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Reviews

Electronic Nose, Tongue and Eye: Their Usefulness for the Food Industry
Nariz, lengua y ojo electrónico: su utilidad para la industria alimentaria

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Abstract
Background: The electronic nose, tongue, and eye are futuristic technologies that have been used for many years; they have been gaining market in different types of industries and can increasingly be found in the food area; their function is to determine sensory characteristics (smell, aroma, and flavor) and objective visuals, without the subjectivity that can be represented by sensory analysis by people (the study that can complement the analysis of machines, without being exclusive).
Objective: Find the main generalities of these mechanisms, their sensors, software, mechanism of action, and applications within the food industry.
Methods: A search was carried out in the main databases of indexed articles, with terms that allowed collecting the necessary information, and 89 articles were used that met different inclusion criteria.
Results: The main outcomes were to understand the operation of each of these technologies, what their main components are, and how they can be linked in the beer, wine, oil, fruit, vegetable, dairy, etc. industry to determine their quality, safety, and fraud. **Conclusion**: The use of electronic nose, tongue, and eye is found in more food industries every day. Its technology continues to evolve; the future of sensory analysis will undoubtedly apply these mechanisms due to the reliability, speed, and reproducibility of the results.
Key words: Electronic senses, volatile compounds, technology, sensory analysis, quality control.

Resumen
Antecedentes: La nariz, lengua y ojo electrónico son tecnologías futuristas que se vienen empleando hace muchos años, han ido ganando mercado en diferentes tipos de industria y cada vez más se lo puede encontrar en el área de alimentos, su función es el de determinar características sensoriales (olor, aroma y sabor) y visuales objetivas, sin

la subjetividad que puede representar el análisis sensorial por parte de personas (análisis que puede complementar al análisis de las máquinas, sin ser excluyente).
Objetivo: El objetivo de esta investigación fue encontrar las principales generalidades de estos mecanismos, sus sensores, software, mecanismo de acción y aplicaciones dentro de la industria de los alimentos.
Métodos Se realizó una búsqueda en las principales bases de datos de artículos indexados, con términos que permitieran recabar la información necesaria, y se utilizaron 89 artículos que cumplieron distintos criterios de inclusión.
Resultados: Los principales resultados fueron entender el funcionamiento de cada una de estas tecnologías, cuales son sus principales componentes y cómo pueden estar ligados en la industria de la cerveza, vino, aceites, frutas, hortalizas, lácteos, etc., para determinar su calidad, inocuidad y fraude.
Conclusión: El uso de nariz, lengua y ojo electrónico cada día se encuentra en más industrias de alimentos y su tecnología sigue evolucionando, el futuro del análisis sensorial será sin duda la aplicación de estos mecanismos por la fiabilidad, rapidez y reproducibilidad de los resultados.
Palabras clave: Sentidos electrónicos, compuestos volátiles, tecnología, análisis sensorial, control de calidad.

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Introduction

In recent decades the food industry has experienced remarkable growth in terms of the quantity of food produced and sold, and the quality of the product. The productivity of the agri-food sector experiences continuous and growing challenges by the demand of consumers that make the use of innovative technologies a priority to maintain and improve its competitiveness (1–3). Electronics play a vital role in the food industry's automation. Automated food production systems come in different functions and sizes, depending very much on the type of food and the manufacturers' specific requirements (4).
Electronic sensors are products of advanced chemical and physical sciences combined with the intuitive integration of microprocessors, computing, and statistics. They include resistive, optical, electrochemical, or piezoelectric platforms, where a variety of sensing materials have been immobilized. The electronic nose, tongue, and eye have been used to characterize components that contribute to sensory or compositional profiles, from ripening to harvest, from raw material storage to packaging and consumption, allowing complex sensory information to be processed (stimuli for the human sensory system). This multisensory approach reflects more closely the complexity of human perception of different stimuli. Due to various factors it can become subjective; therefore, this technology allows us to have objective data (5,6).
This research was developed to guide on the main aspects of the nose, tongue and electronic eye. Many studies and bibliographic reviews of these technologies can be found separately, but not one that integrates all three. With this review we can

understand the importance that represents for the food industry the possible use of the three technologies together for food control, as in studies where the quality of tea and olive oil has been evaluated (7,8).

Materials and methods

A bibliographic review was carried out using the following databases: Web of Science, ProQuest, Scielo, Springer, Redalyc, and ScienceDirect. The terms used in the search were: electronic nose, electronic tongue, electronic eye, computer vision system, volatile aromatic compounds, electronic sensors, biological sensors.
The selection of the cited bibliography took into account the following inclusion criteria:

1. Relevance: Articles had to be clear for review according to their title, generally related to electronic sensors.
2. Language: Articles had to be written in English or Spanish.
3. Journal and year of publication: Articles published during the last 10 years (to have updated information) in indexed journals were selected for further review.

In total, 229 scientific articles were identified. Repeated papers were excluded, of which 64 were omitted because their titles were not relevant for the review. Of the 165 manuscripts under review, 40 were dropped due to languages other than English or Spanish. 125 articles followed the study, and 36 were excluded because they did not match the journal and year requirements. A total of 89 articles remained that satisfied the inclusion criteria (figure 1).

Source: self made

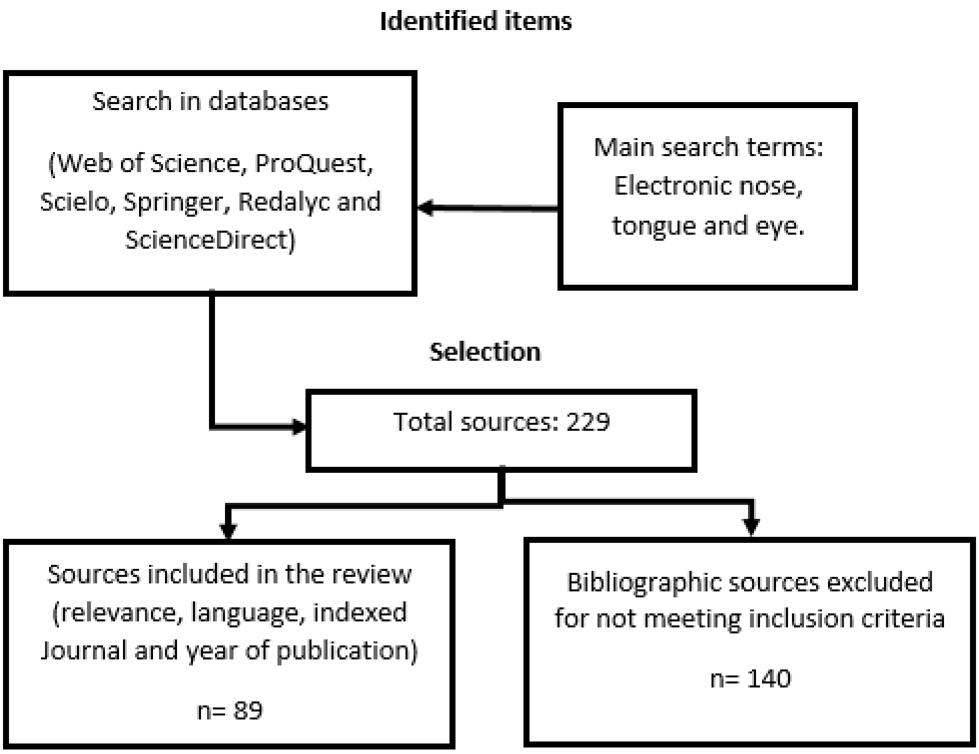

Figure 1. Flow chart of the bibliographic search and delimitation of information.

Results and discussion

1. Electronic nose

The electronic nose (E-nose) is a tool that contains mainly three parts, a sample delivery system, an array of gas or chemical sensors, and a pattern recognition system. This technology is normally used to detect simple or complex volatile organic compounds and has become one of the most useful devices in the food industry (9). Since the first report of an electronic nose based on chemical sensors and pattern recognition in 1982, the instruments have experienced significant development by advancing technology. The most interesting and promising sectors for applying electronic noses that can be found in the scientific literature concern the food industry, medical diagnostics, and environmental monitoring (10–12).

The electronic nose concept is parallel to the human nasal system that works in coordination with the brain. Each time the orthonasal (external olfactory sense) smells a compound, it reaches the olfactory epithelium located in the upper nasal cavity (13). In similar lines to a human nose, the electronic nose works through a series of sensors. After detecting the aroma, the set of sensors generates a pattern based on the type of smell. Besides, the patterns obtained are trained to interpret and distinguish between various odors and recognize new patterns depending on the food industry needs (14).

There is a great difference compared to the human olfactory system, it is worth mentioning that an electronic nose can present certain types of limitations due to sensors and analytical methods. The set of gas or chemical sensors have limitations such as sensor poisoning, calibration and sensitivity, these limitations have improved in recent decades (15).
When a volatile compound or odor (chemical input) is exposed to the electronic nose, a physical change occurs in the sensors, detected by the transducers, and converted into an electrical signal creating a specific olfactory signature or fingerprint (16). The increase and decrease of the signal depending on some parameters: nature of the odor (type and concentration of the compounds), reaction and diffusion between odor and sensors, type of sensor, and environmental conditions (17).

Components

Electronic nose systems consist of hardware and software parts. The E-nose's main hardware parts are the odor handling and delivery systems, the sensor assembly, and the interface circuit. The E-nose software parts are the pre-processing and pattern recognition (PR) algorithms (18). They have a classifier that discriminates the odor classes to reduce the dimensionality of the data; in some studies, the genetic algorithm (GA) has been used to find the best combination of characteristics. For the attributes projection, the principal component analysis (PCA) and the Fisher linear discriminant analysis (LDA) are usually used in the data preparation unit (19). The odors classification unit needs a supervised pattern of sorting algorithms such as the nonparametric k-nearest neighbors (k-NN) method, the Support Vector Machines (SVM) supervised learning algorithm, or artificial neural networks (ANN) (20).

Odor management and delivery system

These systems were designed, taking inspiration from the anatomy of the biological nose. The odor emission rate is a factor that points to the source of odor emission and shows the amount of odor emitted per unit of time (21). Generating airflow between samples is one of the most popular types of odor handling, and delivery systems called the sample flow system. As air flows, the odor of the sample increases, leading to more accurate measurements. There are other methods, such as" the static system" and "the direct exposure", which could be chosen considering the application and nature of the samples (22).

Sensors

As mentioned, the electronic nose is a set of receptors that can bind groups of particular volatile compounds. The resulting matrix response is processed using pattern

recognition techniques to generate an output signal. Although individual sensors are generally not highly selective, their combined signals allow the characterization of samples as a whole (23). The sensors in an electronic nose perform functions very similar to the olfactory nerves in the human olfactory system. Therefore, the sensor array can be considered the heart and the most important electronic nose component. The instrument is completed by interfacing with the computer’s central processing unit (CPU), the recognition library and the recognition software that serves as the brain to process the input data from the sensor array for further data analysis (24).
Depending on the detection materials, gas sensors can be classified into several types: conductive polymers (CP), metal oxide semiconductors (MOS), quartz crystal microbalance (QCM), and surface acoustic wave sensors (SAW) (25). The target gases react with the sensors, causing reversible electrical properties, such as conductivity. Measurement of conductivity is typically obtained by measuring the sensor's output voltage and characterizes the output voltage pattern using parameters such as peak voltage, response time, and recovery time (26).

Interface circuit

The interface circuitry converts the sensors’ response to electrical signals with the voltage and current based on the sensors’ specific technology. They are designed following the circuit implementation technology of each electronic nose. The interface circuits that make up an electronic nose can be divided into two main ones: integrated and non-integrated circuits. In the first category, both the circuits and large-scale integration sensors (VLSI) are located on a chip (27). Non-integrated circuits use discrete electronic components such as programmable logic devices (PLDs), microcontrollers and field-programmable gate arrays (FPGAs), and operational amplifiers (Op-Amps). The odor detection chip consists of three parts: sensor-on-chip interface circuitry, an adaptive neuromorphic olfactory model on a chip, and a chemosensor-on-chip array (28).

Software

The E-nose software units are data pre-processing and pattern recognition units. The electrical signal produced by interface circuits is generally not suitable to be delivered to the computer to recognize the pattern; these signals must be processed extensively. The pre-processing unit extracts the relevant information from the sensor responses and prepares the data for pattern analysis. The pattern recognition unit is used to predict the kinds of odor samples (29).

Signal preprocessing

Usually, the signals emitted by the analog signal condition unit are wide and associated with noise; this can cause various inconveniences. In fact, when the sensor array is exposed to the odor samples, the sensor output signal changes. This response is fast and is associated with noise (30). After noise reduction, the sensor outputs are digitized and delivered to the pattern recognition unit. In this sense, an analog to digital converter circuit is used (ADC) (31).

Applications of the electronic nose at an industrial level

As an extension of the human smell, the electronic nose has played a significant role in the food and environmental fields; for example, it is used to predict aquaculture products' freshness in China. In the research of Zhiyi, Chenchao, & Jiajia (32), a method was proposed for the freshness prediction of yellow croaker with an electronic nose; the principal component analysis showed that it is a reliable and threadbare method to determine the freshness of fish with a model error of 10%.

Fruits produce and release a wide variety of volatile organic compounds (VOCs) that make up their characteristic aromas with esters, terpenoids, lactones, amino acid derivatives, fatty acids, and phenolic compounds. Those are the dominant classes of volatile organic compounds represented in fruit aromas (33). Within several studies, it has been shown that electronic noses are excellent digital electronic devices for identifying, characterizing, and classifying the fruit aromas of different fruits and varieties. These instruments can quickly and systematically evaluate complex mixtures of volatile gases without identifying all the chemical components present in the ramification of fruit aromas (34).

The electronic nose function in beer technology encompasses many parameters such as detecting defects, classification of hops, barley, yeast, and sort of beer varieties. The sensors are calibrated to measure volatile compounds such as carbon dioxide, ethanol, methane, diacetyl, hydrogen, hydrogen sulfide, carbon monoxide, ammonia, and benzene, which can affect beer quality and differ between fermentation batches (35). In Brazil, Jordan et al. (36) proposed and demonstrated that you could have an electronic nose system to measure effectively and quickly the level of volumetric alcohol in beer; they analyzed 15 samples with different alcohol content. The sensors were able to recognize the amount of ethanol with a 5.47% error; So, this can be applied, and it is viable to identify that parameter in the market, given the rise of microbreweries in the world.

Like every human being that emits its characteristic odor, stored meat emits gases that, when analyzed, can provide information about the condition during storage. Various factors, such as age, breed, diet, health, sex, and storage conditions, influence the type of volatile organic compounds emitted (37). The aforementioned adds to the complexity of developing an electronic nose system that is reliable and consistent for meat product applications. With the help of appropriate chemometric techniques, the detection system's odor patterns can be processed to obtain a result, which provides information on the food product's state. To develop an effective electronic nose system to identify the presence of changes in parameters, decomposition, or pathogenic microorganisms in the meat, the nature of the volatile organoleptic compounds (VOCs) emitted by the meat product must be precise. This will help design the electronic nose system based on the target volatile compounds and develop a reliable validation system (even predicting if organic waste may exist). There is enough information on the volatile gases emitted by changes in the entire range of meat products we can find in the industry (38).

It has been established that heat treatment of milk, especially cow's milk, significantly changes its especially organoleptic chemical properties and promotes the denaturation of whey protein. Heating also affects the salt balance of milk, decreasing the soluble calcium, and if accompanied by a pH reduction, the nature of the colloidal calcium phosphate will change (39). Most investigations of electronic nose in dairy have focused on the analysis of adulteration of milk, which is a common practice in many populations. It is essential to create fast and reliable methods to detect these anomalies (40). There is a developed system to detect possible quality alterations in raw milk, focusing mainly on sodium hypochlorite, hydrogen peroxide, and formalin; chemicals used to prevent the rapid deterioration of milk. The equipment showed precision values between 87 to 95 % identifying samples with those compounds, indicating that the electronic nose is an excellent method to detect fraud in milk in a fast way.

As a new aroma analytical technique, electronic nose detection has been widely applied in the cereal area. If the grain deteriorates during storage, the gas compounds produced by fungi’s metabolism will change depending on the species and concentration (41). The fungi alteration induces nutritional losses, unusual flavors, organoleptic deterioration, and in most cases, the presence of mycotoxins. Research has correlated fungal activity with the production of typical VOCs. The electronic nose technique has been proposed as a new method to detect VOCs as markers of possible grain deterioration, and the detection and differentiation of fungi mycotoxigenic strains in contaminated grains and semi-quantitative/quantitative evaluation of mycotoxin contamination (42).

Due to the complexity of the coffee aroma, various electronic nose applications have been carried out in recent years. The evaluation of the roasting degree of coffee is mainly based on the final empirical observation of the color, requiring well-trained operators with a high degree of skills (43). In the Radi, Rivai, & Purnomo (44) research, a portable electronic nose composed of a series of 10 temperature-moderated metal oxide sensors (MOS) was tested as a possibility for the automation of the roasting process (time, temperature, and color). The method was established and can be replicated for the final characterization of the coffee bean’s quality that can be used as an analogous control to the parameters commonly used in the industry.

Various applications of the electronic nose technique have been studied in bakery products. Different types of electronic nose systems have been used for bakery products and related raw materials, along with techniques for data processing and analysis. The aim is to test and discriminate volatile aromatic compounds from different flours and ingredients used in formulations, processing operations (fermentation and baking), and storage conditions (45). A greater number of electronic nose applications focus on VOCs’ rapid discrimination for the early detection of spoilage and fungal growth in cereals. Rusinek, Gancarz, & Nawrocka (46) developed an electronic nose that allows identifying the deterioration of bread as the days of storage pass. This system can predict the bread aging based on changes in the emission of volatile substances under aerobic conditions and the growth of fungi that can alter characteristics; this system is a fast and non-destructive detection tool.

The electronic nose has been shown to be appropriate to complement the human sensory panel for rice odor evaluation applications due to its complexity in allowing people to distinguish sensory patterns of different varieties, contamination, and storage conditions. The electronic nose will overcome some of the limitations of sensory panel testing by being fast, reliable, and consistent in grading grain quality. This includes evaluating rice samples’ discrimination and classification of and identifying contamination of rice mold and disease of rice plants. Each industry must be analyzed separately to determine the percentages of acceptance or rejection (47).

Analog odor measurement and automated simulation of the sense of smell is complex. For this reason, the development of organoleptic analysis of spices has been considered complex due to their similarity in various chemical compounds that give them odor (48). The ability of the electronic nose to differentiate between different types of spices was demonstrated in a study conducted by Hübert et al. (49) where 12 conductive polymers (CPs) were used with an enhanced time-delay neural network (TDNN) to distinguish between 4 types of spices (basil, cardamom, pepper, and turmeric), 4 tests were performed to determine the final experimental. Finally 16 analyzes were carried out for each spice; the results showed that the mathematical methods applied gave in 4 minutes a correct recognition of spices from 60 to 100%.

2. Electronic tongue

The human sense of taste involves identifying basic flavors, including sweetness, acidity, bitterness, salinity, and umami. The human sensory panel (trained or untrained) has been used to perform taste evaluations on many food products, yet running and training people is relatively time-consuming and expensive. In some cases, sensory panels can introduce bias if the panelists are not well trained; thus, many researchers have used the electronic tongue as a rapid and impartial detection alternative to the human tongue (50).

The electronic tongue is a multi-channel taste sensor (more than five basic flavors) with global selectivity. It is composed of several types of lipid/polymer membranes to transform information about taste substances into electrical signals uploaded into a computer (51). Electronic tongue signals are analyzed in a pattern recognition unit to discriminate between similar samples. It is an analytical tool composed of three parts: (1) non-specific and not very selective chemical sensors that have partial specificity (cross-sensitivity) to different components in a liquid sample; (2) an appropriate method of pattern recognition; (3) multivariate calibration for data processing (52). By decoding the chemical energy of the interaction between the detection unit and the analytes into a primary signal output, the array of detection elements determines the entire analytical system’s performance. Electronic tongue instruments depend on available analytical technologies that operate in the liquid phase. The most common are based on electrochemical techniques such as voltammetry, potentiometry, and conductometry, which require electrodes in the liquid phase to establish a measurement circuit (53).

Taste sensors

Chemical sensors commonly employed for an electronic tongue include electrochemical sensors, biosensors, and optical mass sensors. Like the gas sensors in the electronic nose, the chemical sensors used in electronic tongues react with analytes, creating reversible electrical properties changes. Measurable electrical signals are used to do pattern recognition and classification (54).
The sensor responds to the chemical composition of the taste. This can be understood by the fact that taste interactions, such as the suppression effect, which appears in mixtures of sweet and bitter substances, can be reproduced well; for example, the suppression of the bitterness of the quinine and a drug substance by sucrose can be quantified (55). Amino acids can be classified into various groups based on their flavor profile based on the sensor outputs. Food flavors such as beer, coffee, mineral water, milk, sake, rice, soybean paste, and vegetables can be quantitatively analyzed using the taste sensor, which provides an objective scale to investigate the human sensory expression. The taste of a wine is also discriminated using the sensory fusion of taste and odor performed by combining the taste sensor and an odor sensor array using conductive polymer elements (55).

Potentiometric chemical sensors

Potentiometric chemical sensors are the most used for the electronic tongue. These measures determine the difference in voltage between the working electrodes and the reference electrode. The reference electrode is immersed in an electrolyte solution, and the reference sensor voltage is constant. Regarding the voltage of the working electrode, it depends on the concentration of the analyte in the solution phase (56). The most commonly used membranes for potentiometric chemical sensors are the glass membrane, the solid-state crystalline membrane, the liquid membrane, and the polymer membrane (for example, polyvinyl chloride) (57). The glass membrane electrodes are designed based on silicate glass, which is generally used to determine acidic or alkaline pH. The solid-state crystalline membrane is composed of inorganic salts, such as silver chloride. A liquid membrane is formed by dissolving an ion exchanger or ionophore in a viscous organic membrane. Liquid membrane electrodes are widely used to determine calcium, while a polymer membrane is typically composed of PVC, plasticizers, and an ion exchanger. Polymer membrane electrodes have been used to determine ions such as potassium, calcium, chlorine, etc. (58).

Voltammetric chemical sensors

Unlike potentiometric techniques, the electrode potential in voltammetric instruments is used to drive an electron transfer reaction. The resulting current generated by the reduction and oxidation of analytes is measured. The most straightforward measurement setup uses three electrodes: reference, working, and auxiliary. The working one generally uses a metal electrode or a modified electrode composed of copper, nickel, palladium, silver, tin, titanium, zirconium, gold, platinum, and rhodium (59). The basic principle is that, when employing the electrochemical voltammetry, a multisensor

matrix is placed in the solution to be measured. Then, the step potential is added to the working electrode, and the polarization current of different solutions is estimated to analyze the characteristics of the samples qualitatively and quantitatively (60).
The step potential added to the electronic voltammetry tongue (VE tongue) mainly includes a large conventional pulse and a multi-frequency pulse. Typically, pulse voltammetry is used for the voltametric electronic tongue. The most widely used are large amplitude pulse voltammetry (LAPV) and small amplitude pulse voltammetry (SAPV)(61). In several studies, voltametric electronic tongues have been used to detect the adulteration percentages of argan oil with sunflower oil, the quality control and storage time of unsealed pasteurized milk, discriminate honey samples based on their floral types, and perform quantitative analysis of the quality parameters in spring water (62).

Bioelectric sensors

The application of the biological senses' elements as active parts of the biosensors allows the acquisition of information about bioactive analytes with high sensitivity, selectivity, and specificity. Bioelectric sensors use biomaterials as detection materials (63). Biological materials, including enzymes, whole cells, tissues, receptors, or antibodies, were used extensively to build voltametric sensors, impedimetric, potentiometric, and conductometric sensors applied to the electronic tongue (64). The operation principle of a sensor generally involves a series of biochemical reactions, such as the enzyme-substrate reaction, leading to the transport of electrons, ions, or molecules. Sweeteners and acids are essential ingredients for food, and voltametric bioelectric sensors are commonly used to characterize sweeteners such as glucose, lactate, sucrose, or acids such as lactic, acetic, and sialic acid. Impedimetric biosensors have been used to determine herbicide and pesticide residues in food and to detect food toxins. They are also widely used to detect microbial growth through direct binding of target bacteria or immobilizing metabolites of a target microorganism (65).

Software

As already mentioned, a typical electronic tongue system consists of an array of chemical sensors, a reaction vessel, measuring devices, transducers, data acquisition devices, data processing algorithms, and pattern recognition. An electronic tongue system's functions can be changed using different sensors, other data processing strategies, and pattern recognition algorithms (66).
Electronic tongue signals are generally processed by the same classifiers, including the random forest algorithm, principal component analysis, partial least squares regression, artificial neural networks, and the support vector machine algorithm. To perform pattern recognition some of these algorithms are also used in the electronic nose data processing system for data discrimination (67).

Potentiometric sensor applications in food

Potentiometric electronic tongues have been used in different areas of agro-industrial processes, mostly to classify olive oils obtained from cultivars of individual olives, differentiation of honey produced in different places, discrimination of different varieties of beers and commercial wines, and quantifying the sugar content in solutions (68). The main advantage of using potentiometric sensors is selecting many different membranes, both specific and less specific, for their electrodes. Likewise, these sensors can measure an extensive range of chemical compounds in different solutions. One of the main disadvantages of potentiometric sensors is that they are sensitive to temperature. The membrane can absorb the solution's components, which can affect the nature of the charge transfer. The sensors' temperature should be controlled, and the electrodes should be washed with solvents to minimize the effect (69).

Limitations and future trends

A sensor employed by an electronic tongue exhibits a specific response towards the target analyte. However, most of the chemical sensors used by this system can find matrix defects for real food samples. Therefore, a sample pre-treatment step is usually added so that the sensors are designed to work towards specific analytes in certain types of samples. This pre-treatment step is time-consuming when testing multiple analytes simultaneously (70). Another disadvantage of the electronic tongue is the relatively short lifespan of sensor materials, especially biomaterials. It requires users to examine the electronic tongue's performance frequently; also, a large amount of the sample size is often required (71).

One of the trends in electronic tongues is biosensors' use with high selectivity and specificity; more biomaterials are used, including single-chain nucleic acids (aptamers), antibodies, cells, phages, and enzymes, as recognition elements for said sensors (72). The development of universal standardized electronic tongue functions will help the food processors determine their products' quality. Alike to the electronic nose, the development of a shared online library that stores pattern classifiers trained by data obtained from standardized electronic tongue will allow use in most industries (73).

3. Electronic eye

An electronic eye is a computer vision technology that converts optical images into digital images. It uses an image sensor instead of the human eye to collect images of objects and uses computer simulation criteria to identify the images to avoid subjective deviation of human vision (74). The computer vision process generally includes five steps: image acquisition, image processing, feature extraction, pattern recognition, and decision making. All steps are sequential and could be expressed as a simple flow chart. Decision-making rules are a part of the control system that includes a pre-established set of rules, formalizing the control and optimization strategy. Computer vision is part of the intelligent control system; it could also include supervised or unsupervised learning elements for pattern recognition, modeling, and knowledge base development. In this case, the set of rules could be adjusted, depending on the established interaction procedure and the optimization criteria (75).

Hardware

Computer vision hardware generally consists of a housing, a light source, a digital camera in color with an optical lens (the camera with a charge-coupled device is the most used in electronic eye designs), and a computer (76). In the case of multispectral or hyperspectral vision, a set of narrow-band optical filters (usually 10 nm) is also required. The design of the case, such as the geometry, the walls interior color, and the background, is fundamental to obtain high-quality images. One of the options for offline imaging is flatbed scanners, which provide uniform illumination with good contrast and resolution (77).

Software

Recent versions of Windows have a set of drivers compatible with most imaging devices, allowing simple image or video capture. This set of drivers is specific to the Charge-Coupled Device (CCD) camera, interface, and software (78). However, the standard Windows software functionality is not sufficient to adjust the settings of the CCD camera or time-controlled image acquisition. Therefore, most CCD camera manufacturers usually supply specialized software designed for a particular camera and interface, often leading to compatibility issues. This is probably an explanation why most researchers still use two different software packages: one for image capture (which could be part of the camera software) and another for offline image processing and analysis. Measurement evaluation is performed using software that creates color spectra and applies multivariate principal component analysis (PCA) statistics for statistical analysis (79).

Electronic eye in the food industry

The electronic eye has a complete application and has proven to be a fast, accurate, and non-destructive detection technology for evaluating product quality in shape, size, color monitoring, and texture analysis. The electronic eye has gained popularity in the food industry because it integrates mechanics, optical instrumentation, electromagnetic detection, colorimetry, spectrophotometry, digital video technology, and image processing (80). It is a fast, accurate, and non-invasive technique that also helps test changes in visual quality overtime at each production step (81). The visual aspect of

products, especially food, is critical to consumers' quality experience. Appearance and color are crucial sensory factors that determine products' success and, therefore, must be reliably and consistently monitored (82).
The electronic eye's advantages are objectivity and reliable visual evaluation, such as reproducible color and shape measurements under controlled conditions, product traceability through data storage, and no affectation in product consistency or texture. The process is fast and straightforward (non-destructive analysis, no sample preparation, no sample size limitation, and multiple samples in one analysis), allowing in-depth analysis (evaluation of color and shape in a single run). And finally, it is powerful and flexible (can correlate with sensory panel assessment data) (83).
Among the applications of the electronic eye are the classification and qualification in agricultural processes and the food industry with the monitoring of product aging, fermentation, detection of foreign substances, and verification of color changes in food processing steps such as cooking, frying, baking, freezing, etc. (84). For example, the electronic eye helps the brewing industry through automation solutions that allow integration throughout the equipment process to optimize product lifetime (85).
Computer vision is a technology used in the industry to acquire product images and then process them with a combination of optical and electromagnetic detection technologies. This system allows the detection of imperfections, such as in the structure of meat products, at the beginning of its deterioration, which is invisible to the human eye (86). The investigation of Sreeraj et al. (87) presents studies that describe the use of an electronic eye to predict the ripening parameters of certain citrus fruits such as grapes used for red, white, and rosé wines manufacture. While evaluating this fruit, a flat surface scanner is usually used, and the color levels are analyzed with the help of the RGB color scale. Using the color data set, a calibration model is employed to relate the images' color to the grapes' phenolic composition using an analytical reference method. Therefore the ripening trend can be followed (88). Yang et al. (89) performed the characterization of physical properties and electronic sensory analysis of citrus oil-based nanoemulsions. The electronic eye analysis consisted of using a digital imaging system to measure the color difference of the emulsion samples and demonstrated the reliability to discern color parameters in different samples. This can be replicated to any industry where oils or beverages with high density are handled.

Conclusions

The food industry growth is remarkable. Today the use of electronic senses is of vital importance to safeguard the quality of products. The systems are increasingly fast, reproducible, and small. Being an industry that never stops its processes, speed, reproducibility, consistency, and robustness are needed for commercial applications. Data analysis systems are being developed and applied to these artificial detection systems to integrate responses with sensory and chemical data and combine data from different technologies (such as electronic noses and electronic tongues) to replicate the human detection system better.
There is a wide variety of food products such as vegetables, fruits, meat, seafood, etc. These food products can be divided into very good, good, or bad categories in

individual units. To handle all of these things automatically requires a high level of automation because food products can vary in size, shape, fragrance, color, etc. Considering the food industry's diversity, it is almost impossible to come up with a generic automation solution. Electronics play a critical role in automation in the food industry. Automated food production systems come in different functions and sizes, depending very much on the type of food and the manufacturers' specific requirements.

Conflict of interests

The authors report no conflict of interest.

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Authors' contributions

ROA designed, collected information and wrote the manuscript. JRV and JUV collected information and wrote the manuscript. All authors read and approved the final manuscript.