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REVIEW

Recent Insights into E-tongue Interventions in Food Processing Applications: An Updated Review

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Abstract

Purpose of Review E-tongue, also known as electronic tongue, is an emerging analytical tool that can mimic the human taste sensation using various chemical sensors. This technology can effectively evaluate the taste properties like sourness, sweetness, bitterness, and saltiness, as well as umami, of food products. This tool provides a comprehensive taste profile of food items, leading to improved quality control and product development. This review intends to provide a detail about the E-tongue interventions in diverse food processing applications. One such application is the assessment of food authenticity and quality.

Recent Findings Recent finding suggested that by analyzing the taste characteristics of food samples, E-tongue can detect potential adulteration, contamination, or spoilage, ensuring consumer safety. Additionally, E-tongue interventions can aid in the development of innovative food products by evaluating the taste profile and optimizing formulations. This tool has proven valuable in monitoring fermentation processes, such as wine production, where taste plays a critical role. By continuously measuring taste changes during fermentation, E-tongue can provide specific insights into the maturation and quality of the final product. This technology has also been applied in the assessment of sensory changes in processed foods, enabling the identification of flavor degradation and the optimization of processing parameters.

Summary This technology offers a non-destructive and objective method for evaluating taste properties, enabling quality control, product development, and assessment of food authenticity. The use of E-tongue in food sector can enhance consumer satisfaction, improve product consistency, and ensure food safety.

Keywords Taste profile · Food processing · Authenticity · Quality control · Product development · Fermentation · Sensory changes

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Introduction

The distribution and safety of food are extremely real issues in contemporary life. While overconsumption continues to rise in developed countries, where it is particularly severe in the food industry sector, starvation is still a dreadful reality in other parts of the world even today. To guarantee food availability, quality, and uniform distribution and safety, the food sector must be secure. The latter can be determined by physical characteristics, chemical makeup of the product, degree of toxic and microbiological contamination, and storage conditions, which is governed by the Hazard Analysis and Critical Control Points (HACCP). Consumers today are becoming increasingly picky and demanding when it comes to their food. The consumer's major means of expressing their preferences is through the food's taste and quality. New methods of food authentication have been created as a result of the rising customer demands for food safety and quality issues. However, most of these methods take a long time and call for expensive equipment and knowledgeable workers [1]. Alternative analytical techniques (like e-nose, high-pressure processing, Radio frequency Identification) should be made available as a result of these restrictions. An excellent illustration of a different method for evaluating food is the use of E-tongue multisensory systems, which replicate the functions of the human gustatory system. The e-tongue can distinguish (identify, categorize, and discriminate) various culinary tastes in addition to calculating the quantitative composition of food. Furthermore, it is simple to correlate the artificial sensory evaluation of the examined food products with human perception. Modern E-tongues make it possible to quickly and nondestructively assess the quality of food in both laboratory settings and online studies conducted within the commercial food processing process [2]. The use of e-tongues is especially advantageous for analyzing the taste of compounds that are hazardous to humans and therefore cannot be tasted by them. When used effectively, e-tongue technology may provide online taste monitoring, enabling improved product process maintenance. As a result, e-tongue could aid in lowering waste from careless operations and boosting output for the food processor. E-tongue easily lends itself to automation and computerization; therefore, it is possible to integrate taste quality monitoring into the production process. Its adaptability is an additional benefit. With the advancement of e-tongue, one may now carry sophisticated equipment for continuous, online monitoring of taste quality instead of small, low-cost, handheld devices like those for periodic taste analysis or household products. The ability to study multiple types of unique samples simultaneously is an additional benefit of using e-tongue. Furthermore, the device does not require highly competent operators after a protocol has been developed. Furthermore, as e-tongue monitoring is a label-free detection method, uncertainties related to label effects on molecular conformation, active site blockage, stearic hindrance, and the unavailability of available labels for certain compounds are eliminated [3]. One excellent example of an alternative approach to meal assessment is the employment of E-tongue multimodal systems, which mimic the function of the human gustatory system [2, 4, 5].

The pattern recognition (PARC) viewpoint is used by taste recognition systems depending on E-tongues to recognize, classify, and analyze numerous components in liquids both qualitatively and quantitatively. PARC compares the mixture's profiles with a predefined pattern. Samples in the state of fluid can be directly analyzed, but samples in the solid phase must first be dissolved [6]. Because they produce information from a variety of distinct compounds in a liquid combination, these sensors have low selectivity. A data matrix is created from the chemical sensors' signal. At the multivariate data analysis step, identification and classification are conducted utilizing statistical techniques and machine learning algorithms [4]. The brain may process signals from tongue and olfactory receptors in the human sensory system and combine the two sets of information to create classifications and/or conclusions. Since each instrument has its own software package, the e-nose and e-tongue are not integrated; however, the data from both instruments might be imported into another application and merged. The human sensory system's drawback is that no two brains are alike, which is obviously a good thing from another perspective. Additionally, the same brain may react differently every day based on an individual's health, mood, or environment, making the data subjective and requiring a costly and time-consuming process. Through taste, it is able to guarantee the consistency of a product's flavor throughout the production process, i.e., to ascertain whether the product has been altered, is in excellent working order, or is the same as before. For example, depending on how the product tastes, one may judge if it is a good harvest or not, distinguish between different varieties, and find any faults in the product [7]. A group of highly skilled individuals who utilize their taste senses to verify the quality procedures are developing this method [8].

Chemometrics, a branch of chemistry that employs statistics, mathematics, and formal logic to analyze chemical data and produce useful information, can be used to perform data analysis in an electronic language [9]. In terms of analysis performed by PARC, the methodology is focused on the usage of data and identification of a pattern for comparison and subsequently gather pertinent information regarding monitored process. Data from E-tongues are being analyzed using this method as well as chemometric approaches. These

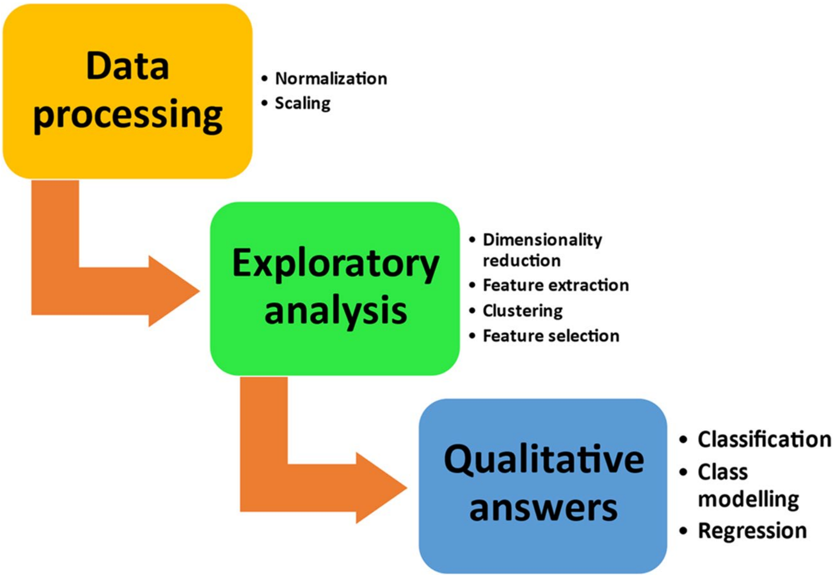

Fig. 1 Essential steps involved in pattern recognition process

methods are shown in Fig. 1. As per Oliveri et al. [10], the three probable outcomes achieved by evaluating a data collection include (1) identifying the existence of structures between the variables and/or objects under study (unsupervised and exploratory analysis); (2) creating mathematical models for the supervised classification and analysis of the class models to predict qualitative responses; and (3) creating mathematical models for the supervised regression analysis to predict quantitative responses [11].

Zhang et al. [12] provides a methodology for analyzing E-tongue data that consists of the following steps: First, it selects and filters features using a sliding window-based smooth filter. After that, it examines various classifier algorithms, including support vector machines (SVMs), and kernelized extreme learning machines (KELM), extreme learning machines (ELMs), and extracts features using the local discriminant preservation projection (LDPP) algorithm. The fivefold cross-validation method can be used to validate the process, and the KELM algorithm achieves an overall average accuracy of 98.22%. Finally, computational time tests between the ELM, KELM, and SVM classification algorithms are performed, with the results indicating KELM approaches.

Working Principle

International Union of Pure and Applied Chemistry (IUPAC) defines an E- tongue as "a multisensory system, which consists of a number of low selective sensors and uses advanced mathematical procedures for signal processing based on Pattern Recognition and/or Multivariate data analysis" [13]. In contemporary E-tongue systems, sensor types that are employed include electrochemical ones such as voltammetric [14], potentiometric [15], impedimetric or capacitors [16], photographic [17], biological sensors powered by enzymes [14], and mixed or hyphenated devices [18]. In addition to the utilization of innovative extraction methods [16, 19] and advancement of the concept of the e-tongue, nonspecific chemical sensors have also been reported in literature [20]. The worldwide data from the E-tongue is still used to establish a digital fingerprint of an item's gustatory qualities, but with the right sensor selection and chemometric procedures, particular variables and the existence of specific compounds can also be revealed. Many sensing components are used in e-tongue technique such as metallic sensors [18], carbon-paste [21], polymeric films [22], molecularly engraved molecules [23], and multitransduction coverings [17]. E-tongue technology uses a few of these sensing materials.

Previously, electronic tongue (e-tongue) devices primarily focused on assessing liquids. However, recent studies have shifted their attention to the evaluation of solid, fatty, fibrous, or non-aqueous items. This shift addresses various challenges related to sample status and specific pretreatment requirements. To ensure accurate assessment and delicate material interaction, solid foods must undergo appropriate phase changes. For example, solid meals may need to be minced or crushed [24–26], cold samples may require heating to the sensor's operating temperature, and hot samples may need to be cooled and homogenized unevenly through techniques such as sonication or stirring [16].

Furthermore, since many sensors in novel e-tongue systems primarily operate in the liquid phase, often in aqueous media, it becomes necessary to wet, dilute, and/or extract the sample using solvents that are deemed "sensor-friendly" [15, 16, 19, 27]. Processes such as mastication, which reduces food particles' size, in-salivation, utilizing saliva enzymes to initiate the initial food transformation and prepare it for the gastrointestinal tract, and tasting on specific tongue regions susceptible to each of the five fundamental flavors are examples of these procedures. These mechanisms parallel the preprocessing of food in the human tongue during meal time.

One of the commonly used uses of e-tongue technique has been and continues to be flavor assessment as well as the determination of taste-determining components, dating back to the early 1990s and beyond [28]. Basic taste chemicals are often utilized for calibrating artificial sensory systems for subjective mono-gustatory characterization tasks [2].

Taste Sensors/Detection of Tastes

According to Jiang et al. [7], optical mass sensors, electrically charged sensors, are some of the chemical sensors that are mostly used for e-tongue. The chemical sensors used by e-tongue interact with analytes to cause bidirectional changes in electrical characteristics, much as the gas detectors of the e-nose. Then, we use electrical impulses that can be measured to recognize patterns and categorize data. Table 1 depicts the different classifiers used in E-tongue.

Potentiometric Chemical Sensors

The most popular e-tongue sensors at the moment are chemical potentiometric ones. The voltage differential between the working and reference electrodes is observed using PTC sensors. Even when the reference electrode is immersed in an electrolyte solution, the reference sensor keeps its voltage constant. However, the concentration of the analyte in the solution phase controls the working electrode's voltage [29]. The electricity-producing potential of the electrode (E) can be expressed using the Nernst equation as a concentration indication of the proportion of the analyte's oxidized state (Co) to reduced type (Cr):

$$E = Eo + RT/nF\ (lnln\ C/Cr) \tag{1}$$

where T (°C) is the temperature and Eo (V) is the electrode's potential under standard conditions. Figure 2a provides an illustration of two-electrode potentiometric chemical sensor. An ion-selective membrane on the electrode allows only a single ion to be absorbed. Many potentiometric chemical sensors include three electrodes, and membranes were not always used. For potentiometric chemical sensors, membranes made of glass, crystalline/solid-state, liquid, and polymers (such polyvinyl chloride) are frequently utilized [30]. Silicate glass is used to make glass membrane electrodes and is commonly used to measure pH, Na + , and H + . AgCl, Ag_2S, and LaF_3 are examples of inorganic salts that make up crystalline/solid-state membranes. Solid-state/crystalline membrane sensors are mostly used to monitor F and Cl. To make a liquid membrane, one ion-exchanger, also known as an ionophore, is submerged in a gelatinous organic membrane. Liquid transmembrane electrodes are mostly used to measure Ca^{2+}. A polymer membrane is usually comprised of plasticizers, PVC, and an ion carrier or exchanger. Polymer membrane electrodes are used to monitor ions like Ca^{2+}, K + , NO_3, and Cl [31]. Potentiometric E-tongues are also used to classify single olive cultivar olive oils [15], distinguish honey prepared in various US states [32], distinguish between various promotional wines and beer [33], and measure the amount of sugar present in solutions. This research has shown good accuracy when compared to conventional analytical approaches. Potentiometric sensors have the essential advantage of offering a large selection of

Table 1 Pattern recognition algorithm and E-tongue classification method

Sensors	Aim	Classifier	Results	References
Potentiometric sensors	Assessment of the umami flavor in extracts from mushrooms	ANOVA	–	[50]
	Identifying adulterated beer kinds using argan oil	PCA SVM	85% of the original oil could be identified, while 87% of the tampered oil could be identified	[18]
Voltametric sensors	Quality and storage duration of open pasteurized milk are being monitored	SVM PLS	–	[38]
	Geographic origins of olive oil	SVM	–	[51]
Commercialized e-tongue	Non-volatile components and beef's sensory qualities	ANOVA PLS	–	[52]
	Differentiate between brands and types of orange beverages and Chinese vinegar	RF ANN	–	[53]
Six piezolelectirc quartz crystals	Analysis of raw and pasteurized milk's role in cheese ripening	PCA PLS-DA	Separation of cheeses based on milk type	[54]

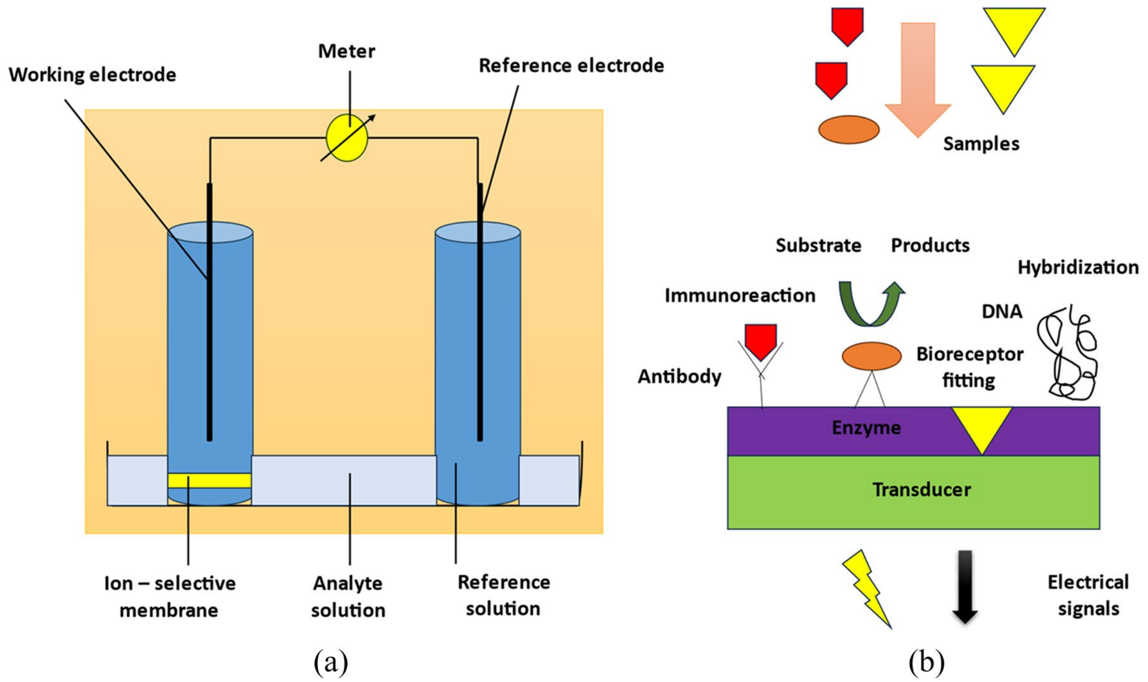

Fig. 2 Diagrammatic representation of a potentiometric chemical sensor (**a**) and a biosensor (**b**)

electrode membranes, both selective and non-specific [34]. Therefore, a huge variety of chemical substances in fluids can be measured by potentiometric sensors. Potentiometric sensors have a number of drawbacks, including a sensitivity to temperature. Therefore, a huge variety of chemical substances in fluids can be measured by potentiometric sensors. Potentiometric sensors have a number of drawbacks, including a sensitivity to temperature [35].

Voltammetric Chemical Sensors

Like potentiometric sensors, these voltammetric sensors have a functioning electrode along with a reference electrode. After measurement, the working electrode is applied a potential (voltage) to measure the current produced by the oxidation and reduction of analytes [36]. The target analytes' concentration and the current's value are correlated. Here is the relationship between E and the resultant current (I):

$$\begin{array}{l} I = E\hat{e} - t/\left(BR_{s}\right) \\ \qquad \text{RS} \end{array} \tag{2}$$

where B is an electrode-related equivalent capacitance constant, t is the time that has passed since the start of a voltage pulse, and RS is the analyte solution's resistance. Pulse voltammetry is frequently used for voltammetric e-tongue measurements. The two types of pulse voltammetry that are most commonly used are large-amplitude pulse voltammetry (LAPV) and short-amplitude pulse voltammetry (SAPV). Staircase voltammetry has also been used in some situations [37]. Previous studies have investigated the amount of diluted argan oil with sunflower oil [18], the quality and shelf life of unsealed pasteurized milk [38], the separation of honey samples according to floral designs [39], and a numerical evaluation of quality parameters in spring water [40].

Bioelectric Sensors

Electronic sensors that are referred to as "bioelectric sensors" sense using biomaterials. Biological materials such as enzymes, whole cells, connective tissue, antibodies, or receptors were often employed to build sensors for the use of e-tongue, including as impedimetric, voltammetric, conductometric, and potentiometric, sensors. One of the common biological processes that leads to the transfer of electrons, which are ions, or molecules is the enzyme–substrate reaction. Figure 2b presents a schematic diagram that summarizes the operation of bioelectric sensors. Because they add sweetness and sourness to food, acidic substances and sweeteners are essential components. Voltammetric bioelectric sensors are widely employed in the identification of sweets like lactate, glucose, and sucrose, as well as acids like lactic acid, citric acid, acetic acid, and sialic acid. The glucose oxidase enzyme, which converted glucose into hydrogen peroxide by ingesting oxygen, was the basis for earlier studies.

The hydrogen peroxide concentration was then measured using voltammetric bioelectric sensors [41]. The reactions is represented in Eqs. (3) and (4):

$$D - glucose = O2\ glucoseoxidase \rightarrow d - gluconicacid + H_2O_2 \tag{3}$$

$$H_2O_2 + (Med)\ red\ peroxidase \rightarrow (Med)Ox + H2O \tag{4}$$

Typically, fructose is calculated using an electron acceptor acting as an electrophysiological mediator and D-fructose-5-dehydrogenase (FDH) [42]:

$$D - fructose + (Med)\ OxFDH \rightarrow 5 - keto - d - fructose + (Med)\ red \tag{5}$$

The quantities of glucose and galactose can be determined by measuring the glucose that was created during the enzymatic hydrolysis of the two sugars. The enzymes used to undergo hydrolysis galactose and sucrose, respectively, were galactosidase and invertase. Similar operating principles were also applied in the enzymatic measurement of malic acid, acetic acid, lactic acid, vitamin C, and citric acid [42].

Typically, the impedimetric biosensor consists of 2–3 electrodes that are subjected to a sinusoidal voltage. As a consequence of the analyte attaching to the electrodes, it detects the change in impedance (Z):

$$Z^2 = R^2 + X_C{}^2 \tag{6}$$

where the components' resistance (R) and capacitive reactance (XC), respectively, are represented. Biomaterials mostly used to immobilize analytical substances on the electrode surface include lectins, nucleic acids, bacterial phage, and antibodies. Consequently, bacteriophage-based sensors, lectin-based detectors, nucleic acid–based detectors, and antibody-based sensors were the four main categories into which impedimetric biosensors were commonly classified. Impedimetric biosensors have been used to identify food poisoning [43, 44] and herbicide coupled with chemical residues in food [45]. Impedimetric biosensors, which stick to the target bacterium directly or render its conductive metabolites immobile, are frequently employed to measure microbial growth [46]. Numerous food pathogens have already been examined, including *Salmonella Typhimurium* [47], *E. Coli* O157:H7 [48], *Staphylococcus aureus*, and *Bacillus cereus* [49].

Potential Food Applications

Dairy Products

Numerous varieties of milk, yoghurts and other fermented beverages, aged and soft cheeses, and sour creams are just a few of the numerous goods that the dairy business creates. The dairy industry uses a variety of fermentation processes, microbes, and food additives, as well as several kinds of raw milk from various mammal species. The increasing use of E-tongue applications to analyze dairy products is due to the need to maintain product homogeneity, ensure freshness, and prevent adulterations [18–20].

E-tongues serve the primary purpose of conducting qualitative analyses, leading to numerous studies exploring their application in recognizing, classifying, or identifying milk and fermented milk samples. A recent experiment focused on classifying fermented milk samples employed a hybrid E-tongue utilizing potentiometric, voltametric, and conductometric measurements. Remarkably, this hybrid approach successfully differentiated all six samples under analysis, with the variations in microbes between various fermentations being evident in the principal component analysis (PCA) results. The study also highlighted the significance of illuminating the measurement situation from multiple positions and combining data from various sources, thereby introducing an additional dimension of information and showcasing the system's potential across diverse fields [55]. Winquist et al. [56] utilized a custom-designed voltametric E-tongue integrated directly into the dairy process line. The combination of E-tongue signals and multivariate statistics proves to be fast and effective for tasks like sample classification, discrimination, recognition, identification, and compound concentration prediction. The versatility of employing various sensors in E-tongue design opens up numerous practical applications.

To find antibiotic residues in cow's milk, Wei and Wang [19] created a voltammetric e-tongue with five metallic electrodes. These antibiotics can enter the milk from medicated animals, potentially affecting milk fermentation and causing allergies in consumers. The study demonstrated the e-tongue's capability to distinguish bovine milk containing various antibiotics through discriminant function analysis (DFA). Moreover, the e-tongue accurately predicted antibiotic concentrations using partial least squares (PLS) with correlation coefficients (R^2) exceeding 0.9. The same research team then used a comparable voltammetric e-tongue with different metallic electrodes (Au, Pt, Ag, and Pd) to track quality and amount of time; 26 pasteurized milk samples were stored for 72 h after being unsealed at various intervals. They also assessed the physical characteristics of several kinds of set yogurts using the e-tongue [57, 58]. Chemical field effect transistors (chemFETs) were used by Hruskar et al. [59] to compare sensory analysis with an Astree potentiometric e-tongue in order to track changes and categorize different kinds of probiotic fermented milk with various flavors. ANN and PLS approaches were used to link the e-tongue responses with sensory assessments, during 20 days at two temperatures (+4 and +25 °C). The study established the e-tongue's capacity to evaluate milk quality by demonstrating its ability to monitor deterioration during storage, forecast sensory qualities, and categorize probiotic fermented milk based on flavor. Hruskar et al. [60] described a different use in which 40 samples of probiotic-fermented milk were subjected to simultaneous measurements using an Astree e-tongue. ANN was used to link the e-tongue data with milk component levels ascertained by enzymatic methods via reactivity with appropriate enzymes. Similar to this, Bougrini et al. [18] used a hybrid e-nose—which consists of commercial and homemade MOX sensors, humidity sensor, and temperature probe, as well as voltammetric e-tongue, which consists of different metallic working electrodes (Pt, Ag, Au, glassy carbon) to distinguish pasteurized milk brands and determine its storage period. Since there was no pretreatment applied to the milk samples before analysis, the first storage day's variation in the milk brands could be easily distinguished, resulting in 80.8% of the variance. Using PCA classification to combine e-nose along with e-tongue data allowed for identification during all milk storage days. After combining the data, the SVM was successfully used to identify all pasteurized milk storage days. Lvova et al. [20] showed how multimodal systems might be used to track the release of salt from model domestic soft cheeses while they were being digested in an artificial gut system. These methods were also applied to determine the salinity of packaged Italian mozzarella cheeses made from cow and buffalo milk. Na + amount was determined by HPLC and compared with the data obtained from two sodium-sensitive electrodes that select ions (ISEs): a handmade Na-ISE 2 based on monensin dodecyl ester and a Na-ISE 1 from Metrohm Ion Analysis as well as an ISE array consisting of five homemade ISEs for calcium, nitrate, ammonia, chloride, and potassium. When it came to determining the Na + content, the ISE array outperformed individual selective sensors. The ISE array predicted PLS findings for Na + that revealed high slopes (0.887), correlation coefficients (0.952), and RMSEPs of 14.4 mM. Furthermore, the ISE array successfully identified the kind of milk (bovine or buffalo) and assessed the saltiness of samples of commercial mozzarella cheese. Two grams of freshly made for examination, mozzarella cheese or partially metabolized cheese was removed from artificial mouth and other parts of an artificial digestive tract. Ten milliliters of distilled water was used to extract the samples after they had been reduced to fragments, if needed. One milliliter of the liquid extract was taken for sensory examination following centrifugation. In ISE array, 87.5% of the mozzarella cheese were accurately detected (Table 2).

Fish and Meat

The crucial significance that protein-rich foods—especially meat and seafood—play in maintaining a balanced diet has drawn a lot of attention to the precise quality and safety management of these commodities. The meat and seafood market industry places a high value on freshness, and multisensory analysis has shown to be a useful tool for tracking postmortem and shelf-life durations. The utilization of e-tongue technique for fish freshness control, quality assessment, and taste evaluation has been investigated in a number of research [21, 70, 71]. When fish from the Cyprinid family spoiled, Rodríguez-Méndez et al. [70] used phthalocyanine-modified screen-printed electrodes and voltammetric carbon paste which are used to detect a variety of amines, including histamine, cadaverine, ammonia, dimethylamine, and trimethylamine. They employed the methods of PCA identification and discriminant analysis using partial least square (PLS-DA) to determine the freshness of the fish and determine the postmortem time. Before measuring, 1 g of fish muscle was cut into pieces and under ultrasound for 5 min in 25 mL of 0.1 M KCl to produce the liquid component for e-tongue measurements. In a related study, Apetrei et al. [21] demonstrated the usefulness of employing screen-printed conductors altered with polypyrrole in a voltammetric e-tongue for determining the freshness of Pontic shad fish. Ruiz-Rico et al. [72] employed a voltametric e-tongue with two arrays of metallic electrodes, one containing noble metals like Ir, Pt, Rh, and Au, and the other non-noble ones like Ag, Cu, Co, and Ni, to ascertain the shelf-stability of fresh cod fish. The cumulative volatile basic nitrogen (TVB-N), pH, humidity, ATP-related compounds, mesophilic microbes, and Enterobacteriaceae counts were evaluated using the e-tongue data in accordance with published protocols. The successful completion of PLS fitting for TVB-N and mesophilic bacteria validated the possible use of the voltammetric e-tongue in evaluating cod degradation.

More often than not, e-tongues are used for categorization tasks instead of taste evaluation. Research on the extraction and structural behavior of taste peptides from raw, farmed puffer fish muscle was carried out by Zhang et al. [73]. Using matrix-assisted laser desorption/ionization time-of-flight mass spectrometry, the taste peptides in the various fish muscle fractions were identified (MALDI-TOF–MS). These protein molecules were discovered to elicit distinct tastes (such as umami, bitter, kokumi) based on their structural makeup. Gil et al. [74] used a range of potentiometric electrodes to track the freshness of pork loin that was refrigerated for 10 days. The electrodes and a reference electrode were put straight on the beef slice sample in order to gather data. Significant connections between the e-tongue data and the K-index, which gauges the byproducts of ATP degradation, were discovered through the use of PLS regression. Furthermore, PCA and ANN analysis let us determine the postmortem time of meat. Similar research team measured nitrate, nitrite, and chloride levels in brines

Table 2 Uses, advantages, and application of E-tongue in different food products

Food product	Uses of E-tongue	Advantages	Applications	References
Wine	Quality assessment Detecting adulteration Differentiate varietals Monitoring fermentation process	Quick and accurate results Non-destructive testing Can analyze multiple wine samples simultaneously Cost-effective alternative to human sensory panels	Winemaking industry Wine quality control Wine authentication	[61•]
Fruit Juice	Flavor profiling Quality control Sensory analysis	Eliminates subjective human sensory evaluation Consistent and repeatable results Faster analysis compared to traditional methods	Beverage industry Quality assessment of fruit juices Flavor optimization	[62••]
Cheese	Defect detection Cheese classification based on age or type Sensory profiling	Objective and reliable analysis Reduced time and labor Less sample consumption	Dairy industry Quality control of cheese production Cheese flavor and texture analysis	[63•]
Coffee	Flavor evaluation Quality control Blending optimization	Analyzes multiple characteristics of coffee Non-invasive testing preserves the integrity of the sample Reduces the reliance on human sensory panels Provides actionable insights for product improvement	Coffee industry Quality assessment of coffee beans Blending and roasting optimization	[64•]
Meat	Flavor profiling Quality control Sensory analysis Detecting spoilage	Objective analysis Reduced time and resource consumption Can detect subtle changes in quality or spoilage	Meat industry Quality assessment of meat products Spoilage detection	[65•, 66••] Nasiru et al., 2022
Soft Drinks	Flavor analysis Quality control Sensory evaluation	Provides detailed flavor profile analysis Speeds up quality control processes Non-destructive testing	Beverage industry Quality assessment of soft drinks Flavor optimization	[67]
Olive Oil	Authenticity determination Sensory profile analysis Quality control	Fast and reliable results Non-destructive testing Reduces reliance on costly chemical laboratory tests Can detect adulteration or fraud	Olive oil production industry Quality control of olive oil Authentication and fraud detection	[68••, 69••]

and minced meat using an e-tongue based on pulse voltammetry. It was comprised of a collection of noble and non-noble electrodes [25].

Fruits and Vegetables

Multisensory systems find applications in assessing the freshness, sweetness, and nutrient components of fruits and vegetables. Grapes, being a vital starting product for wine, are particularly important in this regard, often focusing on evaluating phenolic antioxidants. Using voltammetric biosensors based on nanostructured materials and phenol oxidases, Medina-Plaza et al. [14] created the E-tongue system, which allows for the differentiation of many grape varieties based on their phenolic content (laccase and tyrosinase). Enzymes were added to an arachidic acid (AA) Langmuir–Blodgett (LB) film doped with lutetium bisphthalocyanine (LuPc2) as an electron mediator to create the sensors. The grape samples were assessed as 50% diluted musts in water, and the bio E-tongue demonstrated the ability to differentiate five distinct grape varietals and identify phenols by measuring the quantity of phenolic groups that bound to the grape samples' structure. A metallic voltammetric e-tongue was used by Campos et al. [26] to measure the ripeness of seven Spanish grape varietals. After harvesting, the grapes were cut and crushed, and juice that was taken out of the pulp was tested. With errors of less than 15%, the e-tongue showed good prediction ability for both total acidity and sugar content. Wang's study group evaluated firmness and sugar content in several pear varieties and distinguished preserved licorice apricots using both voltammetric metallic e-tongue and a-Astree potentiometric e-tongue [24]. The apricots have been diced and cooked in deionized water following centrifugation. Next, an e-tongue was used to measure the supernatant. Juice extracted from fruit cores and filtered through double-decked filter sheets was subjected to peer analysis. Kutyła-Olesiuk et al. [75] evaluated the effects of lead buildup in maize leaves using a flow-through analytical system equipped with a miniature ISE array. Following a 24-h exposure to 5–10 mM lead nitrate solutions, the leaves from 3–4-week-old plants were removed and lyophilized. In order to perform potentiometric tests, 0.2 g of dry weight plant material was mixed in flow-through mode with 0.3 mL of 96% H_2SO_4 and 10 mL of 30% H_2O_2. According to the study, when used in combination with PLS-DA, the developed e-tongue system may be able to evaluate the growing circumstances of plants undergoing bioindication or phytoremediation. In a follow-up investigation, the same team used a hybrid E-tongue to do qualitative as well as quantitative evaluations of water-based extracts from fresh and dried apples produced using various drying methods [76]. The system includes five potentiometric ISEs, conductometric, spectrophotometric, and amperometric sensors that depend on Au and glucose oxidase (GOx) readings. The findings showed that, in comparison to utilizing separate approaches, combining data from several measuring techniques increased the distinction of dried apple extract samples.

Wines and Vodka

Riul Jr et al. [77] utilized an e-tongue and artificial neural networks to accurately recognize wine samples stored under different circumstances, achieving 100% accuracy in identifying vintage, vineyard, and brands (Fig. 3). Buratti et al. [78] used an E-nose and an amperometric e-tongue to evaluate Italian wines according to grape category, pH value, bitterness, hues, astringency, and taste. In order to obtain outstanding judgment with good accuracy for particular sensory measures connected to the general excellence of dry red wines, they used genetic algorithms. PCA was used by Wu et al. [79] to categorize Chinese wines using cyclic voltammograms of copper electrodes, showing that the technique was successful in distinguishing between the samples. In a study looking at the effects of various variables in the wine industry, like aging in oak barrels, an e-tongue using perylene and polypyrrole chemicals in sensing units was employed. In addition, Rudnitskaya et al. [80] connected the deterioration of wine flavor to the lignin in wine bottles decomposing due to an elevated amount of phenol compounds in the cork damaged by fungus. Potentiometric e-tongues were used in a different investigation

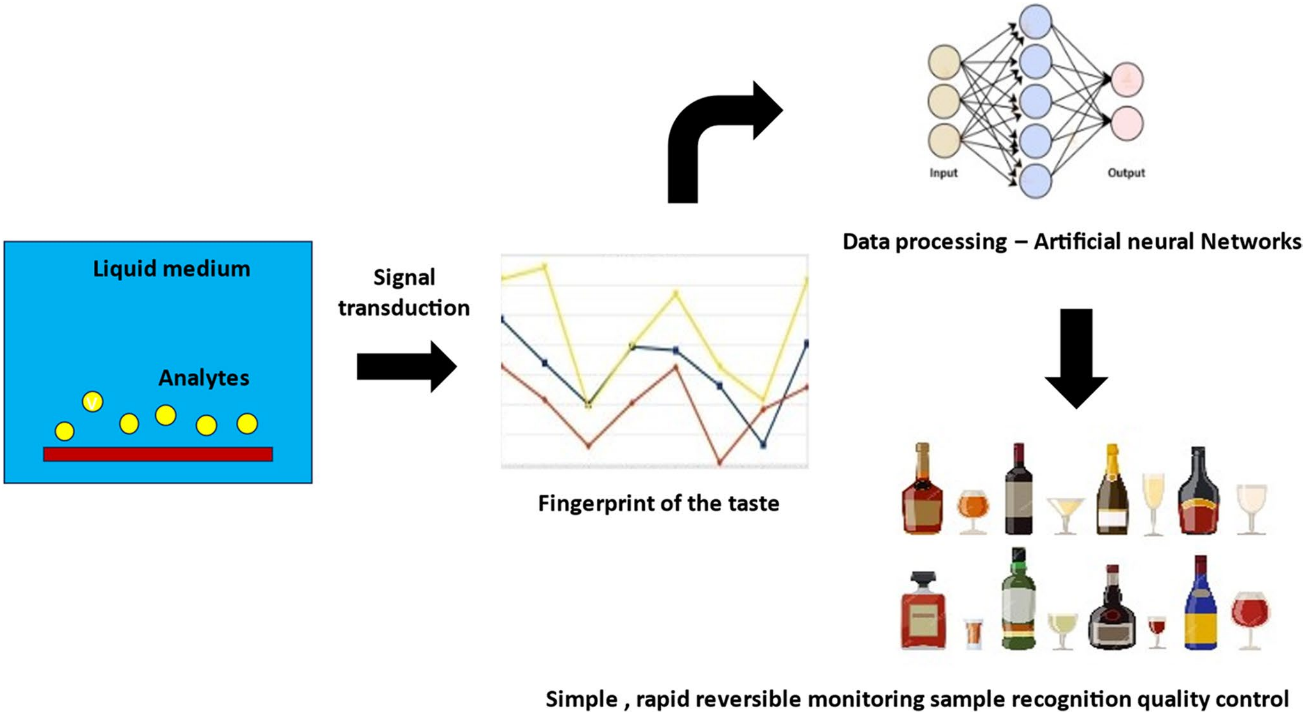

Fig. 3 Diagram illustrating the utilization of artificial neural networks for the processing of data from an e-tongue based on impedance spectroscopy. This process allowed different varieties of wine to be distinguished

to successfully discern between various vodka brands and characteristics [81].

Food Authenticity and Quality

E-tongues are also emerging as promising supplemental techniques to classical analytical methods for a fast and low-cost detection of malpractices. E-tongues have shown their capability in the detection of food adulteration as well as in the authenticity assessment of different types of foodstuffs. Electronic tongue devices have been widely used to detect different analytes, among which it is possible to find adulterants in olive oil and other adulterants in different matrices (Morais et al*.*, 2019). E-tongues can aid in authenticating food products by analyzing their taste signatures. For instance, expensive food products like olive oil, honey, and spices are often adulterated with cheaper substitutes. E-tongue analysis can distinguish between genuine and adulterated samples based on their taste profiles, helping to ensure product authenticity [82]. By analyzing the taste profile of a food product, the e-tongue can identify any deviations from the expected taste characteristics. For example, in milk, the presence of water or other additives can alter its taste profile, which can be detected by the e-tongue. Beverages such as juices, wines, and soft drinks are susceptible to adulteration with water, sugar, or artificial flavors. E-tongue technology can help in monitoring the taste consistency of these beverages by comparing the taste profile of each batch with a reference standard [83]. Any deviations can signal potential adulteration. E-tongue technology can assist regulatory bodies in enforcing food safety and quality standards by providing rapid and reliable detection of adulteration. It can be used as a screening tool for large-scale monitoring of food products in the market, helping to identify potential risks and take appropriate actions to ensure consumer safety [84]. Zaukuu et al. [85] investigated the authentication of Tokaj Wine (Hungaricum) with the electronic tongue and near infrared spectroscopy. The study aimed to develop models to rapidly discriminate lower grade Tokaj wines, "Forditas I" and "Forditas II," that were artificially adulterated with grape which must concentrate to match the sugar content of high-grade Tokaj wines using an electronic tongue (e-tongue) and two near infrared spectrometers (NIRS). There was a noticeable pattern of separation in PCA for all three instruments and 100% classification of adulterated and nonadulterated wines in LDA using the e-tongue. In summary, e-tongue technology offers a promising approach to combat food adulteration by providing sensitive and accurate detection of taste-based deviations in food products. Its application can contribute to maintaining the integrity and safety of the food supply chain, thereby safeguarding consumer trust and public health.

Limitations and Future Trends of e-Tongue

A sensor employed by an e-tongue presents a specific response toward the target analyte. However, most of the chemical sensors employed by e-tongue encountered significant matrix effects when dealing with real food samples. Therefore, a sample pre-treatment step is typically added so that the sensors are designed to work toward specific analytes in certain types of samples. This pretreatment step is time-consuming when multiple analytes are analyzed at a time. Another limitation of e-tongue is the relatively short lifetime of the sensing materials, especially biomaterials, of the sensors. It requires the users to frequently examine the performances of the e-tongue. In addition, a great number of sample size (typically $N = 10$) for each type of sample is often required for training and validation. In some cases, the sample size needs to be even greater. One trend of e-tongue is the employment of biosensor with high selectivity and specificity, which reduces the impact of a complex and interferents. More biomaterials, including nucleic acids and aptamers, antibodies, cells, phages, and, namely, enzymes, will be used as recognition elements for those sensors. The development of standardized universal functions e-tongues will be very useful for food processors to determine the quality of their products. Similar to e-nose, the development of a shared online library where store pattern classifiers trained by data were obtained from standardized e-tongue. This can significantly improve the precision of e-tongues and make universal function e-tongues possible.

Conclusion

This review summarized the applications of e-tongue in determining the quality-related properties of foods. The functioning principles of a variety of sensors and the electronic gadgets that use them—such e-tongues—are introduced in this article. Frequently employed algorithms for pattern identification and classification techniques—like ANN, CNN, PCA, PLS, and SVM—are also covered in the study because they are essential to the analysis. In conclusion, pattern recognition algorithms in conjunction with e-tongue provide strong and affordable analytical instruments that produce fast and precise findings. These methods can be employed for in-line and off-line measurements that make them helpful for tracking food processing and assessing the nutritional value of the final product. However, strict control over the collection of samples, testing, and data processing is required for the successful use of e-tongue technique. It is necessary to appropriately handle issues like low measurement repeatability and comparability and data processing. These developments will definitely increase the e-tongue technologies' potential in a variety of applications.

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Shivangi Srivastava—formal analysis.
Aamir Hussain Dar—revised the manuscript.
Ufaq Fayaz—reviewing and editing figures.
Sobia Manzoor—writing reviewing and editing.
Vinay Kumar Pandey—conceptualization and supervision.
Rafeeya Shams—writing reviewing and editing.
Kshirod Kumar Dash—visualization and editing.

Data Availability As this is a review article, no data was generated.

Declarations

Human and Animal Rights and Informed Consent This article does not include any experiments with human or animal subjects done by the authors.

Competing Interests The authors declare no competing interests.

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Particullary interesting articles published recently have been highlighted as:

- • Of importance
- •• Of major importance

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