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Review

# Fusion of electronic nose, electronic tongue and computer vision for animal source food authentication and quality assessment – A review

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ABSTRACT

Electronic nose, electronic tongue and computer vision systems, designed to artificially perceive flavour and appearance, have been increasingly used in the food industry as rapid and reliable tools for quality assessment. The use of multivariate analysis methods, together with electronic senses, has shown to be very powerful; however, due to the high complexity of food, the employment of just single sensor data is often insufficient. In recent years, much research has been performed to develop several data fusion strategies, combining the outputs of multiple instrumental sources, for improving the quality assessment and authentication of food. The aim of this work is to review the recent achievements in the field of artificial sensors' application, in the evaluation of animal source food products.



**Contents**



## 1. Introduction

Nowadays, all food products need to be monitored, in order to ensure an acceptable level of quality and safety. To achieve this objective, several analysis steps must be implemented across the entire food supply chain; beginning from the raw ingredients and extending to the final product (Nielsen, 2010). Consumers prefer safe, nutritious and high-quality food products, and are willing to pay more than the normal price, as long as they receive guarantees about the food they purchased (Kealesitse and Kabama, 2012). Therefore, to compete effectively in the marketplace, food companies must produce foods that meet these consumers' expectations. In addition, to market safe and high-quality foods, attention must be paid to the government regulations and to the policies and standards of international organizations (Nielsen, 2010). Generally, food quality is specified in terms of traceable origin, known

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chemical composition, adequate physical properties, satisfactory sensory evaluation, safety and health safeguards with respect to microbiological and toxic contamination, and is influenced by the processing and storage. Once food authentication has been granted, the main basic technique for quality assessment from the consumer point of view is sensory analysis (Borras et al., 2015), which is based on the examination of a product through the evaluation of the attributes perceptible by the five sense organs (Piana et al., 2004). This method allows to establish the organoleptic profile of diverse products, however, suffers from several disadvantages. Sensory analysis is considered time consuming and expensive (Kiani et al., 2016), subjective (depending upon the professional acumen of the personnel involved), inconsistent and unpredictable, due to various human factors (Banerjee et al., 2016), and requires a panel of skilled assessors. On the other hand, conventional standard methods for gas or liquid-phase detection and analysis usually rely on the utilization of precision laboratory instruments like gas chromatography–mass spectrometry (GC-MS). These methods, providing an accurate approach for the analysis of type and concentration of the single component in a mixture of substances, may be considered a useful sensorial tool for food flavour analysis. However, they are laborious and time-consuming, require considerable analytical skills, involve a lot of tedious and complex pretreatment of samples, and use many hazardous organic reagents that require high costs for storage and disposal (Huang et al., 2015). In recent years, much research has been performed to substitute the perception of human senses with "artificial sensors", instruments providing signals related to the sensory attributes (Borras et al., 2015). In this regard, advances in sensor technology, electronics, biochemistry and artificial intelligence led to the development of instruments such as electronic nose (E-Nose), electronic tongue (E-Tongue) and computer vision systems (CVSs), capable of measuring and characterizing aroma, taste and colour of various products (Wilson and Baietto, 2009; Ghasemi-Varnamkhasti et al., 2011; Cubero et al., 2011). Despite commercial systems are still expensive, their cost can be amortized in terms of reduced time and cost of analysis. Several advantages are offered by the applying of electronic senses, over the aforementioned techniques, and a complete view is given in Table 1.

As the ideal method for in-line process control should enable direct, rapid, precise, and accurate determination of several target compounds, with minimal or no sample preparation and reagent consumption, chemical multisensor systems are one of the most promising approaches in this field (Fig. 1). The real time monitoring of production processes is an actual food industry need; however, the analysis are performed off-line by wet chemical assays, often involving enzymatic reactions or separation techniques (Peris and Escuder-Gilabert, 2013). In this regard, several papers were recently published in the literature (Peris and Escuder-Gilabert, 2013; Ghasemi-Varnamkhasti and Aghbashlo, 2014; Wei et al., 2017; Hosseinpour et al., 2013). A novel method combining the

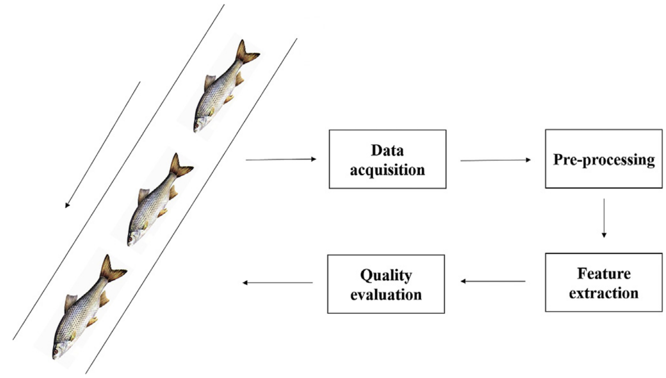


**Fig. 1.** Suitability of E-Nose, E-Tongue and CVS for in-line monitoring, modified from Gunasekaran (1996).

artificial senses, called "sensor fusion", is increasingly used in food quality assessment. Fusion of data coming from complementary sensors has been applied to a wide range of food and beverages, to authenticate origin and assess quality, enhancing significantly the performance of the same instruments when used individually. The aim of this work is to review the achievements in the field of artificial sensor (nose, tongue and eye) application in the evaluation of animal source food products considering the most relevant contributions in this field over the past five years. After a brief comment of the principles behind the design of electronic sensors, the review will focus on the description of data analysis and fusion methods.

## 2. E-Nose

In the food' industry, monitoring of products, in terms of quality and control of production processes, are performed via physico-chemical measurements, despite the extreme importance of aroma as an indicator of quality and product conformity. This was mainly due to the lack of reliable odour assessing instruments (Ampuero and Bosset, 2003). The electronic nose is a technology designed to mimic the olfactory system of humans (Song et al., 2013). Gardner and Bartlett (1994) defined an electronic nose as an instrument that comprises an array of electronic chemical sensors with partial specificity and an appropriate pattern-recognition system that is capable of recognizing simple or complex odours (Fig. 2). Before the advent of solid-state gas sensors arrays, the term "electronic nose" was related to the techniques used in the identification and quantification of volatile compounds, in the headspace of a product, such as gas chromatography-mass spectrometry (GC-MS), gas chromatography-flame ionization detector (GC-FID) and solid-phase micro extraction-mass spectrometry (SPME-MS), coupled with multivariate statistical analysis (Marsili, 1999). Today, the electronic noses are instruments, based on the interaction of

**Table 1**
Comparison between electronic senses, sensory analysis and conventional laboratory instruments features.

| Feature | E-Nose | E-Tongue | Computer Vision | Sensory analysis | Conventional laboratory instruments |
|---|---|---|---|---|---|
| Rapidness | Yes | Yes | Yes | No | No |
| Low-cost analysis | Yes | Yes | Yes | No | No |
| Use of chemicals | No | No | No | No | Yes |
| Objectiveness | Yes | Yes | Yes | No | Yes |
| Non-destructive measurements | Yes | No | Yes | Yes | No |
| Sample pre-treatment | No | Yes | No | No | Yes |
| Simplicity | Yes | Yes | Yes | No | No |
| Single operator | Yes | Yes | Yes | No | Yes |
| Permanent storage of data | Yes | Yes | Yes | Yes | Yes |

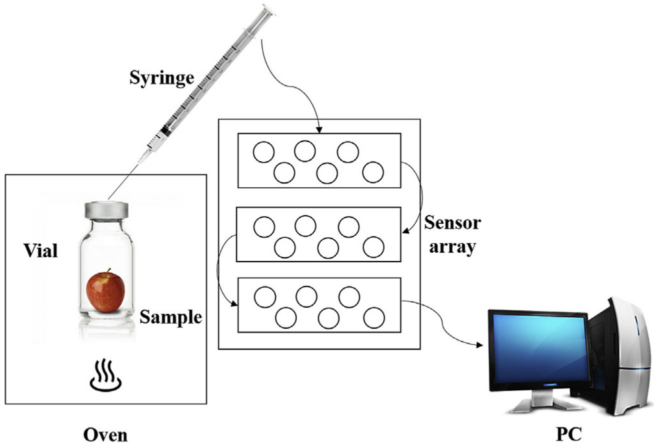


**Fig. 2.** Components of E-Nose.

semi-selective sensors with volatile compounds. Several types of sensors are employed in the electronic nose architectures, and the most popular are reported in Table 2.

A specific description of sensor characteristics and properties is outside the scope of this review. Interested readers are referred to the following reviews for details on this topic (Albert et al., 2000; Schaller et al., 1998; Nagle et al., 2002; Ampuero and Bosset, 2003; James et al., 2005). The concept of an artificial nose system was proposed by Persaud and Dodd (1982). At the beginning of the 1990s the first applications of the electronic nose for food analysis appeared (Winquist et al., 1993; Olafsson et al., 1992). Later on, E-Noses have been used in various research fields; however, the most attention has been paid to the food industry. At research and food industry levels, the E-Nose technology have been employed for quality control of raw and manufactured products: process, freshness and maturity monitoring, shelf-life investigations, authenticity assessments of premium products and microbial pathogen detection. These research topics and food industry requirements in term of food analysis have been identified by Schaller et al. (1998). Since then, a huge literature regarding this topic can be found (Loutfi et al., 2015). The most recent applications, last 5 years, of electronic noses in food assessment are listed in Table 3.

These results indicate that the most recent E-Nose applications, in food industry, remained unchanged over time. Many differences are found, instead, in the data collection and elaboration processes. The technologic advance led to the wide diffusion of commercial electronic noses, automated and with a greater number of sensors, further, the devices miniaturization brought to portable electronic noses. Next to the instrumental evolution, there was an improvement of the signal processing techniques. An example is the building of accurate predictive models, based on PLS, MLR, SVM and ANN, for the determination of quality parameters (Huang et al., 2015) or adulterants detection and quantification (Tian et al., 2013). Although the E-Nose technology offers various advantages over traditional analysis, such as the reduction in time and cost of analysis, and its environmentally friendly nature (Smyth and Cozzolino, 2013); the sensors still present a number of weak points. These includes the noise by major compounds, which may not be relevant to aroma (Rodriguez-Mendez et al., 2004); the sensor drift or poisoning (Loutfi et al., 2015), and the responses obtained by each sensor, which provide highly ambiguous qualitative or quantitative information, resulting in a sort of "fingerprint" of the sample (Ampuero and Bosset, 2003).

Recent trends to overcome sensor shortcomings include:

- The integration of electronic nose analysis with gas chromatography: Cheng et al. (2013), for example, employed an electronic nose to distinguish different propolis samples, according to their geographical origin. Moreover, via DHS-GC/MS, they were able to identify the volatile compounds most correlated with the discrimination;
- The development of hybrid electronic noses, based on the combination of different sensor technologies: the most common utilization of hybrid systems involve MOS and MOSFET, however, commercial system are available that use MOS, MOSFET and BAW in various combinations. The major advantage of this type of electronic nose is that it incorporates the advantages inherent to the different transducer technologies, at the same time giving a choice for which chemical sensors can be used (Kiani et al., 2016).

Another aspect is the humidity of the headspace above a food sample. With sensors that are reactive to the presence of water, this may be an interfering factor, as the water vapour concentration in the headspace is normally orders of magnitude higher than the concentration of the aroma compounds, whose presence one wishes to detect (Visser and Taylor, 1998). To deal with this interference, two methodologies are commonly used. One is sample pre-treatment to obtain fixed experimental conditions, and the other is a parametric compensation by additional measuring of the variable parameters and calibration under, *e.g.*, different humidity conditions (Rock et al., 2008). An universal E-Nose, able to cope with every odour type, is non realistic. Therefore, data processing and instrumentation must be specifically designed for each application.

**Table 2**
E-Nose: most popular sensors.

| Sensors | Description | References |
|---|---|---|
| MOS (Metal-oxide semiconductor) | metal-oxide semiconducting film (SnO2, $TiO_2$, ZnO, $ZrO_2$), coated onto a substrate. Oxygen from the air is dissolved in the sensor lattice setting its electrical resistance to a background level. During the measurement, the volatile molecules are adsorbed at the surface of the semiconductor, where they react with the oxygen species, causing a modification of the sensor resistance. | Ampuero and Bosset, 2003 |
| CP (Conducting polymer) | conducting organic polymer sensors, made of semiconducting materials, aromatic or heteroaromatic, such as polypyrrole, polyaniline, polythiophene, polyindole, deposited onto a substrate and between two gold-plated electrodes, whose electrical conductivity is altered in response to organic vapours. | Ampuero and Bosset, 2003; James et al., 2005 |
| Piezoelectric crystal sensors, including BAW (Bulk acoustic wave) and SAW (Surface acoustic wave) | consist of a piezoelectric quartz, $LiNbO_3$, or $LiTaO_3$ crystal, coated with a membrane, which, depending on its affinity, selectively adsorbs the volatile molecules present. Adsorption of volatile compounds onto the sensing membrane increases the mass of the device resulting in a change in its resonance frequency | Ampuero and Bosset, 2003 |

**Table 3**
Application of electronic noses, in the last 5 years, on food assessment.

| Category | Application | Electronic nose model | Number of sensors and technology | Reference |
|---|---|---|---|---|
| Pork | Rapid identification for *halal* authentication | zNose | 1 SAW | Nurjuliana et al., 2011 |
| | Predicting shelf-life | FOX 4000 | 18 MOS | Tang et al., 2013 |
| | Effects of kimchi and smoking on quality characteristics and shelf-life of cooked sausages | 7100 zNose | 1 SAW | Kim et al., 2014 |
| | Measuring total volatile basic nitrogen and total viable counts during refrigerated storage | PEN3 | 10 MOS | Li et al., 2016 |
| Cheese | Classification of Pecorino | EOS 507 | 6 MOS | Cevoli et al., 2011 |
| | Consumer acceptability of ovine cheese from ewes fed extruded linseed-enriched diets | EOS 835 | 6 MOS | Branciari et al., 2012 |
| | Physicochemical and textural properties of reduced fat Cheddar | zNose | 1 SAW | Nateghi et al., 2012 |
| | Discrimination of cow feeding with olive by-product from cheese | FOX 4000 | 18 MOS | Di Rosa et al., 2015 |
| | Detect the authenticity of Parmigiano-Reggiano | EOS 835 | 6 MOS | Sberveglieri et al., 2015 |
| Egg | Prediction of TVB-N in eggs | PEN3 | 10 MOS | Liu and Tu, 2012 |
| | Discriminating eggs from different poultry species | FOX 4000 | 18 MOS | Wang et al., 2014 |
| Fish | Species discrimination among three kinds of puffer fish | FOX 4000 | 18 MOS | Zhang et al., 2012 |
| | Detection of off-flavours in catfish | AromaScan A32S | 15 CP | Wilson et al., 2013 |
| | A model for discrimination freshness of shrimp | Figaro Engineering | 6 MOS | Du et al., 2015 |
| Mutton | Analysis of pork adulteration in minced mutton | PEN2 | 10 MOS | Tian et al., 2013 |
| Butter | Development of a method for butter type differentiation | PEN2 | 10 MOS | Lorenzen et al., 2013 |
| Ham | Characterization and differentiation of Italian Parma, San Daniele and Toscano dry-cured hams | PEN2 | 10 MOS | Laureati et al., 2014 |
| Yogurt | Flavour analysis of stirred yoghurt with cheddar cheese adding | FOX 4000 | 18 MOS | Li et al., 2014 |
| Honey | Botanical origin identification and quality determination of honey | FOX 4000 | 18 MOS | Huang et al., 2015 |
| Poultry | Contribution of chicken base addition to aroma characteristics of Maillard reaction products | FOX 4000 | 18 MOS | Xiao et al., 2015 |
| | Rapid measuring and modelling flavour quality changes of oxidized chicken fat | FOX 4000 | 18 MOS | Song et al., 2013 |
| Beef | Quality assessment of beef fillets | LibraNose | 8 BAW | Mohareb et al., 2016 |
| | Rapid detection of meat spoilage | LibraNose | 8 BAW | Kodogiannis, 2016 |

## 3. E-Tongue

Hayashi et al. (1990) proposed the first electronic tongue concept, called “taste sensor”, which consisted of a multichannel electrode with transducers composed of lipid membranes immobilized with a polymer, for the intension of mimicking the functions of human gustatory receptors. The taste we perceive is composed of five kinds of taste qualities: sourness, saltiness, sweetness, bitterness and umami. Additional quality are pungency and astringency, which are related to the sense of pain (Tahara et al., 2013) (Table 4). The objective of the electronic tongue technology is to study the chemical substances showing the five basic taste qualities. Afterward, other tastes like astringent and pungent substances were investigated (Zou et al., 2015).

The electronic tongue can be described as an analytical tool, including an array of non-specific, poorly selective chemical sensors, with partial specificity (cross-selectivity), coupled with chemometric processing, for recognizing the qualitative and quantitative composition of multispecies solutions (Fig. 3) (Ha et al., 2015). A variety of chemical sensors can be employed in the design of electronic tongues: electrochemical (voltammetric, potentiometric, amperometric, impedimetric, conductimetric), optical or enzymatic sensors (biosensors). However, most of these systems are based on potentiometric sensors (Ciosek and Wroblewski, 2011). In potentiometry, a potential is measured between two electrodes under the conditions of no current flow. The measured potential may then be used to determine the analytical quantity of interest, generally the concentration of some component of the solution (Zou et al., 2015). Ion-selective electrodes (ISEs) represent the largest group among potentiometric sensors (Ciosek and Wroblewski, 2011). The potential of the ion-selective electrodes is a function of the activity of ionic species in a sample

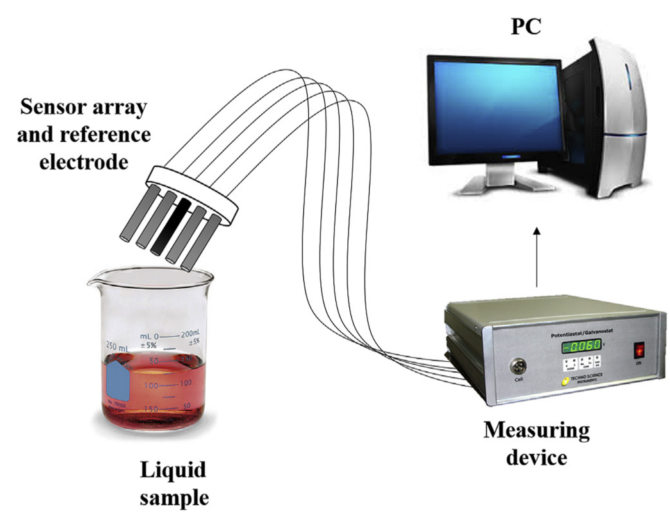


**Fig. 3.** Components of E-Tongue.

**Table 4**
Chemical substances showing the five basic taste qualities, pungency and astringency, as reported by Toko et al., 2016.

| Taste | Main materials |
|---|---|
| Sweetness | Sucrose, glucose, artificial sweetener |
| Saltiness | Cations, represented by sodium ions |
| Sourness | Dissociated hydrogen ions from acetic acid, hydrochloric acid, citric acid, etc. |
| Bitterness | Caffeine, theobromine, quinine, humulone |
| Umami | Monosodium glutamate (MSG), disodium inosinate (IMP), disodium guanylate (GMP) |
| Astringency | Tannin-based compounds |
| Pungency | Capsaicin, allyl isothiocyanate, piperine |

solution and is formed in the ion-sensitive membrane, where selective complexation (ion recognition) of the analyte molecules occurs (Ciosek and Wroblewski, 2007). Potentiometric ion and chemical sensors based on field-effect devices form another group of transducers that can be easily miniaturized and are fabricated by means of microelectronic technology. Among them, most studies are ion-sensitive field-effect transistors (ISFETs), with different ion-selective membranes (often also called chemically sensitive field-effect transistors or Chem-FETs) (Zou et al., 2015). Voltammetric sensors have been extensively used in E-Tongue systems, as well. Voltammetry is a very powerful analytical technique, due to features such as its very high sensitivity, versatility, simplicity and robustness. Normally, redox-active compounds are oxidized or reduced at the working electrode, giving rise to a current, which is measured at a fixed potential. When a complex media, consisting of several redox-active species and various ions, is analysed, the selectivity of the system is often insufficient for specific analysis of single components. Thus, rather complicated voltammograms are obtained and the interpretation of data usually rely on multivariate analysis methods. The first prototype of a voltammetric E-Tongue was proposed by Winquist et al. (1997), which were able to classify various fruit drinks and milk, and also follow some aging processes. Later, an E-Tongue based on chemically modified voltammetric electrodes was successfully employed for the evaluation of polyphenolic content in extra virgin oils (Rodriguez-Mendez et al., 2008). Finally, the group of del Valle developed an E-Tongue system, based on voltammetric sensors with different modifiers (metallic nano-sized particles and conducting polymers), capable of distinguishing between different kinds of Cava wines (Cetò et al., 2010). However, we suggest the reading of the following reviews for detailed information about E-Tongue sensor technologies (Ha et al., 2015; Zou et al., 2015; Ciosek and Wroblewski, 2007). Over the past years, the E-Tongues have emerged as rapid and easy-to-use tools, very promising for evaluation of food quality, especially in such situations in which only qualitative or semi-quantitative information is required (Escuder-Gilabert and Peris, 2010). A search of the recent, relevant literature shows that the major categories of use for electronic tongues are freshness evaluation and shelf life investigation; process monitoring; quality control studies; authenticity assessment and foodstuff recognition (Escuder-Gilabert and Peris, 2010). Some examples of the most recent electronic tongue applications are reported in Table 5.

The E-Tongue employment is easy for liquid food products (milk, eggs, yogurt and honey), whose preparation is limited to dilution and/or filtration, but laborious for solids. Different authors reported the procedure for ham (Dang et al., 2015) and beef (Zhang et al., 2015; Apetrei and Apetrei, 2016) test sample solutions preparation. The process involves the sample homogenization with a solvent, a centrifugation, the aqueous supernatant separation and its filtration. However, other authors (Gil et al., 2011; Ruiz-Rico et al., 2013), using laboratory-made electronic tongues, based on metallic electrodes, reported an alternative method, which consist in introducing the sensors directly in the crude samples. The main disadvantages of E-Tongue sensors are that they are easily affected by environmental conditions *i.e*. temperature and humidity, which may cause sensor drift (Wadehra and Patil, 2016), and the adsorption of solution components that influence the membrane potential (Escuder-Gilabert and Peris, 2010). These factors can be minimized by controlling the room temperature and washing the electrodes, alternating a cleaning beaker (containing water) to the samples solutions during the analysis. Even with technological advances and promising results, these sensors still cannot mimic the biological features of human tongue, concerning identifying elusive analytes in complicated mixtures. In this case, bio-electronics tongues, equipped with enzymatic and gustatory receptor-based biosensors array, can provide taste signals triggered by the binding activities between selective taste receptors and tastants, making it possible to develop artificial taste sensors that more closely mimic human taste system (Ha et al., 2015).

## 4. CVS

Computer vision is the science that develops theoretical and algorithmic basis to automatically extract and analyse useful information about physical objects from images (Wu and Sun, 2013). Timmermans (1998) states that it encloses the capturing, processing and analysis of two-dimensional images, with others noting that it aims to duplicate the effect of human vision by electronically perceiving and understanding an image (Sonka et al., 1993). In general, the hardware configuration of a computer vision system consists of an illumination device, a camera, a personal computer and a high-resolution monitor (Wu and Sun, 2013) (Fig. 4). As in the case of the human eye, the operation of CVS depends on the intensity of lighting. Properly designed lighting can improve the precision of analysis and decrease analysis time. Fluorescent and incandescent bulbs are the most frequently used light sources. Luminescent electric diodes (LEDs), quartz halogen lamps, metal halide lamps and high-pressure sodium lamps are also used (Sliwinska et al., 2014). Moreover, a camera converting photons to electrical signals is used (Wu and Sun, 2013). There are two types of cameras, that is, analog and digital cameras, which are equipped with CCD (Charged-coupled device) or CMOS (Complementary metal-oxide semiconductor) sensor arrays. In an analog camera, the recorded image is transformed into the analog signal and then transferred to a frame grabber, which transforms the analog signal into a digital data stream and sends it to the computer memory. In digital cameras, a frame grabber is not needed because the analog signal is sent directly to the computer via a USB or FireWire adapter (Sliwinska et al., 2014). Interested readers are referred to the following reviews for a specific description of computer vision systems components (Wu and Sun, 2013; Sliwinska et al., 2014). The image processing and the image analysis represent the core of computer vision (Krutz et al., 2000). Image processing involves a series of operation that enhance the quality of an image in order to remove defects. Image analysis is the process of distinguishing the objects from the background and producing quantitative information (Brosnan and Sun, 2004). As a non-destructive detecting approach, CVS have been used increasingly in the food industry for inspection and evaluation purposes as they provide suitably rapid, economic, consistent and objective assessment (Sun, 2000). Precisely, CVSs are feasible to classify food products into specific grades, detect defects and estimate properties such as colour, shape, size, surface defects, and contamination (Ma et al., 2016). Some examples are listed in Table 6.

Results show how CVS applications are targeted at those food products for which the appearance is the main key quality attribute evaluated by the consumers. In freshness assessment of seafood products, sensory evaluation is a prevalent procedure and gives valuable information about the quality and consumer acceptance. This method is based on significant appearance parameters such as, skin, slime, eyes, gills and belly (Dowlati et al., 2013). Further, consumers associate freshness of red meat with a homogeneous, bright cherry-red colour and consider dark red, purple or brown meat as unacceptable (Sun et al., 2011). Traditionally, quality inspection of agricultural and food products has been performed by human graders. However, in most cases these manual inspections are time-consuming and laborious. Moreover, the accuracy of the tests cannot be guaranteed (Park et al., 1996). The applying of computer vision techniques could offer several advantages, including:

**Table 5**
Electronic tongues applications, in the last 5 years, on animal source food assessment.

| Category | Object of investigation | Principle of detection | Reference |
|---|---|---|---|
| Milk | Detection of antibiotic residues | Voltammetry | Wei and Wang, 2011 |
| | Discrimination of urea and melamine adulterated skimmed milk powder | Voltammetry | Hilding-Ohlsson et al., 2012 |
| | Monitoring of quality and storage time | Voltammetry | Wei et al., 2013a |
| | Brands classification | Voltammetry | Yu et al., 2015 |
| | Qualitative analysis of milk adulterated with urea | Voltammetry | Li et al., 2015 |
| Pork | Monitoring of physical–chemical and microbiological changes under cold storage | Potentiometry | Gil et al., 2011 |
| Poultry | Changes of flavour compounds of hydrolysed chicken bones during Maillard reaction | Potentiometry | Sun et al., 2014 |
| Honey | Discrimination according to the botanical origin | Potentiometry | Escriche et al., 2012 |
| | Tracing floral and geographical origins | Potentiometry and Voltammetry | Wei and Wang, 2014 |
| Ham | Artificial neural networks analysis of the data obtained with an electronic tongue, applied to ham-curing process with different salt formulations | Potentiometry | Gil-Sanchez et al., 2015 |
| | Comparison of umami taste peptides in water-soluble extractions | Voltammetry | Dang et al., 2015 |
| Yogurt | Evaluation of varieties | Voltammetry | Wei et al., 2013b |
| Beef | Flavour assessment, recognition and chemical compositions according to its correlation with flavour | Potentiometry | Zhang et al., 2015 |
| | Detection of ammonia and putrescine | Voltammetry | Apetrei and Apetrei, 2016 |
| Fish | Freshness monitoring | Voltammetry | Apetrei et al., 2013 |
| | Quality assessment | Voltammetry | Ruiz-Rico et al., 2013 |

- The rapidness, preciseness, objectiveness, efficiency and non-destruction of the measurement with low cost and no sample pre-treatment (Wu and Sun, 2013);


**Fig. 4.** Components of CVS.

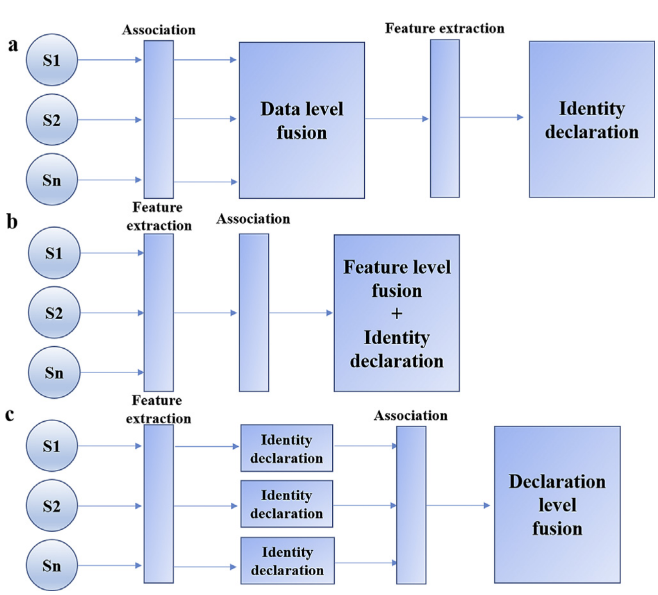


**Fig. 5.** a) Low-level fusion process, b) Mid-level fusion process, c) High-level fusion process.

- The permanent storage of data, allowing further analysis later (Tarbell and Reid, 1991);
- Image capturing and illumination devices are easy to mount, remove, replace, and upgrade;
- The possibility of automation for in-line monitoring and controlling of industrial scale food operations (Hosseinpour et al., 2013).

However, extra chemical composition information cannot be extracted by using CVSs. With the help of spectrometry, chemical composition information can be obtained successfully (Ma et al., 2016). With hyperspectral imaging technique, several authors achieved excellent results in a variety of applications; few examples are reported in Table 7.

Further, the employment of 3-dimensionals cameras may help to improve analysis, provide more information and allow the study of complex or irregular-shape materials with fewer errors and less time (Ma et al., 2016). Mortensen et al. (2016), for example, recently reported the development of a fully automated, 3D camera-based weighing system for broiler chickens. In addition, these devices may find application in texture analysis, so far based on 2D image sequences, where the texture distribution is limited to a single plane. The use of three-dimensional images could help to avoid the loss of information when texture features are studied from different orientations (Avila et al., 2015).

## 5. Statistical approach

A measurement performed by means of electronic senses generates a vast volume of data; therefore, it is necessary to apply methods of data analysis, which allow for data classification (Sliwinska et al., 2014). The use of multivariate analysis methods, together with sensor arrays, has shown to be very powerful. Two main issues are dealt with, to search for a structure and correlation in the data, or to make a model from a training set of data, which is then used to make predictions from test data (Zou et al., 2015). So far, many pattern analysis techniques for data analysis of sensor array measurements were presented (Ciosek and Wroblewski, 2007). The most popular are listed in Table 8:

These techniques are routinely used in conjunction with electronic senses. Some examples are listed below (Table 9).

**Table 6**
Computer vision application, in the last 5 years, on animal source food.

| Category | Object of investigation | Device | Quality attribute measured | References |
|---|---|---|---|---|
| Poultry | Estimation of fat content | Generic digital camera | Colour | Chmiel et al., 2011a |
| Pork | Lightness of the colour as a factor for assessing the quality | CMOS | Colour | Chmiel et al., 2011b |
| | Evaluating the appearance of Lucanian dry sausage | CMOS | Colour | Girolami et al., 2014 |
| | Prediction of colour attributes | Generic digital camera | Colour | Sun et al., 2016 |
| | Detection of PSE | CMOS | Colour | Chmiel et al., 2016 |
| | Defect detection | CMOS | Colour | Chmiel and Slowinski, 2016 |
| | Tracking meat cuts in slaughterhouses | Microsoft Kinect camera | Colour | Larsen et al., 2014 |
| Beef | Predicting colour grade | Generic digital camera | Colour | Sun et al., 2011 |
| | Measurement of colour | CMOS | Colour | Girolami et al., 2013 |
| Egg | Identification of micro-crack | CCD | Defects | Li et al., 2012 |
| | Expert grading system | CCD | Size and defects | Omid et al., 2013 |
| | Volume prediction | CCD | Size | Soltani et al., 2014 |
| | External and internal defect detection | Generic digital camera | Defects | Arivazhagan et al., 2013 |
| Fish | Quantification of gaping, bruising, and blood spots in salmon fillets | Generic digital camera | Defects and colour | Balaban et al., 2011 |
| | Species classification | Smartphone | Colour | Hu et al., 2012 |
| | Estimation of sushi shrimp weight | CCD | Size | Poonnoy and Chum-in, 2012 |
| | An efficient shape analysis method for shrimp | CCD | Size | Lee et al., 2012a |
| | Freshness assessment | CCD | Colour | Dowlati et al., 2013 |
| | Online monitoring of shrimp colour changes during drying | CCD | Colour | Hosseinpour et al., 2013 |
| | Classification of boiled shrimp's shape | Generic digital camera | Shape | Poonnoy et al., 2014 |
| Honey | Characterization | CCD | Colour | Shafiee et al., 2014 |

**Table 7**
Recently reported hyperspectral image applications.

| Object of investigation | Image processing | Optimal wavelength selection | Multivariable data analysis | References |
|---|---|---|---|---|
| Rapid evaluation of thiobarbituric acid (TBA) value in grass carp fillet | Calibration, identification of ROI (Region of interest), spectra extraction, MSC (Multiplicative scatter correction) | RC (Regression coefficients) | PLSR, MLR (Multiple linear regression) | Cheng et al., 2015 |
| Non-destructive prediction of thiobarbituric acid reactive substances (TBARS) value for freshness evaluation of chicken meat | Calibration, identification of ROI, spectra extraction, MSC | SPA (Successive projection algorithm) | PLSR | Xiong et al., 2015a |
| Model improvement for predicting moisture content in pork *longissimus dorsi* muscles under diverse processing conditions | Calibration, identification of ROI, spectra extraction, GLGCM (Grey-level-gradient co-occurrence matrix) | RC | PCA, PLSR | Ma et al., 2017 |
| Rapid prediction of hydroxyproline content in chicken meat | Calibration, identification of ROI, spectra extraction | RC | PLSR | Xiong et al., 2015b |
| Quantitative determination of total pigments in red meats | Calibration, identification of ROI, spectra extraction | RC, SPA | PLSR | Xiong et al., 2015c |

## 6. Sensor fusion

Due to the high complexity of food, the employment of just single sensor data, E-nose or E-tongue or E-eye, is insufficient, and multi-sensor data fusion techniques, combining the outputs of multiple instrumental sources, represent the challenge for improving the quality assessment and authentication of food (Borras et al., 2015). Fusion of data from complementary sensors, responding to different signature phenomena, may increase the probability of correct classification; therefore, characteristics that are not classified by one sensor may be apparent or measured by another (Banerjee et al., 2016). However, this is not always true in practical experience, because not all features are important for understanding or representing the underlying phenomenon of interest (Liu et al., 2009). In general, multi-sensor data fusion is the technique related to problem of how to combine data from one or multiple (and possibly diverse) sensors, in order to make inferences about a physical event, activity or situation (Masnan et al., 2012). Mitchell (2007) defined multi-sensor data fusion as the theory, techniques, and tools, which are used for combining sensor data, or data derived from sensory data into a common representational format (Masnan et al., 2012). Fusion processes are often categorized in a three-level model, distinguishing low, intermediate, and high level fusion (Elmenreich, 2002). It is important to note that all three levels use feature extraction, transforming the raw signal provided by the sensor into a reduced vector of features describing parsimoniously the original information, and identity declaration that assigns a quality class to the measured produce based on the feature extraction process (Zou et al., 2015). The different data fusion approaches are described in Table 10.

In summary, low-level fusion is conceptually simple (Borras et al., 2015) and it is believed the most accurate technique (Hall and Llinas, 1997), due to the fact that the originality information from each sensor is maintained and used in further processes (Masnan et al., 2012). Some limitations are a high volume data and the possible predominance of one data source over the others. This is partially overcome by mid-level fusion, where feature extraction significantly reduces the data dimensionality (Borras et al., 2015). In addition, low-level fusion necessitates consubstantial sensors and extensive data manipulation, takes a lot of time, and could not be used for real-time data processing (Kiani et al., 2016). Feature level fusion is very useful for non-commensurate type data, *i.e.*, if sensors are looking for different physical parameters (Banerjee et al., 2016). Here, the challenge is to find the optimal combination of extracted features and pre-processing that describe the significant variation of the instrumental responses and provides the best final model (Borras et al., 2015). High-level fusion, finally, allows focusing on each individual techniques, but the final identity declaration is

**Table 8**
Most frequently used statistical analysis coupled with sensor arrays.

| Technique | Description | References |
|---|---|---|
| PCA (Principal components analysis) | is a dimension reduction technique that creates a few new variables called principal components (PCs) from linear combination of the original variables. For highly collinear data, a few principal components retain the same information as many original variables, and allow the distribution of samples and variables to be easily plotted and visually analysed. Because is easy to use, this unsupervised exploratory technique is usually applied prior to any other more complex classification or prediction. | Borras et al., 2015 |
| ANNs (Artificial neural networks) | are computational models, inspired by the way biological nervous systems, which goal is to solve problems in the same way that the human brain would. ANNs are composed of a large number of densely interconnected adaptive simple processing elements (called artificial neurons or nodes), distributed in different layers. The first layer is called "input layer" and is responsible for inputting data into the network. The number of neurons in this layer equals the number of values that are concurrently being fed into the network. The last neuron layer, a so-called "output layer", is used to generate the output values. Hidden layers, which do not interact with the external environment, can be present between the input and output layers. Neurons assigned to specific hidden layers process the input information into the output information. A vast number of networks, new or modifications of existing ones are being constantly developed. Backpropagation (BP) and radial basis function (RBF) networks are the most frequently used in data fusion. In the first type, the term backpropagation refers to the way the error is propagated backward from the output layer, to the hidden layer, and finally to the input layer. The second type of networks, unlike the sigmoid transfer function in BPANNs, employ a radial basis function (such as a Gaussian kernel). In general, ANNs are more robust and often outperform other computational tools in solving a variety of problems ranging from modelling, classification, pattern recognition and multivariate data analysis. | Zou et al., 2015<br>Basheer and Hajmeer, 2000<br>Sliwinska et al., 2014<br>Borras et al., 2015<br>Haykin, 1994<br>Goyal and Goyal, 2011<br>Debska and Guzowska-Swider, 2011 |
| LDA (Linear discriminant analysis) | is most commonly used as dimensionality reduction technique in the pre-processing step for pattern classification and machine learning applications. The goal is to project a dataset onto a lower-dimensional space with good class-separability in order avoid overfitting and reduce computational costs. The general LDA approach is very similar to a PCA, but in addition to finding the component axes that maximize the variance of our data, we are additionally interested in the axes that maximize the separation between multiple classes. Both LDA and PCA are linear transformation techniques that are commonly used for dimensionality reduction. PCA can be described as an "unsupervised" algorithm, since it "ignores" class labels and its goal is to find the directions (the so-called principal components) that maximize the variance in a dataset. In contrast to PCA, LDA is "supervised" and computes the directions ("linear discriminants") that will represent the axes that maximize the separation between multiple classes. Although it might sound intuitive that LDA is superior to PCA for a multi-class classification task where the class labels are known, this might not always the case. In practice, it is also not uncommon to use both LDA and PCA in combination, *e.g.*, PCA for dimensionality reduction followed by an LDA. | Raschka, 2014<br>Martinez and Kak, 2001 |
| PLSR (Partial least square regression) | combines features from and generalizes PCA and multiple linear regression. Its goal is to analyse or predict a set of dependent variables from a set of independent variables or predictors. This prediction is achieved by extracting from the predictors a set of orthogonal factors called latent variables, which have the best predictive power. PLSR is particularly useful when we need to predict a set of dependent variables from a (very) large set of independent variables (*i.e.*, predictors). This approach originated in the social sciences, but became popular first in chemometrics and then in sensory evaluation. | Abdi, 2010 |
| SVM (Support vector machines) | is a supervised machine learning algorithm that can be used for either classification or regression challenges. However, it is mostly used in classification problems. Similarly to ANN, the assignment of objects to specific classes by the SVM method is realized with the use of a training set. The underlying principle of SVM is the creation of an optimal hyperplane that would separate the data belonging to the opposite classes, with the highest possible confident margin. | Sliwinska et al., 2014 |

obtained from only a few values. One advantage is that every individual matrix is treated independently, and the results from inefficient techniques do not worsen the overall performance as much as in the other fusion levels. However, the classification or regression models that work best for each block needs to be determined, to ensure better performances than individual models (Borras et al., 2015). This requires a knowledge base of the target, substantial pre-processing and causes considerable information losses (Kiani et al., 2016). Data fusion has been applied to a wide range of food and beverages to authenticate origin and assess quality. Most of the analysis combine gas sensor and liquid sensor devices and, sometimes, UV–Vis spectroscopy or CVSs, considered as an E-eye. These techniques used all together are called "electronic panel" since they emulate the human panel responses when sensory analysing the products (Borras et al., 2015). The following table summarizes the main recently applications of data fusion in animal source food (Table 11).

Overall results shows clearly an increase in the classification accuracies, using fusion methods, compared to any of the single modality data. Zakaria et al. (2011) found the electronic nose and tongue to be ineffective in the discrimination of different honey samples. However, by applying data fusion, the classification of honey with different floral origin, sugar syrups and adulterated samples was achieved. In this experiment, PCA and LDA were chosen to perform the low-level fusion, while PNN was used to verify and validate the fusion of data. Other authors (Subari et al., 2014) reported the honey concentration estimation mean absolute error result of single modality, based on electronic nose or FT-IR that was 15.0%; higher compared to fusion result, which gave 6.9%. In this work, 32 resistances of electronic nose and 5 selected peaks of FT-IR spectra were used to train a MLP-ANN in order to achieve the estimation task. In addition, multi-sensor data fusion

**Table 9**
Multivariate statistical analysis applied to animal source food assessment.

| Technique used | Object of investigation | Device | Reference |
|---|---|---|---|
| PCA | Classification of Hairtail fish and pork freshness | E-nose | Tian et al., 2012 |
| | Geographical origin identification of propolis | E-nose, GC-MS | Cheng et al., 2013 |
| | Discriminating eggs from different poultry species | E-nose | Wang et al., 2014 |
| ANNs | Eggshell crack detection | CVS, Acoustic response | Pan et al., 2011 |
| | Classification of Pecorino cheeses | E-nose | Cevoli et al., 2011 |
| | Honey characterization | CVS | Shafiee et al., 2014 |
| | Classification of boiled shrimp's shape | CVS | Poonnoy et al., 2014 |
| | Eggs volume prediction | CVS | Soltani et al., 2014 |
| | Honey purity estimation | E-nose, FT-IR | Subari et al., 2014 |
| | Analysis of ham-curing processes with different salt formulations | E-tongue | Gil-Sanchez et al., 2015 |
| LDA | Discrimination between products made from Iberian pigs and from other pigs | E-nose | Gonzalez-Martin et al., 2000 |
| | Discrimination of meat from llama and alpaca | E-nose | Neely et al., 2001 |
| | Honey quality assessment | E-nose, E-tongue | Masnan et al., 2012 |
| PLSR | Evaluation of meat quality in relation to storage time | E-nose | Vestergaard et al., 2007 |
| | Rapid measuring and modelling flavor quality changes of oxidized chicken fat | E-nose | Song et al., 2013 |
| SVM | Predict fresh beef colour grading | CVS | Sun et al., 2011 |
| | Fish species classification | CVS | Hu et al., 2012 |
| | Prediction of total viable counts on chilled pork | E-nose | Wang et al., 2012 |
| | Sensory and microbiological quality assessment of beef fillets | E-nose | Papadopoulou et al., 2013 |
| | Quality assessment of beef fillets | E-nose | Mohareb et al., 2016 |

**Table 10**
Description of the different data fusion methodologies.

| Fusion level | Description | References |
|---|---|---|
| Low | data from all sources are simply concatenated sample-wise into a single matrix that has many rows as samples and as many columns as signals measured by the different instruments (Fig. 5a). In order to fuse raw sensor data, the original sensor data must be commensurate, *i.e.*, must be observations of similar physical quantities. For instance, one acoustic wave sensor data that measures sound cannot be merged with visual image data. | Borras et al., 2015<br>Hall and Llinas, 1997<br>Banerjee et al., 2016 |
| Intermediate | some relevant features are first extracted from each data source separately and then concatenated into a single array that is used for multivariate classification and regression (Fig. 5b). The most common approach is to fuse a number of latent variables obtained independently from the signals of each instrument. Usually scores from principal component analysis (PCA) or partial-least square discriminant analysis (PLS-DA) are used. | Borras et al., 2015 |
| High | a separate model is built for each available data set, and then, the model responses are combined to produce a final "fused" response. The majority vote method is the easiest approach in food classification; each of the available models predicts a class label for a sample, and the class label that is predicted by the majority of the models is selected. More advanced methods are available, but they require probabilistic model outputs. The naive Bayes approach, for example, multiplies the class probabilities assuming independence, and selects the class label with the highest probability. In Fig. 5c, decision level fusion is depicted. | Doeswijk et al., 2011<br>Kuncheva, 2004 |

has proven to be efficient, as a non-destructive tool, in the detection of fish freshness (Han et al., 2014). Electronic nose and electronic tongue data were analysed by principal component analysis (PCA) and different three-layer basis function neural network (RBF-NN) were established. Further, performance of RBF-NN models with different numbers of principal components (PCs) as the input were compared. Experimental results revealed that the discrimination rates improved to 94.0% and 93.9% in the training set and prediction set, respectively, building the RBF-NN with the combination of the two instrument data. Finally, Santonico et al. (2015) demonstrate the possibility to analyse mozzarella cheese easily and without damaging the product, using liquid sensors (electronic tongue) and an electro-dynamic probe (to determine the mechanical proprieties). The classification was performed using partial-least squares discriminant analysis (PLS-DA). Of the three levels of data fusion, low and mid-level fusion are the most used. Low-level fusion is the first attempt approach, but, when data are very different in size or scale, the more tuneable mid-level fusion can

**Table 11**
Data fusion main applications on animal source food, reported in the last five years.

| Category | Application | Input data | Fusion level | References |
|---|---|---|---|---|
| Fish | Non-destructive detection of freshness during preservation | E-nose, E-tongue | Intermediate | Han et al., 2014 |
| | Fresh/frozen-thawed discrimination | CVS, NIR, texture analyser | Intermediate | Ottavian et al., 2014 |
| | Freshness detection | CVS, NIR | Intermediate | Huang et al., 2016 |
| Honey | Classification and detection of adulteration | E-nose, E-tongue, FT-IR, GC-MS | Low | Zakaria et al., 2011 |
| | Enhancing classification performance | E-nose, E-tongue | Low | Masnan et al., 2012 |
| | Classification of pure and adulterated | E-nose, NIR | Low and Intermediate | Subari et al., 2012 |
| | Determination of the botanical origin | E-tongue, UV–Vis–NIR | Intermediate | Ulloa et al., 2013 |
| | Taste assessment | E-nose, E-tongue, FT-IR | Intermediate | Maamor et al., 2014 |
| | Purity estimation | E-nose, FT-IR | Low | Subari et al., 2014 |
| | Classify botanical origin and determine adulteration | E-nose, E-tongue, NIR, FT-IR | Intermediate | Gan et al., 2016 |
| Milk | Aging time and brand classification | E-nose, E-tongue | Intermediate | Bougrini et al., 2014 |
| Egg | Shell crack detection | CVS, ARS | High | Pan et al., 2011 |
| Cheese | Mozzarella characterization and authentication | E-tongue, mechanical sensor | Low | Santonico et al., 2015 |
| Pork | Non-destructive measurement of total volatile basic nitrogen (TVB-N) | E-nose, CVS, NIR | Intermediate | Huang et al., 2014 |

yield better results (Borras et al., 2015). High-level fusion, instead, is the least used approach. Several researchers reported various limitations while working with the combined systems. Often, the sensor devices are used separately, with different experimental conditions, which may lead to error in the final decision. Another difficulty is the correlating parameter. The instruments are trained with respect to sensory panel data or chemical analysis data. Sensory panel data are subjective in nature and results in poor classification or quality estimation for these systems. In that respect, chemical analysis data is much more reliable. But, at the same time, the electronic sensor systems are mostly used for natural products, which comprise of a large number of chemicals, and correlation models are developed on the basis of one or two major chemicals and, thus, the limitations of the trained model continues to be there. Concretely, combining multiple artificial sensing systems enhances the performance of classification or quality evaluation of the products under consideration, but the combined system are still in the premature stage and with more research in this area would make numerous applications successful in the coming years (Banerjee et al., 2016).

## 7. Conclusion and future Trends

Traditionally, food quality evaluation has been performed by panels of trained human experts; despite this approach still suffers from several disadvantages, such as being time consuming, expensive and subjective, it is the most common used. On the other hand, also instrumental standard methods, relying on precision laboratory devices, suffers of similar drawbacks, being time-consuming, labour intensive and expensive. In recent years, human senses were substituted with artificial sensors, which have been increasingly employed in the food industry for quality control purposes; process, freshness and maturity monitoring; shelf life investigations; authenticity assessments and microbial pathogen detection. Electronic senses offers various advantages over traditional analysis, such as the rapidness, preciseness, objectiveness, efficiency and non-destruction of the measurement with low cost, environmentally friendly nature and no sample pre-treatment. Nevertheless, the permanent storage of data and the possibility of automation for on-line monitoring of industrial scale operations should be considered. These techniques used all together are called "electronic panel" and this approach is possible due to the fusion of data coming from complementary sensors. Data fusion has been applied to a wide range of food and beverages to authenticate origin and assess quality, enhancing significantly the performance of classification or quality evaluation. Most of the analysis combine gas and liquid sensors and, sometimes, UV–Vis spectroscopy or CVSs, considered as an E-eye. Despite the promising results obtained so far, there is still room for improvement. Novel artificial sensing devices, such as E-Noses and E-Tongues based on hybrid or bioelectronic sensors, are being studied. Hybrid systems are equipped with a combination of different sensor technologies, incorporating the advantages inherent to the different transducers and, at the same time, giving a choice for which chemical sensors can be used. Even with technological advances and promising results, these sensors still cannot mimic the biological features of human counterparts. Bioelectronic systems can provide signals triggered by the binding activities between selective receptors and odorous compounds or tastants. Recently, bioelectronic noses, using human olfactory receptors as primary recognition elements and nanomaterials as secondary transducers, have been reported (Yoon et al., 2009; Kim et al., 2008, Lee et al., 2012b, c; Jin et al., 2012; Park et al., 2012a). Bioelectronic noses rapidly recognize target molecules and can be operated relatively simply. In addition, they can be easily integrated and multiplexed into small chips that enable the systems to be portable and, thus, suitable for on-site analysis (Son et al., 2017). Beyond human receptors, some efforts to design bioelectronic noses have used olfactory receptors of various mammals, such as dogs and mice, which perform better than humans in smell sensing (Park et al., 2012b; Goldsmith et al., 2011). Nevertheless, electronic mucosa, which is an improvement of the E-Nose technology, was developed. In this instrument, the sensor arrays have been combined with two retentive columns (mimicking two nasal paths) in order to add another dimension to the common E-Nose, using temporal information from sensors. The retentive columns, coated with an absorbent material, acts like the mucous layer in the nasal cavity by delaying selectively some odour molecules, while letting other pass through with minimal delay. This provides differential temporal data, which are complementary to the conventional response (Ghasemi-Varnamkhasti and Aghbashlo, 2014; Gardner et al., 2012). In addition to these, considered as the evolution of traditional instruments, tactile sensors are being developed, *e.g.*, Nakamoto et al. (2015) presented the prototype of a sensor, inspired by human teeth, successfully applied to food texture measurements. Moreover, also data fusion strategies are object of investigations. Borras et al. (2015) identified several future trends, including combination of low and mid-level data fusion, fusion of second and higher-order data, i.e., hyperspectral images or data from hyphenated techniques, and the combination of first order-data from evolving systems, i.e., on-line monitored systems.

## Declaration of interest

The authors declare no conflict of interest.

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