptic characteristics, quality assessment, and traceability of food origin [2]. Often, there are many products on the market that are presented as authentic or 100% natural, but are imitations or counterfeit versions of high-quality products, causing great harm to health and destroying consumer confidence. In this area, e-noses and e-tongues are starting to be used as tools to strengthen quality control and to guarantee the authenticity of products in a faster but also reliable way [3].

The shelf life of food is primarily determined by its inherent quality characteristics, packaging, and environment factors, such as transport, storage conditions, and climate.

They contribute to the modification of the sensory, chemical, physical, and microbiological characteristics of the product [4]. From the moment of processing and storage to the moment when products reach consumers, food quality and safety must be constantly monitored and controlled. This is to protect people from food poisoning and potentially reduce food waste [5]. Ensuring food safety is complex and requires monitoring many variables at every stage of the food supply chain, such as freshness, authenticity, toxin levels, and the presence of pathogenic bacteria and contaminants [5].

A reduction in quality characteristics may result in the loss of the commercial quality of the product, but not necessarily the loss of its hygienic, sensory, or nutritional properties. Furthermore, the shelf life of a perishable product depends mainly on environmental and hygienic conditions at the stages of production and storage [6]. The introduction of inappropriate food products into the market is a huge threat to consumer health. Therefore, it is very important to use appropriate hazard detection technology to ensure rapid, accurate, and real-time detection of unsafe food products [7–9].

The global food industry is facing increasing challenges in ensuring food safety, sustainability, and quality due to the increasing demands of consumers in a changing environment. To address these challenges, industry experts and researchers are using artificial intelligence (AI) and machine learning (ML) technologies as effective tools to transform safety assessment and quality management [10]. These technologies use visual, acoustic, chemical, and electronic sensors. Intermodal intelligent sensing technologies play a key role in food science and are widely used in food assessment [11].

Food assessment methods can be divided into subjective sensory evaluation and objective instrumental tests. Subjective sensory evaluation methods are based on personal observations of experienced discriminators using the senses of sight, touch, and smell to evaluate food. Objective instrumental control involves testing and analyzing food products using various types of testing equipment [2]. Traditional instrumental analysis methods are often complex, time-consuming, and have limited detection capabilities. As a result, the number of studies aimed at developing intelligent, efficient, and precise techniques for detecting food analysis has multiplied [12,13].

Appearance, odor, taste, and texture are commonly used to assess changes in food quality and safety. The human nose has about 400 olfactory receptors and can detect at least one trillion odors [14]. The human nose can assess odor, but individual evaluation can be biased. The human nose cannot be used to detect toxic gases. Additionally, the human nose has limitations regarding gas mixtures. Thus, the human nose is not a universal tool for identifying and classifying odors [15]. Volatile organic compounds (VOCs) are chemicals that evaporate at room temperature (vapor pressure $\geq$10 Pa at 20 °C) and are important indicators contributing to the odor signature specific to each food product [16,17]. Volatile compounds, which are indicators of food freshness, undergo significant changes during processing and storage, so gas sensors are essential for their detection and the evaluation of food [18]. Excessive food oxidation indicates degradation of fats and oils, resulting in the overproduction of hexanal. Excess hexanal is generally not preferred by consumers and has been identified as one of the major off-flavors in foods such as meat, soy, and dairy products [19,20]. It can also be considered a critical oxidation indicator; therefore, rapid, accurate, and real-time detection of hexanal is essential for food quality assessment [21].

The condition for reducing food waste and protecting consumer well-being is the accurate assessment of food freshness. For this purpose, e-noses are becoming essential tools, providing a multidimensional approach to monitoring the complex trajectory of odor changes inherent to food spoilage [22].

Electrochemical sensors are therefore of fundamental importance for the development of such devices and remain an active area of research. This is partly due to the way they interact and partly because advances in electronics have enabled their use to add important functions. In this sense, both devices have found important applications as monitoring systems. From our point of view, automatic, intelligent e-tongues and e-noses will soon appear as intelligent devices with on-line functionality [23]. Therefore, the aim of this paper was to comprehensively review the current scientific literature presenting the discussed issues, to systematize them, and to present the perspectives, risks, and applications of electronic sensors in food testing.

2. Methodology

The preparation of the work was preceded by a detailed analysis of scientific publications devoted to the development of electronic sensor technology as an alternative to human sense organs: smell, taste, and sight. The authors present the applied solutions, assessing their impact on food safety, the possibilities of monitoring production processes, and their use for the needs of raw material producers or consumers for the ongoing assessment of food freshness. These sensors have the potential to reduce food waste caused by throwing away food that is fit for consumption, which has passed the expiration date set by the manufacturer. In the context of this analysis, the possibilities and potential related to the development and production of e-nose, e-tongue, and e-eye sensors related to increasing the accuracy of identified substances were examined. In this study, the following research question was asked: What arguments speak for the development of electronic sensors for assessing food quality? The literature search from the analyzed scope was performed between January 2024 and October 2024 using the Scopus and Web of Science databases.

To obtain many search results, a combination of keywords was used: food quality assessment and electronic senses. To better define the search, a combination of words was used: "food quality assessment, e-nose", "food quality assessment, e-tongue", and "food quality assessment, e-eye". The search results were checked by the researchers in terms of the topics discussed and the objectives of the study. The initial search scope covered the years 2024–2019. However, to more fully describe the development of individual technologies, earlier publications were included in the review. Duplicate publications from both databases, publications without full access, and publications not containing the searched keywords were excluded from the group of search results. From the group of analyzed publications, 171 were selected, which are the most important regarding the topic and the objective of the study. The articles were selected for review based on two main criteria. The first one was research related to the development of electronic sensory sensors. The second criterion consisted of publications focusing on research on the use of sensors for food assessment, the selection of data processing methods, implementation and improvement in industrial practice, and the consideration of sensor fusion strategies for increasing the efficiency of operation. In these studies, a synthetic approach to the discussed issues was also taken into account.

The selection of articles for the review was based on specific criteria, such as studies involving the use of each type of sensor for food assessment. Another group of articles included publications on studies on the combined use of e-nose, e-tongue, and e-eye. When reviewing the works, attention was paid to the synthetic approach to the topic regarding the current achievements in the use of electronic sensors, which was supported by providing practical examples of their use and the results achieved. Zotero 7.0.11 software was used to manage references.

3. Prospects for the Development of Electronic Sensors as an Alternative to Traditional Instrumental Methods

There are many different methods for assessing food quality, ranging from traditional laboratory chemical analysis to advanced instrumental methods. Accurate instrumental tests are usually performed using gas chromatography [24–26], high-performance liquid chromatography [27–29], gas chromatography–mass spectrometry [30–33], infrared spectroscopy [34–36], nuclear magnetic resonance [37–39], DNA-based methods [40], and immunological tests and sensory analysis [15]. These methods are widely used and have high accuracy [41]. However, these detection methods pose many challenges. Conventional target methods used to assess the shelf life of food are time-consuming, labor-intensive, and expensive and can only be used for offline control [42]. Standard instrumental testing techniques have problems with cost and their time-consuming nature [43–47]. These analyses are performed by trained or specialized personnel in a laboratory infrastructure. Sensory evaluation methods can pose problems such as the length of the training cycles of professionals and personal subjectivity, which makes it difficult to formulate objective assessments [48,49]. Some examples of such problems include microbiological problems that take at least several days to assess; chemical and chromatographic methods that require continuous expenditure of gases, consumables, and expensive equipment; and sensory analysis that involves multiple panelists to evaluate selected attributes. Another key aspect of these methods is the destruction of samples, which makes further analysis difficult [50,51]. Traditional methods are often characterized by complex, time-consuming, and limited detection capabilities. Furthermore, these methods usually address only one aspect of food quality. As a result, there has been an increase in research aimed at developing efficient and accurate quality detection techniques [2,12,13].

The ability to perform rapid, non-destructive analyses is particularly important in today's food market, characterized by increased international trade in fresh produce, as well as the need to have an environmentally efficient product. As a result, the use of more quality control technologies has become a key question that stakeholders in science and industry must answer [52]. In contrast to traditional methods, electronic sensing techniques aim to provide information in real time, thus overcoming the costs and time associated with laboratory methods or with human intervention, as in the case of traditional sensory analysis methods [42].

Compared to traditional analytical methods, electronic systems have special features: they are fast, objective, versatile, and potentially useful for at-line or on-line applications. In addition, these techniques are considered environmentally friendly, as they require little or no chemical reagent for sample preparation [53]. Sensors are generally distinguished by the type of electrochemical, thermometric, piezoelectric, magnetic, or optical transducers used. Their main function is to report physicochemical changes of bioactive materials interacting with the sample under study. Detectors can measure one or more sample variants, enzymatic reaction products, substrate consumption, cofactor consumption, microbial respiration or growth, specific metabolites, antigen binding, etc. [54,55].

Electronic sensors have recently attracted much attention from scientists and many industries, who see their advantages as alternatives to traditional sensory testing. These electronic sensors can solve the problems associated with the use of panelists in sensory methods, such as subjectivity, sensory fatigue, and the high cost and time consumption of the methods [56]. Electronic sensors are used in the food industry to monitor product quality in quality assurance and control departments. The e-tongue and e-nose are expected to be more widely used in on-line work to detect unpleasant odors and tastes in industrial applications. The integration of electronic sensors with product processing and production enables their use for timely control and quality assurance. The development of biological sensors and the increase in the number of identified compounds give these sensory instruments great potential in fruit/vegetable harvesting, post-harvest, and horticultural applications. For example, they could facilitate the prediction of the harvest season of fruits and vegetables using deep learning or machine learning algorithms and advanced regression analysis models [57].

Of note, e-eyes, e-noses, and e-tongues, designed to mimic human senses, can be useful for real evaluation of fresh food products, thus enabling reductions in food waste. These approaches aim to assess quality parameters based on sensory characteristics or quantify specific analytes [6]. The use of intelligent sensors to detect fresh food can provide hierarchical selection and determine the parameters of quality, maturity and freshness, and shelf life. In addition, it can also monitor the product quality in real time and respond to the product quality at any time. At the same time, food traceability can be ensured. Consumers can obtain relevant information on prices, production site, harvest date, variety, authenticity, etc. In this way, the quality of fresh food is guaranteed throughout the supply chain [58]. As these instrumental sensory technologies become the subject of engineering research, we can expect future e-tongues and e-noses that will be portable and much cheaper than today. The continuous development of e-sensor technologies may enable the next generation to rapidly ensure food safety and detection in the coming era when food will not be as abundant as it is today [57].

Although significant progress has been made in more precise and accurate applications of electronic noses, eyes, and tongues, individual applications of electronic systems are not complete enough to simulate humans for the purpose of evaluating meat and meat products. It should be remembered that humans perceive the quality of meat and meat products by combining and simultaneously processing stimuli from the eyes, nose, and tongue. In this sense, the integration/fusion of e-nose and e-tongue data sets is a natural progression towards automation in production and the evaluation of meat and meat products. The benefits of data fusion are proper classification and quality prediction, but new problems pose additional challenges in terms of data, computational time, and applicability to real food processing [59].

Unwanted changes in the data sets that affect data quality can make it difficult to obtain useful data from e-eye and e-tongue measurements, resulting in missing data, noise, baseline shifts, and peak shifts [60,61].

Electronic sensors are based on different principles. The principle of operation of electrochemical sensors is to detect changes or current caused by chemical reactions between a sensing electrode and a reference electrode. Optical sensors detect an analyte using its absorption, fluorescence, or reflective properties. Piezoelectric sensors, on the other hand, use the vibrations of a crystal exposed to the analyte and the generated electric current that can be measured [23,62].

Examples of specific sensors used in electronic sensors are pH sensors, ion electrodes, and gas sensors. Sensors detect chemical properties of the analyte, such as acidity, ionic strength, or gas concentration. In general, the selection of the type of sensor used in e-tongues and e-noses depends on the specific application and the properties of the analyte being studied. Many sensors operating on different principles can be used to provide comprehensive analysis of the odor or composition of a sample. Much information about the achievements in the literature on electronic sensors can be found separately for e-tongue and e-nose applications in specific processes. However, there are increasingly examples of using both systems to increase their efficiency [23]. Of note, e-noses and e-tongues are effective, safe, and economical methods of food identification and are now competing with traditional laboratory tests [63]. E-tongues and e-noses are often used in research to assess the quality, taste, and condition of food. For example, e-tongues have been used to determine the umami taste of Hanwoo meat [64]; compare the tastes of Koji mold and Camembert cheese using different strains of Koji [65]; identify the botanical origin of honey using a potentiometric e-tongue to distinguish among single-flower, multi-flower, and honeydew honey [66]; and differentiate between types of lager based on their electrochemically active compounds using screen-printed electrodes [67]. Precision farming is now important for increasing food production and optimally utilizing the cultivation space. To achieve this, regular soil health checks are important. Regular soil condition monitoring is essential to achieve these goals. This has led to progress in developing a microfluidic system based on four layer-by-layer sensors placed on gold interdigital electrodes (IDEs) in a polydimethylsiloxane microchannel. The system is designed to identify the abundance of nutrients such as sulfur, nitrogen, phosphorus, magnesium, calcium, and potassium in soil samples. Sensor data were extracted and analyzed using PCA, interactive document map (IDMAP) methods, and Sammon mapping [68].

Thanks to the advantages of hardware and software important in obtaining and analyzing information, these technologies are gaining importance. The advantages of e-tongues and e-noses include accuracy, time and financial efficiency, limited human involvement, non-invasiveness, and the possibility of various applications. However, despite numerous advantages, limitations are also indicated, including costs, lack of standardization, the possibility of interference, and the need to compare results with tests conducted by people, especially in the food industry [23,69].

The use of e-nose and e-tongue data combined with chemometric techniques can be useful in the food industry to rapidly and accurately assess the quality, safety, and authenticity of food [70,71]. Unlike ordinary single sensors, intermodal intelligent sensor systems use multiple sensors to collect a variety of information, facilitating accurate food quality assessment. In addition, these systems are flexible and can be applied to a variety of food sample types and forms, allowing for easy adaptation to different needs. In contrast, classical single sensors may have limitations in detecting specific conditions or sample types due to the variety and complexity of food samples [12].

4. e-Nose

In the 1980s, research on machine olfaction led to the accepted definition of e-nose as a device with a variety of electrochemical gas sensors with partial specificity and a pattern recognition system [7]. In order to meet practical needs, an e-nose using nanomaterials was developed, which was inspired by the mammalian sense of smell [72], standing out as a promising biomimetic device [73–75]. Its original design goal was to capture specific odor molecules in the air to enable the recognition of various gases. Importantly, e-nose technology has developed very rapidly over the last thirty years [76–80]. The e-nose concept has gone from its original form to the development of materials and identification methods. Activities related to the commercialization of e-noses have forced efforts to reduce their costs and to give the expanded stationary devices smaller dimensions, which would allow for their mobile use, e.g., in plantations or processing plant conditions. These devices are cost-effective, portable, easy to operate, and above all, allow for rapid analysis [7,81]. The stages of e-nose evolution are presented in Figure 1. Examples of e-nose use in food quality assessment and the obtained results are presented in Table 1.

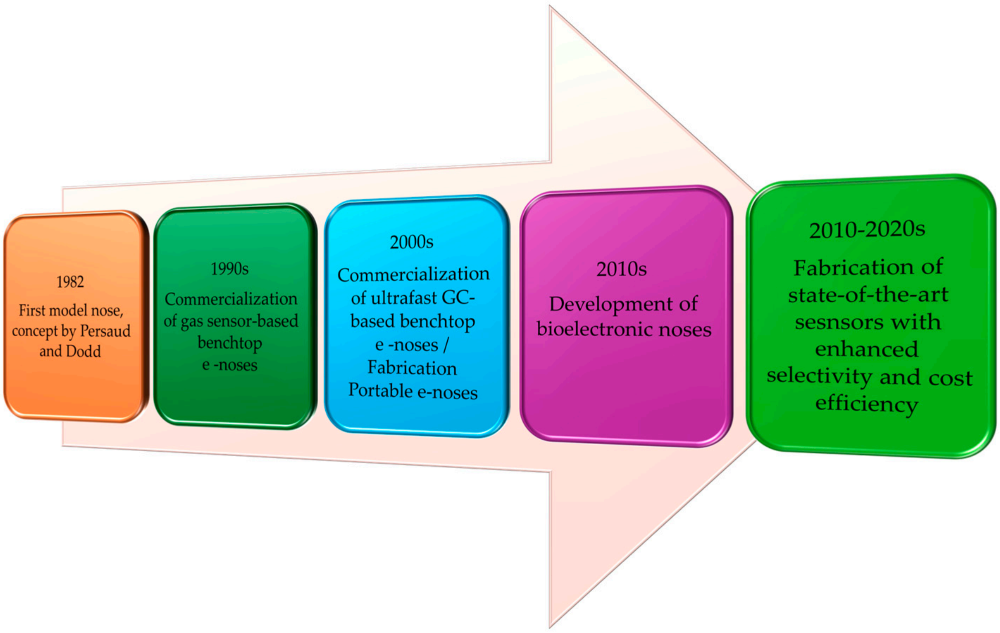

Figure 1. The development of e-nose technology. Developed on the basis of [81].

Table 1. Applications and obtained effects of the e-nose system.

Device Type/Sensors Used	Application	Quantitative Metrics	References
BME680 from Bosch, SGP30 from Sensirion, and CCS811 and iAQ-Core from ScioSense/4 digital gas sensors with integrated MOX sensors	Abnormal fermentations occurring in table olives	Consistency with the results obtained by the tasting panel	[82]
MOS	Moldy bread detection	100% accuracy	[83]
E-nose equipped with a space automation system above the surface and 18 MOS sensors	Longjing tea quality classification	100% recognition rate was achieved using the KLDA-KNN model	[84]
8 MOS gas sensors: (1) two types of Taguchi (Figaro Engineering Inc., Osaka, Japan) sensors (TGS813 and TGS822); (2) five types of MQ sensors (MQ3, MQ4, MQ8, MQ135, and MQ136) (Hanwei Electronics Group Corporation, China); and (3) one FIS sensor (NISSHA FIS, Inc., Tagawa, Yodogawa-ku, Osaka, Japan)	Olive oil classification and fraud detection	Among the seven classification models mentioned, GBC with 97.75% accuracy in the test result had the highest accuracy; linear SVM and Naive Bayes had 95.51% accuracy	[85]
10 MOS sensors with different sensitivities	Identification of instant starch noodle spices based on different flavor profiles	Explained 86.96%, 98.09%, and 94.38% of the total variance, and the CA results were consistent with the PCA results	[86]
MOS sensors: MQ4, MQ5, MQ9, and MQ135	Evaluation of the shelf life of various edible seeds	Exceeding the threshold value on the 120th day of storage	[87]
Heracles Analyzer Neo (Alpha Mos, Toulouse, France)	Characteristics of vinegar quality and volatility	Rapid detection, low sample requirement, and no pre-treatment required; disadvantages include difficulty in absolute quantification of components and inability to determine inorganic flavor components	[88]

Table 1. *Cont.*

Device Type/Sensors Used	Application	Quantitative Metrics	References
E-nose (PEN3, Air-sense Analytics GmbH, Schwerin, Germany)/10 MOS sensors	Analysis of volatile profiles of kiwifruit experiencing soft rot	Combining e-nose and GC–MS to differentiate intact and diseased kiwifruit is feasible	[89]
ISE Nose 2000 (ISE, Pisa, Italy)/12 SnO_2-based MOS sensors (TGS type by Figaro Engineering Inc., Osaka, Japan)	Licorice roots (*Glycyrrhiza glabra* L.) identification	Usefulness in identifying licorice root	[90]
FGC Electronic Nose Heracles II (Alpha MOS, Toulouse, France)	Storage time of peanut butter	A promising method for applications in industrial food quality control	[91]
PEN 3 MOS (Airsense Analytics, Germany)	Detection of the degree of black tea fermentation	e-Nose and computer vision technologies proved that the effect of the multi-source sensor model was better than that of a single sensor	[92]
8 MQ series tin dioxide sensors (MQ135, MQ2, MQ3, MQ4, MQ5, MQ9, MQ7, and MQ8)	Basic detection of various food products	The ability to detect damaged products has been confirmed	[93]
5 MOX Taguchi gas sensors (TGS), including two H_2S and three SO_2 sensors	On-line wine fermentation monitoring	Good ability to distinguish different phases of wine fermentation in real time	[94]
TGS Sensors (Figaro Engineering Inc., Osaka, Japan) for alcohol, alcohol, ammonia, ammonia, alcohol, hydrogen, and carbon monoxide	Rice quality assessment	Suitability for classifying and estimating rice quality during storage under different temperature and humidity conditions	[95]
Portable acoustic resonator (FBAR)	Real-time detection of banana cold chain storage time	Effectively distinguishes yellow bananas with green necks from completely yellow bananas	[96]
e-Nose (WinMuster Airsense Analytics Inc., Schwerin, Germany)/10 MOS sensors	Detection of volatile components of loquat fruit during the post-harvest shelf life (18 days)	Loquat fruit during different storage periods	[97]
Heracles II GC-E-Nose (Alpha MOS, Toulouse, France)	Characterization of the different quality levels of Congolese black tea	A 44-dimensional characterization data set was obtained to characterize the aroma quality	[98]
Araki Sangyo Co., Ltd. (Osaka, Japan)	Comparison with sensory evaluation of cheese aroma intensity	convergence with the results of sensory evaluation	[99]
PEN3 Portable Electronic Nose, Airsense Analytics GmbH, Schwerin, Germany/10 MOS sensors	Identification of volatile substances dependent on the storage time of lamb	The usefulness of rapid identification of sheep storage stages	[100]
Ultrafast gas chromatography HERACLES NEO e-nose	Identifying differences in odor profiles in different varieties of bee pollen	Usefulness of quality control of bee pollen products	[101]
e-Nose designed and manufactured by PHT laboratory, MOS sensors	Investigation of garlic aroma as a quality control factor	Processing methods and pathogen contamination make it difficult to assess quality	[102]
e-Nose/10 MOS sensors	Evaluation of the quality of mushrooms during storage	The usefulness of assessing storage conditions on the quality of mushrooms	[103]

Table 1. *Cont.*

Device Type/Sensors Used	Application	Quantitative Metrics	References
Two sensor arrays: (1) 4 micromachined gas sensors; the microsensor substrates consisted of a $SiO_2/Si_3N_4/SiO_2$ membrane with insulated platinum heaters and platinum electrodes (2) 4 SnO_2 sensors: TGS 8xx (with xx = 15, 22, 24 and 42) Figaro Engineering Inc. (Osaka, Japan)	Distinguishing between different brands of pasteurized milk	Combined use with an electronic voltammeter increases the accuracy of identification and suitability for on-line control	[104]
6 MQ sensors (MQ-3; MQ-4; MQ-7; MQ-8; MQ-9; MQ-135) (Hanwei Electronics Group Corporation, Zhengzhou, China) 2 × TGS Figaro family sensors (TGS 822; TGS 2602) (Figaro Engineering Inc., Osaka, Japan)	Carrying out preliminary and quick quality assessments of wines	Analysis of the set of components of the blueberry wine bouquet to identify adulteration in the distribution process	[105]
e-Nose (PEN2, WMA Airsense Analysentechnik GmbH, Schwerin, Germany)/10 MOS sensors	Quality assessment of satsuma mandarin (*Citrus unshiu* Marc.) depending on storage conditions	In terms of identifying storage conditions, the e-nose system showed 100% accuracy; the e-nose and e-tongue fusion system achieved a performance index of 100% in the identification of tangerines and a significantly higher correlation with tangerine quality	[106]
Electronic nose PEN3 (Airsense, Analysentechnik GmbH, Schwerin, Germany)/10 MOS sensors	Identifying the aromatic and flavor compounds of seven traditional Chinese pancakes	e-Nose using PCA effectively distinguishes the odor profiles of seven Chinese pancakes	[107]

Abbreviations: MOX—metal oxide; MOS—metal oxide semi-conductor; GBC—gradient boosting classifier; MQ4—detects released methane; MQ5—detects released isobutane and propane; MQ9—detects flammable gases; MQ135—detects gases present in the environment and determines the quality of the air in the surroundings; H_2S—hydrogen sulfide; SO_2—sulfur dioxide; TGS 815—detects released hydrocarbon; TGS 822—detects released alcohol; TGS 824—detects released ammonia; TGS 842—detects released methane; TGS 2602—detects of air contaminants; PCA—principal component analysis.

The e-nose system combines hardware and software. It uses a network of sensors to detect released gases and convert them into signals that can be analyzed using various statistical methods. With the introduction of artificial intelligence, automated algorithms have been employed to assess food quality based on these signals [108]. The e-nose system comprises four main components: a sampling system to manage samples during analysis, a detection system that includes a set of sensors, a data collection and processing system, and software designed for pattern recognition [15,76,109–111]. In the e-nose system, a sampling system collects samples of volatile compounds. These samples are then transported through a gas path to a gas chamber, where they contact a sensor array. This interaction causes a chemical reaction. The electronic converter transforms the chemical signals into electrical signals fed into the data acquisition system. A computer processes this information, which is subsequently analyzed using various methods [49]. The sensors within the e-nose device interact with the volatile substances, causing chemical reactions. The input port of the data acquisition (DAQ) system is linked to the sensor output, and an interface circuit converts the sensor signals into electrical signals, such as voltage and current [112].

Electronic noses, or e-noses, consist of multiple sensors coated with nanomaterials. They can detect VOCs and respond to them in distinct ways. These responses are analyzed using a pattern recognition algorithm that operates similarly to the human brain [113,114]. e-Noses are advanced analytical tools that mimic the human sense of smell, allowing them to detect additives in food products. Typically equipped with multiple sensors, these devices can identify and differentiate odors within complex samples. They are relatively inexpensive, making them highly useful in many fields, particularly the food industry [115,116].

The emergence of the electronic nose (e-nose) system has made it possible to assess the quality of food products in a non-destructive manner. This system provides a rapid evaluation compared to traditional methods, which are often expensive and time-consuming [108,116]. The e-nose is an essential tool in the food industry, offering a variety of applications that help ensure product quality, trace origins, optimized processes, and reduced waste. These advanced devices are designed to detect and analyze VOCs emitted by various food products. They are crucial in enhancing food safety, maintaining freshness, and improving overall quality management [117]. The e-nose is known for its rapid response, effective detection capabilities, accurate assessments, and ability to reduce human error. Furthermore, it can identify colorless and odorless gases that may harm human health [118,119]. The e-nose system is increasingly utilized in medical auxiliary diagnostics, public safety monitoring, and environmental pollution control, particularly within the food industry [120–122]. Table 2 provides examples of VOC markers.

Table 2. Examples of VOC markers.

The Use of	LZO Marker	Accuracy	References
Acinetobacter johnsonii XY27 in cold stored stock (*Thunnus obese*)	Benzaldehyde 1-Hexanol 2,4-Di-tert-butylphenol		[123]
Ochratoxin A in grape-based food from *Aspergillus carbonarius* breeding	1-Octen-3-one and 2-octen-1-ol biomarkers for detecting *A. carbonarius* strains with low OTA production	Accuracy, R^2, and Q^2: 91.7%, 0.882, and 0.790	[124]
Ant-nose	Four VOCs: MeOH, PrOH, BuOH, and EtOH	100%	[114]
	Six VOCs with isomers: MeOH, PrOH, IPA, 2-BuOH, BuOH, and EtOH	96.7%	
Detection of *Penicillium expansum* in 'Golden Delicious' apples	3-Methyl butan-1-ol and methyl acetate	Diagnosis rates over 87%; 97% for samples with early stage fungal infection	[125]

Abbreviations: MeOH—methanol, PrOH—1-proponal, IPA—2-proponal, 2BuOH—2-butanol, BuOH—1-butanol, EtOH—ethanol.

e-Nose technology is known for its low cost, quick response time, and efficient identification of substances being tested [126–128]. Rapid advancements in new materials, pattern recognition, and electronic detection technologies are driving progress in gas detection technology within the food industry [2,82,129,130]. Furthermore, the evolution of this technology is influenced not only by the development of detection techniques and materials but also by a deeper understanding of the processes that underpin the human sense of smell [7].

The benefits of electronic noses (e-noses) are tied to the specific types of sensors used. Metal oxide semiconductor sensors are highly sensitive and detect active substances as low as 1 part per million (ppm). Polymer-based sensors, on the other hand, are effective for identifying specific flavor compounds. Their sensitivity allows for detection at levels around 10 ppm. Polymer-based sensors are also more energy efficient than metal oxide semiconductor sensors. However, there are some drawbacks to using these sensors. They require high operating temperatures, sometimes reaching 400 °C, and strict control of experimental conditions, such as humidity, pressure, temperature, and gas velocity [15]. Additionally, a limited number of sensors are available compared to the human nose. Recent research on e-noses has led to advancements in several areas, including assessing freshness, taste, authenticity, quality control, process monitoring, traceability, and detecting pesticide residues [2]. A significant challenge in utilizing e-noses is the selection of appropriate sensors and developing complex recognition algorithms, especially for implementation on cost-effective devices. Nevertheless, the significance of e-noses in the food industry continues to grow [7].

Electronic sensors are becoming more prevalent in food analysis. These sensors utilize electronic noses (e-noses) equipped with neon or partially selective gas sensors, combined with data processing and pattern recognition systems, to analyze aromas without separating volatile components. This technology enables the identification of complex aroma profiles, offering a more cost-effective and efficient alternative to traditional, labor-intensive methods [115,131].

Using electronic noses (e-noses) to monitor the freshness of food products can transform how we store food and manage our distribution networks. This innovative solution could significantly impact the food industry. As these devices evolve, incorporating advanced sensing technologies and pattern recognition algorithms, their ability to detect and analyze various volatile substances related to food spoilage will improve. Ultimately, employing e-noses as dependable freshness monitors promotes sustainability, ensures food safety, and provides consumers with a safe and uncontaminated experience [117].

Supervising and controlling production processes is essential for ensuring consistency and maintaining high food quality. One significant technological advancement in this area is the e-nose, which plays a vital role in accurately monitoring and evaluating complex production procedures, such as roasting coffee beans [132]. By analyzing subtle changes in aroma during the roasting process, e-noses enable continuous assessment of the roast level, helping to ensure product uniformity.

The variety of sensors allows for accurate profiling and classification of the studied analytes. The graphene e-nose developed by Caman et al. [133], which consists of 432 sensors and 36 different receptors, achieved an impressive 89% accuracy in recognizing six odorants at four different concentrations. Another graphene e-nose developed by Kybert et al. [134], featuring 56 sensors connected by 4 DNA oligomers, could visually distinguish eight chemical vapors. Additionally, the e-nose presented by Weerakody et al. [72], which comprises five elements, effectively distinguished four VOCs. Furthermore, the semiconductor e-nose developed by Wang et al. [114,135] based on five sensors made of various metal oxides achieved a remarkable 99% accuracy in classifying six VOCs.

The conductivity or resistivity of the sensing material changes due to charge transfer, ion exchange, or interaction with ions when odor molecules attach to its surface. The electrical signals generated by the sensors undergo processes such as noise reduction or amplification and are then converted from analog to digital form using an analog-to-digital converter (ADC). In the subsequent step, this information is further analyzed with machine learning algorithms, including principal component analysis (PCA), linear discriminant analysis (LDA), K-nearest neighbor (K-NN), artificial neural networks (ANNs), partial least squares regression (PLSR), and partial least squares discrimination analysis (PLS-DA) [136]. Integrating multiple transducers and sensitive nanomaterials in electronic noses (e-noses) increases complexity, power consumption, and overall size. To ensure diverse fingerprint profiling patterns of analytes, sensors are often coated with different nanomaterials [137], or the same nanomaterial undergoes various functionalization processes [133,134,138], which can be complex and time-consuming. Additionally, sophisticated sensors may require extra circuits and infrastructure to supply power and collect data from multiple channels [74]. The malfunction of even one component can lead to the failure of the entire system. In the case of wireless sensor networks (WSN), installing numerous sensors can result in high costs and added complexity [114].

Using non-selective chemical sensors enables a comprehensive response to the volatile compounds present in a sample, allowing for recognizing odor patterns [139]. Electronic noses (e-noses) detect various dairy products and meats, including beef, poultry, and fish. These odor-detecting devices electronically record the volatile substances produced during decomposition, facilitating the accurate assessment of spoilage levels. By monitoring the different odors emitted by meat as it deteriorates, e-noses assist in identifying early signs of spoilage, reducing health risks, and minimizing food waste [117].

5. e-Tongue

E-tongues are analytical devices designed to recognize and classify the various flavors of chemicals present in food liquids or samples. They operate on principles similar to the human sense of taste, employing sensors. These devices can evaluate multi-component mixtures regarding quality and quantity, which is why they are becoming increasingly prominent in food analysis [116,140]. The primary objective of e-tongue technology is to analyze food samples using a set of sensors, such as ion-selective electrodes with specific properties, and to perform statistical analyses on the data collected. e-Tongues can describe the taste profiles of complex liquids or food samples converted to liquid form. This technology can provide insights into aspects like freshness and ripeness [141,142]. Examples of e-tongue applications and the results obtained in food quality research are summarized in Table 3.

Table 3. Application and obtained effects of the e-tongue system.

Device Type/Sensors Used	Application	Quantitative Metrics	References
The sensor set consists of seven different chemical sensors and a reference electrode (Ag/AgCl)	Development of an effective method for identifying spices for instant noodles	In combination with the e-nose, it provides fast, objective, highly automated, and inexpensive food odor analysis	[86]
SA-402B Electronic Tongue (E-tongue) (Intelligent Sensor Technology, Inc., Atsugi, Japan) Sensor array: 6 taste sensors for bitter, umami, sour, astringent, salty, and sweet; and two reference electrodes	Detection of flavor characteristics of loquat fruit during the post-harvest shelf life (18 days)	Shows changes in sensory taste indices typical of loquats	[97]
ASTREE E-tongue (Alpha M.O.S., Toulouse, France); sensor array consists of 7 sensors (AHS, ANS, SCS, CTS, NMS, PKS, and CPS) and a standard reference electrode (Ag/AgCl)	Characterization of the different quality levels of Congolese black tea	A 7-dimensional feature data set (AHS, ANS, SCS, CTS, NMS, PKS, and CPS) was obtained to characterize the flavor quality of the tea infusion	[98]
Tongue system, a 6th generation sensor system consisting of AHS, ANS, SCS, CTS, NMS, PKS, and CPS sensors together with a standard reference electrode (Ag/AgCl), giving a total of 7 sensors	Identifying differences in flavor profiles in different varieties of bee pollen	The basis for comprehensive processing and quality control of bee pollen products	[101]
The voltametric e-tongue used in this study consisted of 4 working electrodes (platinum, gold, crystalline carbon, and silver), a reference electrode (Ag/AgCl), and a platinum auxiliary electrode	Distinguishing between different brands of pasteurized milk	Clear differentiation of milk brands on the first day of storage, combined use with e-nose very promising for monitoring milk quality in the dairy industry, mainly where on-line control is needed	[104]

Table 3. *Cont.*

Device Type/Sensors Used	Application	Quantitative Metrics	References
ASTREE e-tongue (Alpha MOS Co., Toulouse, France)/7 chemical sensors and reference electrode (Ag/AgCl)	Identification of instant starch noodle spices based on different flavor profiles	e-Tongue correctly evaluates different brands of instant noodle seasonings; fusion with e-nose increases the speed and accuracy of food odor analysis, allows for its auto-aromatization, and reduces costs	[86]
E-tongue (α-Astree, Alpha MOS Company, France)/7 potentiometric chemical sensors, Ag/AgCl reference electrode	Assessment of the quality of satsuma mandarin (*Citrus unshiu* Marc.) under different storage conditions	Combined use with e-nose provided 100% tangerine identification and significantly higher correlation with tangerine quality compared to the single system	[106]
ASTREE e-tongue system (Alpha MOS, France)/7 chemical sensors including AHS, NMS, CTS, ANS, SCS, PKS, and CPS and one Ag/AgCl reference electrode	Identification of aromatic and flavor compounds of 7 traditional Chinese pancakes	Enables proper identification of products	[107]
Ultimate 3000 HPLC system coupled with a 16-channel coularray detector (Thermo Fisher Scientific Dionex, Sunnyvale, CA, USA)	Quick fresh lettuce	The e-tongue sensors showed similarity in evaluation with the traditional analytical method	[143]
PEN3 E-nose (Airsense Analytics GmbH, Schwerin, Germany)/10 single-layer metal oxide thick-film sensors	Taste evaluation of traditional Chinese fermented soybean paste	Combining e-nose data and LDA analysis allowed for a clearer discrimination (with a discrimination accuracy of 97.22%)	[144]
Astree flavor system consisting of 3 parts: a sensor array and Ag/AgC reference electrode; the sensors were made of silicon transistors with an organic coating	Detecting adulteration of ground lamb	Together with e-nose data, it is a promising perspective for the development of a rapid method for meat identification	[145]
E-tongue (SA402B; Intelligent Sensor Technology, Inc., Tokyo, Japan)	e-Tongue was used to compare sensory differences in coffee quality depending on processing method	Makes it possible to identify taste sensations that are undetectable by humans	[146]
e-Type tongue (α Astree, Alpha MOS, Toulouse, France), 7 potentiometric sensors marked by the manufacturer (Alpha MOS), Ag/AgCl reference electrode (Metrohm, Ltd., Herisau, Switzerland)	Development of a simple instrument, without the need for sample preparation and inexpensive analysis, which can be performed by manufacturers	The usefulness of the e-tongue for the construction of a fast and economical tool supporting melissopalynological analysis, which can be routinely used in the future	[147]

Abbreviations: AHS—sour taste, ANS—sweet, SCS—bitter, CTS—salty, NMS—umami. PKS and CPS are responsible for all-round taste.

The sensors that form the core of the e-tongue system can be categorized into three main types: electrochemical (which includes voltametric, potentiometric, amperometric, impedimetric, and conductometric), optical, and enzymatic (biosensors). Typically, e-tongue systems consist of up to ten sensors, with potentiometric and voltametric sensors being the most common. Voltametric e-tongues are particularly useful for multi-component measurements, such as determining the levels of chlorides, nitrites, and nitrates in meat. However, they are limited to samples that involve oxidation and reduction reactions [6,51].

e-Tongues utilize various sensors and data processing techniques to analyze complex fluid systems [136]. The electrodes assess the taste or character of a substance by measuring changes in resistance or current between them [71]. Once this information is converted into a digital format, it is input into a mathematical model and evaluated using computer simulations that define the substance's taste or character [140]. In e-cigarette applications, potentiometric sensors are the most commonly used; they are cost-effective, easy to install, and closely mimic natural taste recognition [148]. Among these sensors, ion-selective electrodes (ISEs) are the most prevalent [141]. The potential can be determined by placing two electrodes in the solution to be analyzed, ensuring no current flows. The concentration of the component can be determined by measuring the change in potential relative to a reference electrode [76]. The main benefits of the electronic tongue (e-tongue) include its simplicity, especially when using impedance-based sensors; long-term stability, particularly with optical mass sensors; and the ability to customize it for specific compounds, especially with potentiometric sensors. Additionally, e-tongues can test foods containing harmful substances, such as mycotoxins. In amperometric sensors, the working electrodes are modified to either oxidize or reduce the analyte, while the counter electrode is placed in a solution containing the analyte of interest. These sensors can detect and quantify specific analytes in gases, liquids, or solutions, offering high sensitivity and selectivity and a wide dynamic range [149,150].

Examples of electrode materials used in e-tongues and their applications are presented in the Table 4.

Table 4. Examples of electrode materials used in e-tongues and their applications.

Sensor Material	Detection Limit	Recovery Rate	Application	References
β-GICNT/rGO electrochemical sensor-based rGO/PEI—CNTs/β-CD	0.01–100 μmol/L	94.80–112.20%	Quantitative content of capsaicinoids in soy sauce and roasted meat products	[151]
FI-PAD working electrode Au, auxiliary electrode platinum wire, reference electrode Ag/AgCl	0.005 g/L	93.00–109.5%	Detecting the concentration of chlorine ions in raw milk	[152]
PPy-based voltametric sensors 7 electrodes: PPy/AQDS, PPy/SO_4, PPy/DBS, PPy/PC, PPy/SF, PPy/FCN, and PPy/TSA		91.3%	Coffee quality assessment and adulteration detection	[153]
Hydrogel containing mucin, NaCl as an ion-transporting electrolyte, and chitosan/poly(acrylamide—acrylic acid) as the main 3D structure maintaining the hydrogel network	Astringency 29.3 mM–0.59 μM at a sensitivity of 0.2 wt%$^{-1}$ Bitterness 63.8 mM–6.38 μM at a sensitivity of 0.12 wt%$^{-1}$		Sensing an astringent and bitter taste	[154]
T1R1-VFT biosensor	The lower limits of detection (LOD) of IMP, MSG, BMP, and WSA were 0.1, 0.1, 0.1, and 0.01 pM, respectively	Over 90% first 4 days	Detecting umami flavors	[155]
Silver nanoparticles (AgNPs) in multilayer structures (LbL)	Silhouette coefficient (SC) 91.2%		Increased ability to distinguish between basic tastes and samples that have an umami flavor	[156]

Abbreviations: rGO—reduced graphene oxide; PEI—polyethylene imine; CNTs—carbon nanotubes; β-CD—β-cyclodextrin; β-GICNT/rGO—electrochemical sensor-based rGO/PEI—CNTs/β-CD; FI-PAD—pulsed amperometric detection in flow injection system; IMP—inosine-5′-monophosphate, MSG—sodium L-glutamate, BMP—meat peptide; WSA—sodium succinate; PPy—polypyrrole; PPy/AQDS—anthraquinone-2,6-disulfonic acid disodium salt; PPy/SO_4—sodium sulfate; PPy/DBS—sodium dodecylbenzenesulfonate; PPy/PC—lithium perchlorate; PPy/SF—ammonium persulfate; PPy/FCN—potassium ferrocyanide; PPy/TSA—p-toluenesulfonic acid; VFT—a ligand called the Venus flytrap domain; T1R1—umami taste receptor proteins.

The most notable disadvantages of the electronic tongue (e-tongue) include the requirement for sample preparation, particularly for solid foods such as meat and meat products. Additionally, the sensors have a short lifespan due to nutrient absorption, especially in the case of potentiometric sensors [15,157].

6. e-Eye

The appearance of food refers to how it is visually perceived, including its color, structure, surface texture, and morphological features. These aspects are influenced by physical, chemical, microbiological, and sensory changes, which indicate product quality [6]. e-Eye systems can analyze surface texture in ways that exceed the human eye's capabilities, examining characteristics such as graininess, smoothness, and roughness. Furthermore, appearance is crucial for describing fresh food products in terms of their structure. While it is not always feasible to cover all measurable features since they vary depending on the specific product and the purpose of the analysis, understanding these attributes is essential [158]. e-Eye is a modern technology that offers several advantages, including sample preservation, user-friendliness, non-invasiveness, minimal or no sample preparation, and the capability to generate and permanently store high-quality images. However, there are some disadvantages to consider. This tool must be operated in a controlled environment devoid of light to prevent interference. Additionally, it can only assess one side of the samples at a time and requires careful attention to separate the background to obtain accurate data. Regular calibration is also necessary to ensure optimal performance [159,160].

Images captured by e-eye typically result from colorimetric, spectrophotometric, or computer vision measurements. The most commonly used color space in the food industry is L*a*b*. Spectrophotometers measure the entire spectrum of a sample within the visible range, and using mathematical conversions, the results are expressed as color coordinates in the L*a*b* format. The computer vision system comprises a lighting setup, a digital RGB camera, a sample holder, and the necessary hardware and software for image acquisition and processing. The camera sensors convert the intensity of the incident light into an electrical signal [161]. Examples of the use of e-eye to assess food quality, along with the results obtained, are presented in Table 5.

Table 5. Application and obtained effects of the e-eye system.

Device Type/Sensors Used	Application	Quantitative Metrics	References
IRIS VA400 E-eye (Alpha MOS, Toulouse, France)	Characterization of the different quality levels of Congolese black tea	A total of 40 characteristic colors were distinguished, mainly reddish-brown, yellowish-brown, orange, and brown	[98]
A system consisting of an electronic eyepiece (aperture: f/2.5) equipped with a 5 million-element CMOS (complementary metal oxide semiconductor) sensor, a holder, a light-emitting diode (LED) lamp, an LED lamp switch, and image processing software	A method for detecting the geographical origin of black pepper, which involves the synergistic use of ET, EN, and EE together with CNN and CAM incorporated into deep learning models	Relationships between sensory characteristics of black pepper and traceability of origin have been developed	[162]
Combination of 3 intelligent sensory techniques (e-eye, e-nose, and e-tongue) with multivariate statistical methods	Understanding the impact of different processing methods on the sensory quality of chestnuts	Fast, non-destructive, and intelligent sensory technology introduced in the assessment of the sensory quality of chestnuts showed the inhibiting effect of N_2 packaging on the browning of chestnuts after cooking	[163]

Table 5. *Cont.*

Device Type/Sensors Used	Application	Quantitative Metrics	References
The e-eye system consists of (1) a 5 million electronic eyepiece (RuiHoge), (2) a holder, (3) an LED lamp, and (4) an LED lamp adapter	Combined use of VE and EE to identify the storage time of Pu-erh tea	The detection efficiency of the intelligent sensor system has been improved compared to conventional pattern recognition methods using CNN	[164]
W100 wine color analyzer (Hanon Advanced Technology Group Co., Ltd., Jinan, China)	L*, a*, b*, C*, and h of the samples	The results of the e-nose project showed that the aromatic profiles of the wines studied were mostly similar, but there were color differences between regions	[165]
Color digital camera (Firewire Scion 1394 camera; Scion Corporation, Frederick, MD, USA) with maximum resolution (1600 × 1200 pixels) in jpeg format, illumination by two lamps (23 W/865, Philips MASTER PL-Electronic) placed at an angle of 45°	Use of electronic sensors to assess the effect of different thermal profiles of water during the percolation process on the sensory properties of 100% *Arabica* espresso coffees	Higher brewing temperatures resulted in greater foaming and greater foam stability	[166]
Aparat E-eye (IRIS VA400, Alpha MOS, Francja)	Study of the color change of the Saffron floral bio-residues (SFB) sample under different storage conditions	It has been suggested that SFB should be stored at 25 °C with 23% relative humidity	[167]
SC-80C colorimeter (Kangguang Instrument Co. Ltd., Beijing, China) in transmission mode under CIE D65/10°/observer illumination conditions	Used to reveal sensory characteristics of infusions of 12 representative yellow teas	Yellow large tea was significantly different from yellow bud teas and yellow small teas, but yellow bud teas could not be effectively distinguished from yellow small teas based on chemical components and electronic sensory characteristics	[168]

Abbreviations: L*—lightness; a*—green/red component; b*—yellow/blue component, C*—chrominance; h—hue.

The quality of the e-eye system relies on several components, including the electronics, camera, frame grabber, and lighting system. Depending on their application, CCDs can vary in construction types (such as linear, interline, and frame transfer) and resolutions (which refers to the number and size of pixels). A properly designed lighting system is crucial as it enhances the analysis's precision and minimizes artifact occurrence. The lighting can be adjusted for two construction types: circular lighting works best for flat samples, while diffuse lighting is more suitable for round and/or reflective objects [6].

Computer vision equipment utilizes sensors to mimic the human visual system. Using advanced image acquisition devices, relevant sample data are collected and sent to a computer to analyze and identify target areas. This technology enables the detection and sorting of fresh food. Computer vision equipment consists of two main components: the information processing device and the image acquisition device [169]. As computer vision technology develops, many computer vision devices are being created. This technology has numerous applications in food research, including quality control and classifying fruits and vegetables [58].

The computer vision system is fast, non-invasive, and highly precise. Compared to traditional testing equipment, this new technology significantly enhances the efficiency of food testing. Computer vision offers several advantages, including automatic classification and detection and economic and hygienic benefits. Additionally, it eliminates the influence of personal biases. However, there can be challenges in practical applications. Image acquisition devices, such as smart cameras, are sensitive to environmental factors like lighting, weather conditions, and high humidity. As a result, the images captured may vary in color brightness, become unstable, or exhibit other issues, which can lead to misinterpretation of the observed images [170]. Preprocessing the original image to enhance the final image analysis is known as low-level processing. This includes adjusting brightness and colors, cropping images to focus on the region of interest, and removing noise or digital artifacts caused by low light levels. Mid-level processing involves image segmentation, which separates the target object from unwanted information to improve accuracy. The most advanced stage is high-level processing, encompassing image recognition and interpretation. Algorithms such as KNN, support vector machines (SVMs), neural networks, fuzzy logic, and genetic algorithms help interpret the information extracted from images [171].

7. Conclusions

Artificial sense technology imitates the senses such as smell, taste, and vision using sensors and pattern recognition technology. e-Tongue is able to reproduce the human sense of taste using a matrix of different sensors to obtain a "taste fingerprint" from a sample. e-Nose can imitate the human sense of smell to determine the smell of a sample through the reaction of the device's sensor system with the sample gas. High-quality e-eye cameras can obtain visual data on colors, shapes, and textures. Since the beginning of sensor research, many studies have focused mainly on individual tools, including e-nose, e-tongue, and e-eye, which did not allow for obtaining complete data on the sensory characteristics of samples, negatively affecting the detection accuracy and generalization capabilities. The bibliography analysis shows that the use of e-nose is the most popular among researchers in food quality assessment. Fewer publications were found for e-tongue, and the smallest number of works focused on e-eye. Food quality testing using electronic sensors has evolved from identifying specific components of a sample to using pattern recognition analyses that provide detailed information about sample properties. Recently, many studies have been undertaken using fusion at the output and hardware level, and the use of various ML algorithms has been analyzed. This is evidenced by the work on the use of e-nose fusion with e-tongue and e-eye characterized by high accuracy, which allows for a comprehensive assessment of food quality. We should also expect the increasingly widespread use of e-sensors in on-line production conditions for real-time quality control and assurance.

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Abbreviations

Abbreviation	Meaning
AI	artificial intelligence
2BuOH	2-butanol
a*	color parameter—green/red component

ADC	analog to digital converter
AHS	e-tongue sensors sensitive to sour taste
ANN	artificial neural network
ANS	e-tongue sensors sensitive to sweet
b*	color parameter—yellow/blue component
BMP	meat peptide
BuOH	1-butanol
C*	color parameter—chrominance
CNT	carbon nanotube
CTS	e-tongue sensors sensitive to salty
DAQ	data acquisition
EtOH	ethanol
FI-PAD	pulsed amperometric detection in flow injection system
GBC	gradient boosting classifier
h	color parameter—hue
H_2S	hydrogen sulfide
IDE	interdigital electrode
IDMAP	interactive document map
IMP	inosine-5′-monophosphate
IPA	2-proponal
K-NN	K-nearest neighbor
L*	color parameter—lightness
LDA	linear discriminant analysis
MeOH	methanol
ML	machine learning
MOS	metal oxide semi-conductor
MOX	metal oxide
MQ135	sensor detecting gases present in the environment and determines the quality of the air in the surroundings
MQ4	sensor detecting released methane
MQ5	sensor detecting released isobutane and propane
MQ9	sensor detecting flammable gases
MSG	sodium L-glutamate
NMS	e-tongue sensors sensitive to umami
PCA	principal component analysis
PEI	polyethylene imine
PKS and CPS	e-tongue sensors responsible for all-round taste
PLS-DA	partial least squares discrimination analysis
PLSR	partial least squares regression
PPy	polypyrrole
PPy/AQDS	anthraquinone-2,6-disulfonic acid disodium salt
PPy/DBS	sodium dodecylbenzenesulfonate
PPy/FCN	potassium ferrocyanide
PPy/PC	lithium perchlorate
PPy/SF	ammonium persulfate
PPy/SO_4	sodium sulfate
PPy/TSA	p-toluenesulfonic acid
PrOH	1-proponal
rGO	reduced graphene oxide
SCS	e-tongue sensors sensitive to bitter
SO_2	sulfur dioxide
SVM	support vector machine
T1R1	umami taste receptor protein
TGS 2602	gas sensor detects air contaminants
TGS 815	gas sensor detects released hydrocarbon

TGS 822	gas sensor detects released alcohol
TGS 824	gas sensor detects released ammonia
TGS 842	gas sensor detects released methane
VFT	a ligand called the Venus flytrap domain
VOC	volatile organic compound
WSA	sodium succinate
β-CD	β-cyclodextrin

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