E-Senses to Measure Main Chemical/Physical Features of Food

Subjects: Food Science & Technology

Contributor: Margherita Modesti, Alessandro Tonacci, Francesco Sansone, Lucia Billeci, Andrea Bellincontro, Gloria Cacopardo, Chiara Sanmartin, Isabella Taglieri, Francesca Venturi

Food quality is nowadays an extremely important issue: it must not only comply with commercial regulations but also meet consumers' expectations; this aspect includes sensory features capable of triggering emotions through the consumers' perception. In food quality assessment, the sensory approach gives an immediate measurement of perceived attributes and returns important information, which helps to better understand human responses. However, sensory analysis carried out by human panels can be tricky. Thus, e-senses have been used to characterize food features associated with sensory and compositional profiles, in a quick and objective way.

Keywords: chemosensory analysis ; e-senses ; emotions ; consumers choice ; food quality

1. E-Nose

An electronic nose (E-nose) is a tool that works through a series of sensors able to detect volatile organic compounds (VOCs) in different types of samples. It is composed of three main parts: sample delivery system, chemical sensors, and pattern recognition system [1]. Gas sensors can be classified into different types, based on the materials: conducting polymers (CP), metal-oxide semiconductors (MOS), metal-oxide-semiconductor field-effect transistors (MOSFET), and mass-sensitive (such as quartz microbalance), and acoustic and optical sensors [1][2]. The VOCs emitted by the samples react with the sensors, causing reversible electrical signals, which are properly analyzed to extrapolate a possible pattern of some significance for the given analysis [2]. The intensity of the sensor's signal depends on specific parameters, such as the nature of the VOC (type and concentration), reaction between VOCs and sensors, type of sensor, and environmental and sampling conditions [1]. After the processing, what is obtained is an aromatic fingerprint. The E-nose can be trained to interpret the results differentially depending on the food industry needs, and the sensors can be customized based on the desired application [3]. As being able to mimic the human smell, the E-nose has been largely tested in the food industry to identify specific aromatic fingerprints associated with food quality, especially considering that different aspects influence the intensity and composition of food aroma profile. Hence, the food aroma plays a crucial role in assessing food quality and internal composition, as well as consumers' expectations. Consequently, aromatic evaluation has become part and parcel of the food production process for quality inspection purposes [4]. An e-nose finds application in different steps of the agri-food production chain, such as ripening stages and harvesting time evaluation, storage conditions, and shelf-life evaluation, including the assessment of freshness or decay degree, microbial contamination, and off-flavor formation [2]. This appears particularly important considering that food pathogens and off-flavor production can lead to important economic loss and consumer rejection. For instance, Viejo et al. [5] proposed an integrated artificial intelligence system to detect off-flavors in beer using a low-cost, portable e-nose coupled with machine learning modeling. The Authors were able to build three highly accurate models able to predict beer faults with 95, 96, and 97% accuracy. Moreover, Fuentes and colleagues [6] evaluated the potential of a low-cost e-nose to assess the smoke-taint fault in wines. Using the e-nose measurements as input in the machine learning model, it was possible to assess the number of smoke-related compounds in wines, such as 20 glycoconjugates and 10 volatile phenols with high accuracy (with R2 ranging from 0.95 to 0.99). Some examples of e-nose applications for food quality evaluation are shown in **Table 1**. The e-nose shows to be a rapid, reliable, and low-cost technology to assess food and beverages quality [7]. Moreover, the e-noses can be installed at different production stages for quality monitoring during the whole production process, which can help in taking fast corrective actions before obtaining the final product [8]. Besides the considerable advantages of the e-noses, there is still a great difference with the human olfactory system. Hence, the technological approach has a certain type of limitation due to sensor structure and analytical methods. For instance, sensor poisoning, calibration, and sensitivity can represent important drawbacks [4]. Additionally, even though the analysis is cheap and fast, a large number of samples is often required. Gas sensors are very sensitive to external environmental conditions, especially to temperature, humidity, and pressure. Therefore, an external condition during sampling strongly affects the response of the sensor. As such, controlled conditions are required during the analysis, which makes it difficult to use E-noses in outdoor settings [2]. Considering the obvious limitations of the e-nose systems, a valuable approach to take key decisions in the food production chain could be the combination of e-nose with sensory analysis approaches discussed above. In this sense, it would make it possible to combine the ability of the e-nose to perceive chemical compounds with the ability of the human nose to perceive the synergic interaction of chemical compounds mixture. Moreover, the combined use of e- and human senses would reduce the necessary resources (in terms of times and samples) of both approaches [1][2][4][9].

Table 1. Examples of E-Nose application for Food Analysis. MOS: metal-oxide semiconductors. ANN: artificial neural network; CDA: Critical discourse analysis; CT classification and regression tree; HCA: hierarchical cluster analysis; LDA: linear discriminant analysis; MARS: multivariate adaptive regression splines; PCA: principal component analysis; PLS: and partial least square; RBFNNs: radial basis function neural networks; SVM: support vector machine; SNV: standard normal variate.

Food Category	Sample	Application	Sensor	Chemometric Approach	Reference
Agri food	Rice	Detection of fungal infection during storage	MOS	PCA, LDA, and PLS	[10]
	Peach	Fruit decay	MOS	PLS and SVM	[11]
	Apple	Detection of pathogen contamination	MOS	PCA and HCA	[12]
	Dragon fruit, pear, kiwi fruit, apple	Fruit deterioration	MOS	PCA	[13]
	Potato	Soft-rot infection	MOS	LDA, MARS, CT	[14]
	Broccoli	Freshness evaluation	MOS	PCA, HCA, CDA	[15]
	Citrus	Early detection of *Bactrocera dorsalis* infection	MOS	PCA and LDA	[16]
	Bell pepper	Freshness	MOS	PCA and PLS	[17]
	Mushrooms	Early detection of contamination	MOS	PCA and PLS	[18]
	Apple	Detection of pathogens (Salmonella, Erwinia, Streptococcus, and Staphylococcus) contamination	MOS	PCA and HCA	[12]
	Grapes	Identification of smoke-related volatiles	MOS	PCA	[19]
Oils and Dairy products	Olive oil	Evaluation of rancidity and oxidation	MOS	PCA and LDA	[20]
	Olive oil	Presence of defects	MOS	PCA	[21]
	Peony seed oil	Adulteration	MOS	PCA and LDA	[22]
	Edible oils	Adulteration	MOS	HCA, PCA, PCR, LDA, and ANN	[23]
	Parmigiano Reggiano cheese	Adulteration	MOS	PLS and ANN	[24]
	Butter	Adulteration	MOS	PCA and ANN	[25]
Meat and fish	Fish	Spoilage monitoring	MOS	-	[26]
	Tuna	Process development	MOS	PCA	[27]
	Salmon	Freshness evaluation during storage	MOS	RBFNNs and PCA	[28]
	Squid	Formaldehyde identification	MOS	PLS	[29]
Processed food	Grape syrup	Adulteration	MOS	PCA, HCA, SVM, and LDA	[30]
	Tomato paste	Adulteration	MOS	PCA, PLS, SVM, and LDA	[31]
	Chicken	Evaluation of roasted chicken deterioration	MOS	PCA	[32]

Food Category	Sample	Application	Sensor	Chemometric Approach	Reference
Beverages	Vinegar	Classification	MOS	PCA, SNV, and LDA	[33]
	Orange juice	Adulteration	MOS	HCA, ANN, and CT	[34]
	Beer	Off-flavor identification	MOS	ANN	[35]
	Wine	Smoke taint evaluation	MOS	ANN	[6]

2. E-Tongue

The human sense of taste involves identifying basic flavors, namely, sweetness, acidity, bitterness, salinity, and umami. Many researchers have introduced the electronic tongue (E-tongue) as a rapid and objective method to replace the human tongue [36]. The e-tongue is the analytical device based on the principles of functioning of the human sense of taste able to classify the tastes of various chemical compounds in liquid phase samples. Like the e-nose system, it allows the identification, classification, and analysis (both qualitative and quantitative) of the multicomponent mixtures, returning a taste fingerprint. Overall, it is based on a multi-channel taste sensor, composed of three parts: a sample-dispensing chamber, a sensory array with different selectivity, and software for data processing. The interaction between the sensors and the analytes gives a primary chemical energy output, which is a function of components' structure and concentration, and it is transformed into electrical output [37]. These measurable electrical signals are used to recognize and classify the pattern. Most of the e-tongue instruments are based on electrochemical techniques, namely, conductometry, voltammetry, and potentiometry [38]; the latter representing the most common and versatile one. These sensors are able to measure a great number of different compounds in different solutions. In several studies, voltammetric e-tongues have been used to identify sweeteners and acids (such as glucose, lactate, sucrose, lactic, and acetic acid) in different food products. In the agri-food sector, potentiometric sensors have been used to classify beers and wines [39]. Specifically, the e-tongue, based on potentiometric electrodes sensitive to sodium, calcium, ammonia, and anion was able to discriminate 34 types of beers from different brands and types. Moreover, it was able to discriminate the presence of stabilizers and antioxidants, unmalted cereals, and carbohydrates added during fermentation. The same system was used to analyze wines and was able to discriminate the different wines based on the varieties used for the winemaking (Chardonnay, Americanas, Malbec, and Merlot). In **Table 2** are reported some examples of e-tongues used for food analysis.

Table 2. Examples of E-tongue application for Food Analysis. ANN: artificial neural network; CDA: Critical discourse analysis; CT classification and regression tree; ELM: extreme learning machine; HCA: hierarchical cluster analysis; LDA: linear discriminant analysis; MARS: multivariate adaptive regression splines; PCA: principal component analysis; PLS: and partial least square; RA: regressive analysis; RBFNNs: radial basis function neural networks; SNV: standard normal variate; SVM: support vector machine.

Food Category	Sample	Application	Sensor	Chemometric Approach	Reference
Agri food	Coffee beans	Evaluation of bitterness	Potentiometric	RA	[40]
	Melon	Evaluation of storage condition	Potentiometric	PLS and LDA	[41]
	Corn seeds	Aflatoxin detection	Potentiometric	PLS	[42]
Oils and Dairy products	Vegetable oil	Adulteration with low-grade oils	Solid-state electrodes	RA	[43]
	Olive oil	Rancidity evaluation	Potentiometric	LDA	[44]
	Milk	Discrimination based on storage days	Voltammetric	ANN	[45]
	Paneer cheese	Evaluation of capsaicin content	Potentiometric	PCA	[46]

Food Category	Sample	Application	Sensor	Chemometric Approach	Reference
Meat and fish	Fish	Presence of heavy metals	Colorimetric	PLS and ELM	[47]
	Mutton	Adulteration with pork or chicken meat	Potentiometric	PCA, LDA, CDA, and BAD	[48]
	Fish	Freshness evaluation during storage	Potentiometric	PCA-RBFNNs	[49]
	Carp	Evaluation of flavor changes during steam cooking	Potentiometric	PCA	[50]
Processed products	Tomato soup	Comparison of consumer perception and e-tongue of different salts	Potentiometric	PCA	[51]
	Soy sauce	Identification of rare sugars	Potentiometric	PCA	[52]
	Surimi	Flavor after different processing methods	Potentiometric	PCA	[53]
Beverages	Wine	Evaluation of phenols content	Voltammetric	PLS	[54]
	Wine	Adulteration of tokaj	Potentiometric	PCA, LDA, and PLS	[55]
	Wine	Off-flavor identification	Potentiometric	PCA	[56]
	Apple juice	Evaluation of sweetness	Impedance spectroscopy	PCA	[57]
	Liquor	Comparison of human perception and e-tongue in differentiating liquors	Potentiometric	PCA	[58]
	Coconut water	Taste deterioration during time	Potentiometric	PCA	[59]

As such, the e-tongue represents a powerful tool to characterize the sensory properties of different food products; however, like the e-nose, it still has some important limitations. One of the main disadvantages of e-tongue sensors is that they can be sensitive to temperature and, therefore, sensors' temperature control is often required. Furthermore, the sensors are often characterized by a relatively short lifespan and a frequent and careful check of e-tongue performance and reliability is pivotal; in this case, a large number of samples is also required to have a solid and reliable result [3]. Lastly, considering that human taste also perceives astringency, viscosity, heat, spicy, and so on, a complete description of the overall taste with the e-tongue alone is not possible. Again, and even more important than in the case of the e-nose, the combined approach of the e- and human tongue would bypass these limitations.

3. E-Eye

Contrary to smell and taste, visual perception is not a chemical sense. Eye photoreceptors are capable of reacting to light and, therefore, collecting information from the external environment, which will be transformed into electrical signals. In this sense, this section may sound inconsistent with the other topics. However, it must be highlighted that the visual appearance of food products is a critical aspect of consumers' quality expectations, and it plays a crucial role in the decision to purchase—or consume—or not a specific product. Appearance, color, lightness, and texture are the first sensory factors that the consumers perceive, and they determine products' success. As such, careful and reliable monitoring of food visual traits is crucial and cannot be ignored [60]. In this context, the electronic eye (E-eye) has proven to give a fast, accurate, and cheap evaluation of food shape, size, color, lightness, morphology, and texture. Moreover, it can measure changes in appearance over time at each step of the production chain [61]. The e-eye system is based on different elements: light source, camera (in the case of an analog camera, a frame grabber to convert the analog to a digital signal is necessary), computer with software, and high-resolution monitor. As for the human eye, the main factors influencing the operation of vision are the intensity and the type of light. As such, properly designed lights should be considered in order to improve the precision and reliability of the analysis [62]. Generally, the most used light sources include fluorescent and incandescent bulbs, but also LED, quartz halogen, metal halide, and high-pressure sodium lamps are quite popular. The lamp system can be arranged in a circular layout, which is used for flat samples, or scattered layout, used for round-shaped products. The other crucial component of the system is the camera (analog or digital), which is needed to record the image of the samples that are then sent to the computer [61]. Analysis with e-eye is fast and extremely easy: it is non-destructive, it does not require sample preparation and it allows multiple samples and different parameters (i.e., color and shape) in just one run [63]. Among the multiple applications, the e-eye is widespread in the food industry: it is used for the classification of fruits and vegetables, to monitor specific production processes such as aging, fermentation, or roasting, to detect defects and imperfections, and to verify color changes during food storage or processing [64]. Hence, color is strictly linked with food freshness evaluation, especially in perishable food products or processed food quality. For instance, the maturity level of grapes strongly influences the quality traits of the resulting wines. Among the different parameters generally used to monitor the ripening, such as sugar and acidity, polyphenol content plays a crucial role in the color, structure, astringency, and body of the final wine. As such, Orlandi and colleagues [65] tested an e-eye to predict the ripening stages of wine grapes based on their polyphenol content. With e-eye output and modeling approaches, the system was able to predict some important parameters related to grape phenolic ripening, such as color index, tonality, anthocyanins content, and specifically, malvidin-3-O-glucoside and petunidin-3-O-glucoside. The visual parameters detected with the e-eye allow the exclusion of faulty, substandard, or deteriorated products. Some proposed applications are summarized in **Table 3**. However, an important point is that poor and inadequate working conditions, such as scarce illumination, can dramatically change the quality of the images, therefore returning unreliable information. Additionally, the characteristic of the sample surface can scatter or reflect the light and, consequently, the quality of the image. As such, an accurate choice of light sources and intensity based on the environmental conditions and food properties is crucial to obtaining satisfactory results.

Table 3. Examples of E-Eye application for Food Analysis. CCD: Charge-Coupled Device; NIR: near-infrared; CMOS: complementary metal-oxide semiconductor. ANN: artificial neural network; CNN: convolutional neural networks; DFA: discriminant factor analysis; PCA: principal component analysis; PLS: and partial least square; RA: regressive analysis; RF: random forest; SVM: support vector machine; RA: regressive analysis; RF: random forest.

Food Category	Sample	Application	Sensor	Chemometric Approach	Reference
Agri food	Wine grapes	Color changes during ripening	Colorimetric	PLS and PCA	[65]
	Climacteric fruits	Identification of artificially ripened fruits	Colorimetric	CNN	[66]
	Corni Fructus	Discrimination based on color graduation	Colorimetric	DA, PCA, PLS, SVM, and DA	[67]
	Tomato	Quality monitoring during storage	CCD camera	PLS	[68]
	Strawberries	Evaluation of Fungal Contamination	Vis-NIR hyperspectral imaging system	-	[69]
Oils and Dairy products	Citrus oil	Measure the color difference	Colorimetric	DFA	[70]
	Olive oil	Characterization	Colorimetric	PCA	[71]
Meat and fish	Meat	Freshness evaluation	Vis-NIR hyperspectral imaging system	PLS	[72]
Processed products	Dried tangerine peel	Quality evaluation after different processing methods	Colorimetric	DFA	[73]
	Carasau Bread	Monitoring manufacturing process	Colorimetric	ANN	[74]
Beverages	Tea	Quality evaluation	CMOS camera	PLS, SVM, and RF	[75]

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