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E-sensing systems for shelf life evaluation: A review on applications to fresh food of animal origin

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ABSTRACT

The quality of fresh food of animal origin, as meat, fish, dairy products, and eggs, is pivotal for consumers and producers; however, due to the action of microorganisms, enzymes, and oxidation during storage, fresh foods are subject to spoilage. Chemical and sensory parameters are shelf life indicators requiring innovative evaluation methods, as those currently used, are expensive, laborious and rather technical. E-sensing devices, overcome many of these drawbacks. This paper overviews the shelf life assessment of fresh food of animal origin by e-sensing. The fundamentals of electronic eye, electronic nose, electronic tongue and data analysis are reviewed in the first part, whereas their application for shelf life evaluation, considering them individually or in combination by data fusion, are considered in the second part.

1. Introduction

Food shelf life represents a complex problem with a still significant knowledge gap to be covered. Indeed, the loss of some quality characteristics could lead to the end of the product marketability, but not necessarily to the loss of hygienic, sensory, or nutritional characteristics. In addition, the shelf life of a perishable product can only be referred to a given environmental and production situation. Thus, talking about food shelf life, all the factors involved should be considered. Consequently, in a pivotal book (Piergiovanni & Limbo, 2010) shelf life is defined as "*The period of time which corresponds – under defined circumstances (packaging, transport, storage conditions and climate) – to an acceptable decrease in product quality*".

The factors influencing the shelf life are mainly the food product with its intrinsic quality characteristics, the packaging, and the environment - transport, storage conditions and climate. They contribute to the change of sensory, chemical, physical, and/or microbiological properties of the product (Class, Kuhnen, Rohn, & Kuballa, 2021). These properties can be assessed by target analytical evaluation of external attributes (from color to taste and flavor), and internal factors related to chemical, biochemical, and microbiological changes resulting in nutritional and safety decay (Lakshmi et al., 2017). Conventional target methods applied for the evaluation of food shelf life are time-consuming, labor demanding, expensive, and applicable only for off-line control. On the contrary e-sensing techniques are designed to give real time information, overcoming cost and time associated with conventional laboratory methods or related to human involvement, as in the case of traditional sensory analysis (Yakubu, Kovacs, Toth, & Bazar, 2022). The possibility of rapid and non-destructive analysis is particularly relevant in the current food market, characterized by an increased international trade of fresh food, together with the need of effective controlled product in an environmentally sustainable vision. Thus, the application of more advanced quality control technologies has become a key issue (Palumbo et al., 2022) which the scientific and industrial stakeholders are looking to face.

Therefore, this review overviews the application of e-sensing systems for the shelf life assessment of fresh food of animal origin. The paper aims to synthetize the fundamentals of electronic eye (e-eye), nose (e-nose) and tongue (e-tongue) and required data analysis. Subsequently the applications of e-sensing for shelf life assessment in the last ten years, considering each technique individually or in combination, are considered and some conclusion and future perspective are drawn.

2. E-sensing system

As shelf life assessment should allow an accurate, but rapid, determination of defined compounds, with little or no sample pretreatment and without the use of reagents, e-sensing systems are among the approaches resulting interesting in this context.

E-eye, e-nose and e-tongue designed to mimic the human senses, can

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be useful for real time evaluation of fresh food, allowing the sample pretreatment reduction. The approaches are intended for the evaluation of the quality parameters, related to sensory characteristics, or for the quantification of specific analytes.

With regard to e-eye, a number of visual system could be considered, colorimeters are traditionally applied to objectively define the color of food, while the use of e-eye by computer or mobile phones has rapidly emerged in the last years; for the e-nose and e-tongue, a- or partially-specific sensor arrays are applied to analyze volatile compounds or liquid samples (Fig. 1).

Compared to traditional analytical methods (microbiological, chemical, physical and sensory), e-sensing systems have some peculiar characteristics since they are rapid, simple, objective, versatile and potentially useful for at-line or on-line applications. Furthermore, these techniques are considered environmentally friendly since do not require, or minimally require, the use of chemical reagents and sample preparation (Tufvesson, Tufvesson, Woodley, & Börjesson, 2013).

A further advantage, when considering e-eye and e-nose, is linked to economic aspects. Yavuzer (2021) and Castrica et al. (2021) highlighted the possibility of developing tailored made e-noses with cost lower than 150 $. Similarly, e-eye hardware, i.e., two digital cameras equipped with an illumination set, could be easily implemented on a food production line with a cost of around 500 $ (Fan et al., 2020). To the hardware costs, software development should be added, which cost is highly dependent on the graphical-user- interface and the model complexity, thus more difficult to estimate. However, it is plausible that e-sensing systems will be cheaper then microbiological, chromatographic, or chemical analysis, for which not only the investment in hardware and software, should be considered but also reagents and sample depletions.

The main advantages and characteristics of e-sensing systems are summarized in Fig. 2.

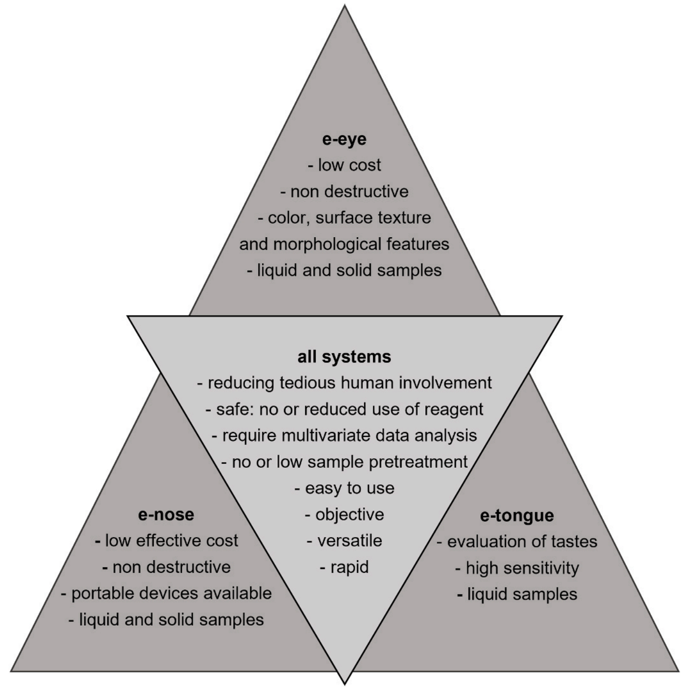

Fig. 2. Advantages and characteristics of e-sensing systems.

2.1. E-eye

The visual appearance of food concerns visually perceived structure - including color, surface texture properties, and morphological features – affected by physical, chemical, microbiological, and sensorial changes which are indicators of product quality, i.e., with the estimation of product shelf life.

Among the characteristics determining the perceived food quality, color plays a pivotal role. Color results from the interaction between the incident light and the object in the visible electromagnetic region, i.e., from 400 to 700 nm (Cairone, Carradori, Locatelli, Casadei, & Cesa, 2020).

The science which enables to objectively describe and quantify the human color perception is colorimetry (Fan, Li, Guo, Xie, & Zhang, 2021). In particular, the objective determination of food color, to which we will refer as e-eye, can be obtained by colorimeters, spectrophotometers, scanners and digital cameras.

Colorimeters (Fig. 2a) are the most used instruments and, nowadays, could be considered a traditional approach to food characteristics evaluation. Even if colorimeters are extensively applied for food quality analysis, they permit to analyze no more than few square centimeters at a time, thus leading to results not always representative of heterogeneous food surfaces.

Other well-established systems are the spectrophotometers that measure color by recording the light transmitted or reflected by a product, resulting in a spectrum in the visible range (Pathare, Opara, & Al-Said, 2013).

In the recent years, digital image colorimetry (DIC) made inroads as e-eye color analyzers. Scanners, digital cameras, and mobile phones are used to acquire information and store them as digital images (Fan et al., 2021) (Fig. 2a). Digital images could describe both macroscopic (Grassi, Casiraghi, & Alamprese, 2018) and microscopic (Ong et al., 2020)

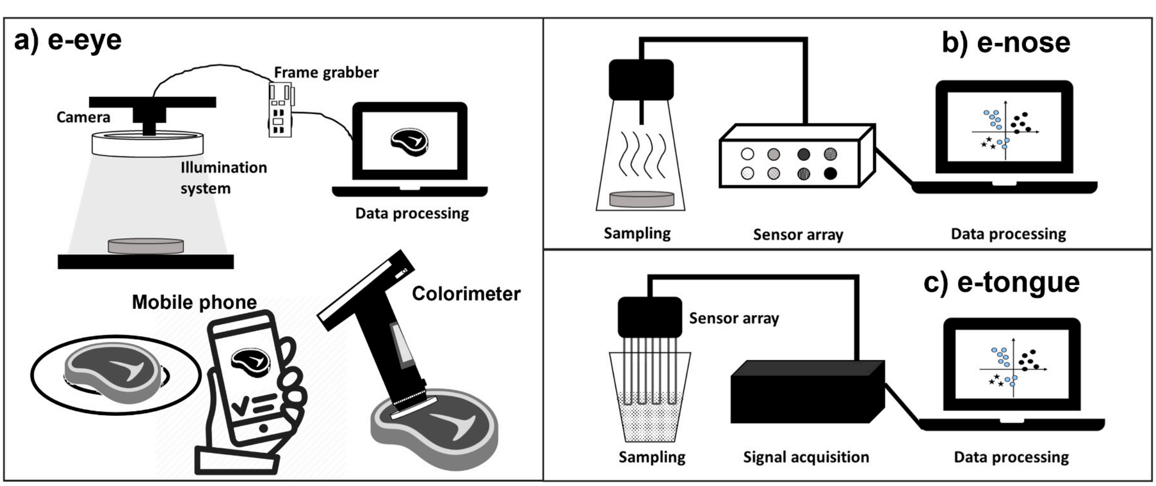

Fig. 1. Schematic illustration of e-sensing systems.

features, acting as an e-eye. In this manuscript the assessment of food product external features will be described, whereas the microscopic appearance assessment is out of the scope of this review.

In DIC the color information is collected by the image sensors, which quantify the received primary color intensity, and convert the optical signal into an electrical one. Among the type of commercial sensors, available at RadhaKrishna, Govindh, & Veni (2021), charge-coupled devices (CCDs) are the most used to convert an optical image into electrical signal, being highly sensitive photon detectors. The CCD is divided up into light-sensitive small areas (a.k.a. the pixels), each acting like a bucket for electrons. During the exposure, each pixel fills up with electrons in proportion to the amount of light that enters it. The CCD takes this input and converts it into an electronic signal. Finally, an analog-to-digital converter turns the signal into digital information.

Flatbed scanners are widely available and, thus, the most used. In this type of scanners, the light, generated by light source on a moving arm, reaches the product understudy positioned on a glass surface, then it is reflected to a photosensitive element, such as a CCD, by a series of mirrors and lenses (Garcia-Rojo et al. 2019).

The combination of a scanner geometry with a system of optics results in a digital camera. The digital cameras are part of the e-eye system, together with an illumination system, a frame grabber and a processor (Fig. 2a). Though more difficult to design for the specific application, e-eye are adaptable to a wide array of cases. The quality of an e-eye system is determined by the electronics, both camera and frame grabber, and by the illumination system. Depending on the application, CCDs could have different architectures (linear, interlinear and frame-transfer) and resolution (number and size of pixels). Together with that, the setup of a properly designed illumination system improves the analytical precision and reduces the artifacts. Lighting can be arranged according to two types of design: circular design (or ring illuminator) for flat samples or a scattered design (diffuse illuminator) for roundish and/or reflective objects.

Most image detectors provide information in RGB coordinates, deriving from a cubic color space composed by three perpendicular axes (red, R: green, G; and blue, B), each of them ranging from 0 to 255. The coordinates vary from black [0, 0, 0] to white [255, 255, 255]. If the measured color should be converted in other color spaces, such as CIE-Lab format, the illumination must be standardized to obtain reliable results (Leon, Mery, Pedreschi, & Leon, 2006). The CIELab space is recognized as the best system for food, able to approximately describe the human perception of color. Indeed, it enables to obtain information about the lightness (L*), and the unique colors (a*, from green to red; and b*, from blue to yellow) perceived by the human eye (McLaren, 1976).

As said before, color is crucial, but to characterize the appearance of food, more complex features are involved. E-eye systems analyze surface texture, going beyond what perceived by the human eye (Jackman & Sun, 2013), and represent features such as graininess, smoothness, and roughness. Lastly, morphological features are important to describe fresh products of animal origin in terms of their structure, even if it is difficult to discuss all the possible features to be measured as they depend on the sample understudy and on the fixed goal. In any case, they encompass simple features, such as area, aspect, and diameter, and more peculiar ones, i.e., roundness and hole presence. Typical morphology features that can be calculated are described by Du & Sun (2004).

2.2. Electronic nose

The e-nose device originated in the work of Persaud & Dodd (1982) and developed in a tool allowing the detection of odors, simple and complex, by an array of a-specific or partially specific gas sensors that mimic human olfactory perception (Gardner & Bartlett, 1994).

Basically, this device consists of three parts: a sampling system for handling samples during analysis, a detecting system composed by the sensor array and a computer for the acquisition and the processing of data (Fig. 1b) (Munekata et al., 2023; Tudor Kalit, Marković, Kalit, Vahčić, & Havranek, 2014).

The gas sensors represent the heart of the system, and they can be classified into several types. Few technologies are applied in commercial e-noses: the metal oxide semiconductor sensors (MOS), the metal oxide semiconductor field-effect transistor sensors (MOSFET), the conducting polymers (CP), the acoustic sensors: surface acoustic wave (SAW) and bulk acoustic wave (BAW); the most common bulk acoustic wave sensors are the quartz microbalance (QMB) (Sujatha, Dhivya, Ayyadurai, & Thyagarajan, 2012; Wojnowski, Majchrzak, Dymerski, Gębicki, & Namieśnik, 2017a). In the work of Ghasemi-Varnamkhasti, Mohtasebi, Siadat, & Balasubramanian (2009) the structure of the different types of sensors is well schematized.

MOS sensors are the most widely applied in the commercial e-noses; they measure changes in metal oxide conductivity due to reduction/oxidation reactions taking place on the sensor surface (Wojnowski, Majchrzak, Dymerski, Gębicki, & Namieśnik, 2017a; Berna, 2010).

Commercial devices are typically handy, compact, and exploitable in different fields (food, medical, pharmaceutical, and environmental). Among them, PEN3 e-nose, produced by Airsense Analytics (Schwerin, Germany), is characterized by a particular sampling strategy which allows to operate in laboratory or in mobile applications as well as online for process control. This device consists of 10 MOS sensors, and it is equipped with the WinMaster software for data collection and processing (Airsense Analytics, 2023).

Cyranose320 is another commercial device produced by Sensigent (Baldwin Park, California, USA). It is a fully integrated portable tool, specifically designed to detect and identify complex mixture of volatiles that constitute aromas, odors, fragrances. Cyranose320 is used in several industries, including food ones; it consists of 32 CP sensors blended with carbon black composite (Sensigent – Intelligent Sensing Solution, 2023).

In Italy, a research platform has given rise to the development of a 6 MOS sensors commercial tool named EOS912 (SACMI, Imola, Italy). This e-nose operate in any external environment or weather condition, and can be powered by solar panels combined with fuel cells and a backup battery; this device is able to ensure good performance in absence of a traditional power supply and in the absence of sunlight up to 24–48 h (Sacmi, 2015). Furthermore, a company named Nano Sensor Systems (Brescia, Italy), develops innovative e-nose devices, based on nanochemical sensors, fully customizable according to customer needs. The main application sectors are agri-food, environmental, security and domestic automation (Nano Sensor Systems, 2023).

The HERACLES (Alpha MOS, Toulouse, France) e-nose is dedicated to the analysis of chemical molecules that make up the odor. This device is based on ultrafast chromatography technology and consists of two capillary columns of different polarity and two flame ionization detectors. The AroChemBase software is designed to help the identification and the characterization of the detected molecules by providing a list of possible compounds sorted by relevance index (Alpha-MOS, 2023).

Most of the commercial e-noses are not specifically designed for food industry applications. Therefore, some researchers tested specific devices for food matrices. Food Sniffer® (Redwood City, USA) is a commercial and portable e-nose developed for assessing meat, poultry and fish freshness. This device can be connected wirelessly to a smartphone via an app; it measures gas levels indicating in few seconds the storage condition of the products via a traffic light system: green-fresh, yellow-partially spoiled, red-spoiled. As it is easy to use, this device is intended for the final consumers (FOODSniffer (2023)).

The "Mastersense" e-nose is a portable and simplified prototype system based on 4-MOS sensors and implemented with a classification algorithm to classify meat and fish according to their freshness. An ad hoc cloud platform has been implemented to store the data collected by off-line or on-line procedures (Grassi, Benedetti, Opizzio, di Nardo, & Buratti, 2019).

Recently home-made e-nose systems have been developed for the assessment of food and beverage quality. Low-cost e-noses, consisting of an array with three-twelve MOS sensors, have been applied to assess the aromatic fingerprint of beer, wine, saffron, fruit and fruit juice (Rasekh & Karami, 2021; Wei, Zhang, Wu, Wei, & Chen, 2018; Kiani, Minaei, & Ghasemi-Varnamkhasti, 2016a; Macías, et al., 2013; Viejo, Fuentes, Godbole, Widdicombe, & Unnithan, 2020). These tailored made instruments permits to highly reduce the hardware costs but are limited in the ad hoc use.

2.3. Electronic tongue

E-tongue was developed in the 90s when prof. Toko proposed a system able to imitate the sense of taste, called "taste sensor" (Toko, 1995). An e-tongue is generally composed by a sensor array that reacts in contact with liquid samples, a signal acquisition system, and a pattern recognition system which identify compounds based on their taste (Fig. 1c) (Wadehra & Patil, 2016; Vlasov, Legin, Rudnitskaya, Di Natale & D'Amico, 2005).

As for the e-nose, sensors are the heart of e-tongue system and they are classified into electrochemical (voltammetric, potentiometric, amperometric, impedimetric, and conductimetric), optical and enzymatic (biosensors) (Ciosek & Wroblewski, 2007). Usually, e-tongue systems consist of up to ten sensors, the most widely used are the potentiometric and voltammetric ones.

Voltammetric e-tongues are often used for multi-component measurement, such as chloride, nitrite and nitrate content in meat (Campos et al., 2010; Labrador et al., 2010), however these devices are applicable only to samples in which oxidation and reduction reactions occur (Jiang, Zhang, Bhandari & Adhikari, 2018).

Potentiometric e-tongues are based on polymeric membrane ion-selective electrodes (ISE) and ion-selective field-effect transistors (ISFET). In these devices, the potential difference under no current flow condition is measured (Nery & Kubota, 2016; Cosio, Scampicchio, & Benedetti, 2012). Potentiometric sensors are assembled in the two commercial e-tongue currently available. The first one, built by Toko (Toko, 1996) is TS-5000Z Taste Sensing Systems (Intelligent Sensor Technology Inc., Atsugishi, Kanagawa, Japan). It consists of sensors composed by lipid-polymeric membranes that selectively respond to specific tastes and aftertastes (Tahara and Toko, 2013). This system is mainly used for food (Ujihara, Hayashi & Ikezaki, 2013; Zhang, Zhang, Meng, Li, & Ren, 2015) and pharmaceutical (Akitomi et al., 2013) products. Astree II (Alpha MOS, Toulouse, France), the second e-tongue available on the market, is composed of seven chemically sensitive field-effect transistor (ChemFET) sensors able to recognize different tastes. The applications of this device focus on pharmaceutical (Woertz, Tissen, Kleinebudde, & Breitkreutz, 2011) and food field, for quality control (Tian, Wang & Zhang, 2013), taste assessment (Jung et al., 2017), and process monitoring (Yan, Ping, Weijun, & Haiming, 2017)).

Other two e-tongues are available on regional market; however, the literature concerning their applications is very scarce. These two devices are: the Multiarray Chemical Sensor (McScience Inc., Suwon, Korea), build of polyvinylchloride and polyurethane membranes (Ciosek & Wroblewski, 2007), and the Sensor System (St. Petersburg, Russia) comprised of seven potentiometric ion-selective sensors (Zakaria et al., 2011). Recently, a lot of progress has been made in the study of sensor miniaturization to develop a small portable e-tongue by using wire or screen-printed electrodes for the analysis of wine (Giménez-Gómez et al., (2016)), drinking water (Ouyang, Zhao, & Chen, 2013) and beer (Garcia-Breijo et al., 2011), but the way to their real life application is longer if compared with the miniaturized e-eye and e-nose systems.

3. Data analysis associated with e-sensing systems

Multivariate data analysis techniques are the same for e-eye, e-tongue and e-nose, the main differences consist in data type and, thus, in the preparation strategies required from the different data types. Prior to multivariate data analysis, pre-processing strategies must be applied to profit of the retained information at maximum. Subsequently, after a proper data exploration, prediction models could be built to assess a specific compound (regression models) or to predict a categorical characteristic (classification models).

It should be kept in mind that robust validation procedures are mandatory to guarantee reliable and reproducible results. To the goal, models must always be tested for prediction ability, thus when developing a model, this should be firstly calibrated with a comprehensive set of data, and the validated by an independent test set composed by samples not used in the calibration phase (Grassi et al., 2023). For a comprehensive overview of Chemometric applied to food analysis please refer to Marini (2013).

3.1. E-eye

The data collected by e-eye need several steps of analysis to be optimized to meet the defined purpose (Fig. 3). The first step includes the image acquisition followed by preprocessing strategies that includes the reduction/removal of noise and undesired distortions (second step). The third step is image segmentation aiming at isolating regions of interest (ROI) and extracting statistical data form object or ROI (Gunasekaran, & Ding, 1994). The strategy, or combination of strategies, implemented for image segmentation are pivotal for the accuracy of image analysis, as this operation will affect the data on which statistic will be computed. There are different ROI segmentation techniques which can be grouped in thresholding, edge-based, and region growing methods (Sonka Hlavac, & Boyle, 1993). Thresholding is the simplest approach, and it is based on the intensity of the recorded colors, as single channel, or after grey scale transformation. Edge-based segmentation methods detect discontinuities in the color intensity or in the texture of an image, resulting in borders or edges. Differently from the previously described methods, the region-growing methods construct regions using homogeneity as the main segmentation criterion (Sonka et al., 1993).

The image segmentation will lead to a ROI that can be analyzed as a boundary or as a region (fourth step). In case the final aim is to extract color or texture features the segmentation process will lead to a region, from which quantitative information, such as pixel intensity or co-occurrence, will be extracted. Whereas boundary representation is used for morphological analysis, such as the extraction of size and shape features. To examine in the dept the various algorithms used for the fourth step refers to Meenu et al. (2021) and Zheng, Sun, & Zheng, (2006).

The segmented images can further be processed by modelling strategies based on food quality features thanks to univariate and multivariate statistical methods or machine learning techniques. Univariate statistical methods encompass linear regression, Pearson correlation and Welch's t-test (Russ, 2006), whereas multivariate statistical models include, among others, linear discriminant analysis (LDA), quadratic discriminant analysis (QDA), partial least square (PLS) regression (Prats-Montalbán, de Juan, & Ferrer, 2011). More complex is the use of machine learning strategies, such as support vector machine (SVM) with linear or nonlinear kernels, and artificial neural networks (ANN) (Lin, Ma, Wang, & Sun, 2022).

3.2. E-nose and e-tongue

The steps required for e-nose and e-tongue data analysis are superimposable, thus they will be discussed together. Both analyses generate an output as the response of the sensor array interaction with the compounds (semi-independent variables) which is combined with a set of dependent variables constituted by the a-priori information about odor/taste classes. The response of the sensor arrays consists of a set of curves, generated from the changes in the sensor array, where the x-axis is the time of analysis and the y-axis the voltage/resistance/conductivity. These structures, i.e., the pattern vectors, should a priori undergo to

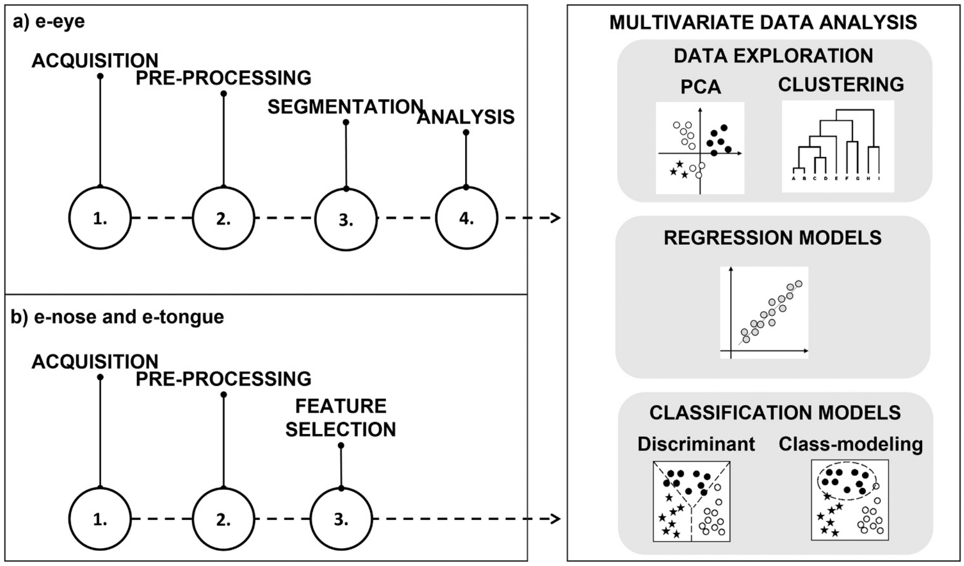

Fig. 3. Fundamental steps for e-sensing data analysis.

preprocessing to enhance relevant features and reduce possible instrumental and analytical noise. An inappropriate data extraction and preprocessing can affect the subsequent multivariate data analysis. The features that are usually considered are the signals at a predefined time, but in some cases the pattern vectors, generated by the considered sensors, can be directly concatenated. In the latter case principal component analysis (PCA) may be applied as dimensionality reduction strategy to select relevant variables. In both cases, difference in sensor sensitivity may have a scaling effect, thus normalization strategies are the most common applied preprocessing techniques; some standard normalization techniques are discussed by Scott, James, and Ali (2006). After pretreatment, data are generally explored by PCA. It allows the inspection of similarities and differences between samples and their relationship with the measured variables (Bro & Smilde, 2014). Furthermore, clustering algorithms (CA), belonging to the unsupervised pattern recognition methods, are applied to split the samples into clusters. There are different families of clustering methods, according to the portioning strategies applied. Hierarchical methods start by the grouping in small clusters, then enlarged by further steps, to finally generate a dendrogram representation of distances. Partitioning methods, such as k-means clustering, start from big groups, then reduced in dimension by optimizing a feature, such as the distance within-group. The main problem is the a priori definition of the desired/expected number of clusters (Grassi et al., 2023; Scott et al., 2006). The unsupervised pattern recognition methods are useful for data representation, data dimensionality reduction and/or to define groups. Whereas, when the aim is to develop models for the classification of samples based on quality categories, classification algorithms or classifiers must be implemented. This is the main difference: the supervised methods require some “a priori” information about the sample, such as a quality class or a measured quality trait. Classification can be performed by discriminant or class-modeling techniques. K-nearest-neighbor (kNN), PLS-discriminant analysis (PLS-DA), and LDA are some of the most used algorithms for discriminant analysis. Instead, class-modeling techniques may include soft independent modeling of class analogy (SIMCA) and unequal class modelling (UNEQ). In recent time, the algorithm most used as classifier for e-nose and e-tongue data handling is ANN. ANN simulates the working flow of the brain by using a collection of neuron-like entities forming networks on which the classification is based. Shaffer, Rose-Pehrsson and McGill (1999) compared several pattern recognition systems (Probabilistic neural networks (PNN), learning vector quantization (LVQ) neural networks, back-propagation ANN (BP-ANN), SIMCA, Bayesian linear discriminant analysis (BLDA), Mahalanobis LDA (MLDA), and the kNN) and proposed a set of requirements that an ideal classification system should have. In any case, it is important to follow a correct road map when developing and validating a classifier, including correct sampling procedures, meaningful preprocessing and reduction strategies, robust validation procedures, and evaluation of the model performance criteria (Grassi et al., 2023).

4. E-sensing application

4.1. E-eye

Meat color can be influenced by many intrinsic and extrinsic factors that are interrelated and, finally, influence consumers’ perception of quality and freshness (Tomasevic, Djekic, Font-i-Furnols, Terjung, & Lorenzo, 2021). The use of colorimetry is not new in the meat sector for shelf life evaluation and it has been widely applied as reported by Gurunathan, Tahseen, & Manyam, 2022 and Roshanak et al. (2023). More recently, e-eye systems have been investigated and applied in the meat industry from carcass composition to sensory quality prediction passing by chemical composition and quality defect evaluation (Modzelewska-Kapituła & Jun, 2022). E-eye in the visible range were successfully applied for the determination of fresh pork quality defects (Chmiel, Słowiński, Dasiewicz, & Florowski, 2016), fat distribution in beef and lamb (Stewart et al., 2021), and eating qualities of beef (Jackman, Sun, Du, & Allen, 2009). These studies are only some of the many setting the basis for meat quality evaluation. However, a reduced number of them focuses on the evaluation of meat products during their shelf life (Table 1). Different studies applied e-eye systems to study the effect of the packaging system - packaging material and environmental conditions - on the color stability and the surface texture changes during beef shelf life (Nassu et al., 2012; Uboldi Lamperti, & Limbo, 2014). In a first study, Arsalane et al. (2018) constructed a database of eighty-one images, collected from beef steaks stored at 4 ± 1 °C up to nine days, from which they extrapolated hue, saturation, and intensity (HSI) values to build an SVM model for freshness classification. In the subsequent study (Arsalane et al., 2019) the color information was merged with surface texture features - calculated by fast wavelet transform - to develop an algorithm based on PNN to classify beef images in two freshness classes (fresh or spoiled). The strength of the studies is the transfer of the developed methods to a digital signal processor (DSP), thus providing portable tools to identify product freshness directly in the

Table 1
Recent application of e-eye systems for shelf life evaluation of fresh food of animal origin.

Food Matrix	Aim of the study	E-eye system model	Parameters	Reference
Meat				
Pork	Detection of PSE in *M. semimembranosus*	Konica Minolta CM2600d spectrophotometer	CIELab color space	Chmiel et al. (2016)
	Development of an on-line detection system for meat freshness	German AVT F-038 industrial camera, a light unit, a computer and a software	Color Region Ratio	Xiao et al. (2014)
Chicken	Development of an on-line detection system for chicken freshness	CANON SX260 camera, an illumination source, a computer, and a software	Texture features extracted from RGB, HSI and CIELab color spaces	Taheri-Garavand et al. (2019)
	Evaluation of packaging systems on quality characteristics of chicken leg meat	HunterLabMiniScan colorimeter EZ 4500	CIELab color space	Gurunathan et al. (2022)
Beef	Effect of CO2 and O3 pretreatments on the quality of vacuum packaged beef meats	Konica Minolta colorimeter CR 310	CIELab color space	Lyu et al. (2016)
	Effects of of low O2 master bag in beef patties shelf life	CanonScan LiDE 200 flat-bed scanner	CIELCh color space	Uboldi et al. (2014)
	Assessment of safety and physicochemical properties of hamburger treated by cold plasma	Canon Power Shot EOS 1000D camera	CIELab color space	Roshanak et al. (2023)
	Development of a rapid model for beef meat freshness prediction and identification	GigEPRO camera, two illumination source at 45°, a computer and a software	HSI color space and surface texture features	Arsalane et al. (2018)
	Assessment of fresh and spoiled meat	GigEPRO camera, two illumination source at 45°, a computer and a software	HSI color space	Arsalane et al. (2019)
	Evaluation of packaging affects on the colour stability of vitamin E enriched meat	Canon EOS Digital Rebel, two illumination source at 45°, a computer and a software	Appearance, RGB lean colour, % surface discolouration (RGB)	Nassu et al. (2012)
Fish				
Sea bream	Assessment of freshness by eyes,and gills	Canon EOS kiss x4 camera, illumination chamber, computer hardware, and software	CIELab color space	Dowlati et al. (2013)
Snappers	Assessment of freshness by eyes in differenet conditions	Nikon D300 camera, two illumination source at 45°, a computer and a software	CIELab color space	Balaban & Alçiçek (2015)
Red mullet	Assessment of freshness by eyes, gills, and skin	Canon PowerShot A70, four illumination source at 45°, a computer and a software	RGB color space	Tappi et al. (2017)
European hake	Assessment of freshness by eye chromatic and morphological characteristics	Nikon D7000 camera, four parallel illumination source, a computer and a software; Next Engine 3D scanner	RGB color space and 3D eyes profile	Rocculi et al. (2019)
European Seabass	Assessment of freshness by eyes, gills, and skin	Nikon D300 digital camera (18–200 mm), illumination system with a polarizing sheet, color reference	CIELab color space	Erdağ & Ayvaz (2021)
Salmon	Assessment of freshness by eyes	A digital camera and four lamps positioned below the fish	RGB, CIELab, and HSI color spaces	Jia et al. (2022)
Tilapia	Prediction of freshness indicators (TVB-N, TBA and TVC) by pupil and gill	A digital camera and four lamps positioned below the fish	RGB, CIELab, and HSI color spaces	Shi et al. (2018a)
Common carp	Assessment of freshness	CCD camera, four lamps with an arc acrylic plate, a computer and a software	RGB color space	Taheri-Garavand et al. (2020)
Indian rohu	Assessment of freshness by gills	Nikon D90	CIELab and HSV color spaces	Issac et al. (2017)
Different fishes	Assessment of freshness, remaining shelf life and number of days from catching	Mobile phone	RGB color space	Suresh et al. (2021)
Dairy products				
Vastedda PDO cheese	Assessment of the effect of refrigerated storage on quality characteristics	Konica Minolta colorimeter CR-310	CIELab color space	Todaro et al. (2017)
White turkish cheese	Assessment of packaging effect on quality charcteristics during storage	Konica Minolta colorimeter CR-410	CIELab color space	Alwazeer et al. (2020)
“Bryndza” sheep lump cheese	Assessment of changes in production effect on quality charcteristics during storage	Konica Minolta colorimeter CR-411	CIELab color space	Štefániková et al. (2020)
Lor whey cheese	Evaluation of continuous type of UV light on quality parameters during shelf life	Konica Minolta colorimeter CR-300	CIELab color space	Urgu-Ozturk (2022)
Crescenza cheese	Evaluation of milk recombination in cheese manufacturing and storage	Konica Minolta colorimeter CR-301	CIELab color space	Alinovi et al. (2022)
Fresh acid coagulated cheese	Evaluation of quality parameters and shelf life ofcheese packed under modified atmosphere	Konica Minolta CM3500d spectrophotometer	CIELab color space	Barukčić et al. (2020)
Cow’s and goat’s fresh cheese	Evaluation of hyperbaric storage on quality characteristics	Konica Minolta CM2300d spectrophotometer	CIELab color space	Duarte et al. (2023)
Yoghurt	Assessment of packaging effect on quality charcteristics during storage	Konica Minolta CM600d spectrophotometer	CIELab color space	Mikloskova et al. (2021)
Smoked Cheddar	Effect of storage time on calcium lactate crystals formation	Nikon 5200	DCR number and distribution	Rajbhandari et al. (2013)
	Effect of surface roughness and packaging tightness on calcium lactate crystals formation	Nikon 5200	DCR number and distribution	Rajbhandari & Kindstedt (2014)
Mozzarella cheese	Evaluation of modified governing liquid on shelf-life parameters	Konica Minolta colorimeter CR-400	CIELab color space	Huang et al. (2022)
	Comparison of different systems to study colorimetric quality parameters	Different CCD or CMOS cameras, two lamps at 45° and 0°, a computer and a software	CIELab color space	Minz & Saini (2021)

(*continued on next page*)

Table 1 (*continued*)

Food Matrix	Aim of the study	E-eye system model	Parameters	Reference
Milk and milk products	Comparison of different systems to study quality parameters	Konica Minolta colorimeter CR-400; Sony Alpha DSLR-A200 camera, four illumination source at 45°, a computer and a software	CIELab color space	Milovanovic et al. (2021)
Egg				
White egg	Crack detection	Apple iSight camera, one alogen lamp source, two LEDs	Gray scale	Priyadumkol et al. (2017)
Brown egg	Crack detection	UI-2230ME-C CCD camera, an aluminum alloy box, illuminator and a compute	RGB	Wu et al. (2018)

supermarket and in real-time.

An online detection system was also proposed by Xiao, Gao, and Shou (2014). They developed an innovative strategy based on color region ratio to identify freshness in samples of pork meat, according to the Chinese National Standard, reaching the 88% of accuracy. E-eye succeeded also in chicken meat freshness prediction (Taheri-Garavand, Fatahi, Shahbazi, & de la Guardia, 2019). To this end, 3000 images were acquired storing thirty skin chicken legs at 4 °C up to 13 days, from images color and texture features were extrapolated and used to develop an ANN model giving a regression coefficient (R) of 0.99 and a prediction error of 0.0025.

Colorimetry and e-eye systems have been applied for freshness evaluation of whole fish, fish fillets and derived products. In particular, the e-eye system resulted highly reliable in the analysis of non-eviscerated fishes. Relevant studies were developed retrieving information by e-eye systems based on the evaluation of gill and eye color changes in sea bream (Dowlati et al., 2013), snappers (Balaban & Alçiçek, 2015), Indian rohu (Issac, Dutta, Sarkar, 2017), red mullet (Tappi et al., 2017), tilapia (Shi et al., 2018a), European hake (Rocculi et al., 2019), European seabass (Erdağ & Ayvaz, 2021), and salmon (Jia, Li, Shi, Zhang, & Yang, 2022) (Table 1).

Issac et al. (2017) designed a robust method based on 144 Indian rohu samples to assess fish freshness with an accurate segmentation strategy and an optimal noise reduction. Taheri-Garavand, Nasiri, Banan, and Zhang, (2020) proposed a convolutional neural network-based method, with low complexity and high accuracy (98.2%), in the prediction of common carp (*Cyprinus carpio*) freshness from the changes occurring in the extracted skin features. However, the mentioned works did not correlate the freshness determined by image analysis with the related microbiological and chemical quality indexes. Interesting, in the work of Jia et al. (2022) the information retrieved from the analysis of salmon eyes images was used to build multiple regression models for the prediction of thiobarbituric acid (TBA), total volatile basic nitrogen (TVB-N), total viable counts (TVC), and K value, obtaining high determination coefficients (R^2 >0.99), F value (from 186.26 to 589.42), and low relative errors. Suresh, Vinayachandran, Philip, Velloor, and Pratap (2021) developed Fresco Pisces, a mobile app which enables to assess fish freshness and formaldehyde presence in fishes from an image of eye and gill acquire anywhere, even at the supermarket, by a mobile phone.

Regarding the visual appearance of dairy products, color, surface texture and morphology has been considered an indicator related to extended storage conditions and shelf life (Lukinac, Jukić, Mastanjević, & Lučan, 2018).

In the dairy sector, colorimeters - especially tristimulus colorimeters - has been widely used for shelf life assessment of a large number of cheeses as classical control technique (Table 1). Color, by a spectrophotometer CM-600d (Konica Minolta, Tokyo, Japan), was used to evaluate changes in CIELab space during the storage of yoghurt packed in traditional or innovative packaging materials up to 42 days (Mikloskova, Witte, Joeres, & Terjung, 2021).

Milovanovic et al. (2021) evaluated both an e-eye system and a portable colorimeter (CR-400, Minolta Co., Osaka, Japan) for color measurements of many milk products. The obtained results demonstrated that e-eye could replace traditional devices, i.e., colorimeters, with improved representativeness and accuracy for both liquid and solid products. Similarly, Minz, & Saini (2021) compared the performance of a spectrophotometer and five different cameras (two CCD and three complementary metal–oxide–semiconductor type image sensors) implemented in a e-eye for color determination in mozzarella cheese. They concluded that the two systems led to equivalent results, but the e-eye system - as already commented - easily allows the measurements over the entire mozzarella cheese surface.

Kindstedt research group (Rajbhandari, Patel, Valentine, & Kindstedt, 2013; Rajbhandari & Kindstedt, 2014) applied an e-eye to measure calcium lactate crystals presence on surfaces of Cheddar cheese. Even if not harmful, their formation leads to quality loss and microbiological problems. The developed method permitted to identify the number of visible crystals, their growth rate, and shape during storage at 1, 5 or 10 °C up to 30 weeks, and the area occupied by the crystals in respect to the cheese surface.

Vasilev, Shivacheva, and Krastev (2021) acquired data about the spectral characteristics and the color digital images of white brined cheese and yellow cheese stored up to 14 days at 20–22 °C, relative humidity of 45%. The storage, in terms of days, of white brine cheese resulted well predicted (R^2: 0.80) combining the color components, the spectral indices and the electrical conductivity features.

Regarding eggs shelf life, e-eye systems were applied for the determination of crack (Priyadumkol, Kittichaikarn, & Thainimit, 2017; Wu et al., 2018). A quite high accuracy (94%) was obtained by the fast-random-forest classifier applied to discriminate images acquired from cracked and intact white eggs by Priyadumkol et al. (2017). The strategy developed by Wu et al. (2018) performed similarly with an accuracy of 93% and 94% in testing and training sets, respectively. In this case, an SVM classifier was implemented to detect cracked brown eggs by transmission imaging.

4.2. E-nose

In the last decade, many works covered the e-nose application to predict freshness quality traits and/or spoilage of fresh food animal origin, since during their storage there is a significant release of volatile compounds due to cellular metabolism and to bacterial degradation processes.

Table 2a summarizes e-nose applications for shelf life assessment of meat, fish, dairy products, and eggs.

Considering the information reported in Table 2a MOS sensors are employed in about 60% of the reviewed papers, due to their advantages of being fast, highly sensitive and commercially available at a low price. In about 40% of the works, the evaluations were carried out using commercial devices, in all the other cases, homemade devices or prototypes, specifically developed for products of animal origin, were applied.

As regards commercial e-noses applied on meat, the PEN2 system (Airsense Analytics, Schwerin, Germany), composed by 10 MOS sensors, has been used to predict microbiological and physical-chemical indices of beef samples stored at 2 °C for a maximum of 14 days (Hong, Wang, & Hai, 2012); the e-nose was used in combination with an enrichment and desorption unit to improve its performance by lowering the detection limit and increasing the selectivity. Prediction models for TVB-N

Table 2
Recent application of e-nose and e-tongue for shelf life evaluation of fresh food of animal origin.

Food Matrix	Aim of the study	Device model	Sensor type	Reference
a) **E-nose applications**				
Meat				
Pork	Volatile evalutaion during storage	PEN3 (Airsense)	10 MOS	Bassey et al. (2022a)
	Shelf life assessment	FOODsniffer	Not indicated	Ramírez et al. (2018)
	Discrimination and prediction of freshness	PEN2 (Airsense)	10 MOS	Hong et al. (2012)
	Freshness evaluation	Prototype	Colorimetric array	Li et al. (2014)
Chicken	Freshness of refrigerated meat	Heracle II & Prototype	Ultrafast GC & 6 MOS, 2 PID	Wojnowski et al. (2017b)
	Evaluation of fresh meat quality	Prototype	3 MOS	Raudienė et al. (2018)
	Freshness evaluation	Home-made	8 not defined	Tang & Yu (2020)
	Odor clustering during shelf life	Home-made	4 MOS	Al Isyrofie et al. (2022)
	Shelf life of fresh and frozen meat	Home-made	8 MOS	Mirzaee-Ghaleh et al. (2020)
	Evaluation of freshness in refrigerated conditions	NST3320 (Applied Sensor)	12 MOSFET & 10 MOS	Hussein et al. (2021)
Beef	Discrimination and prediction of freshness	PEN2 (Airsense)	10 MOS	Hong et al. (2012)
	Beef quality detection	MoLen (prototype)	MOS	Wijaya & Sarno (2015)
	Quality assessment of beef fillets	LibraNose (Technobiochip)	8 QMB	Papadopoulou et al. (2013)
	Freshness determination	Home-made	8 MOS	Xiao et al. (2014)
	Detection of meat spoilage	LibraNose (Technobiochip)	8 QMB	Kodogiannis (2017)
Beef and fish	Freshness inspection	Home-made	8 MOS	Hasan et al. (2012)
	Freshness assessment	Mastersense (prototype)	4 MOS	Grassi et al. (2019)
Fish				
Shrimps	Freshness evaluation	Home-made	8 MOS	Jiang et al. (2016)
	Quality estimation of Pacific white shrimps	Shrimp-Nose (prototype)	6 MOS, Temp & Humidity	Srinivasan et al. (2020)
	Prediction of freshness	Home-made	6 MOS	Du et al. (2015)
Fish	Spoilage monitoring	Impedimetric e-nose	7 nonofibers	Andre et al. (2022)
	Freshness assessment	Home-made	8 MOS	Guney & Atasoy (2013)
Rainbow trout	Identification of spoilage	Home-made	7 MOS	Vajdi et al. (2019)
Horse mackerel	Freshness Testing	Home-made	8 MOS	Atasoy et al. (2015)
Salmon	Freshness assessment	FOX4000 (Alpha-MOS)	18 MOS	Jia et al. (2020)
	Shelf life assessment	FOODsniffer	Not indicated	Castrica et al. (2021)
Tuna	Detection of fresh and contaminated fish	Home-made	8 MOS	Astuti et al. (2023)
Seafood	Quality inspection	Olfosense (Airsense)	4 MOS, 1 PID & 2 EC	Grassi et al. (2022)
Fish and milk	Detection fo freshness and spoilage	Home made	SAW	Verma & Yadava (2015)
Dairy products				
Milk	Characterization of pasteurized milk spoilage	Cyranose320 (Sensigent)	32 CP	Ehsan et al. (2021)
Cheese	Aging discrimination of French cheeses	Home made	5 MOS	Ghasemi-Varnamkhasti et al. (2019)
	Cheese aroma evolution	POLFA (Karumoa Co.)	Not indicated	Fujioka (2021)
Eggs				
	Prediction of egg freshness	Heracles (AlphaMOS)	Ultrafast GC	Yimenu et al. (2017)
	Prediction of egg storage	PEN2 (Airsense)	10 MOS	Li et al. (2017)
b) E-tongue applications				
Beef meat	Detection of ammonia and putrescine during storage	Voltammetric	Modified screen-printed electrodes with bisphthalocyanine and polypyrrole	Apetrei & Apetrei (2016)
Pork	Monitoring of freshness under cold storage	Potentiometric	Metallic (Au, Ag, Cu, Pb, Zn) and graphite electrodes	Gil et al. (2011)
Fish (Cod)	Shelf life quality assessment	Voltammetric	Array 1: 4 noble metal (Ir, Rh, Pt and Au) elettrodes Array 2: 4 non noble metal (Ag, Co, Cu and Ni) elettrodes	Ruiz-Rico et al. (2013)
Fish (Pontic shad)	Freshness monitoring	Voltammetric	Polypyrrole modified screen-printed electrodes	Apetrei et al. (2013)
Fish (Parabramis pekinensis)	Freshness detection	Potentiometric (Astree, AlphaMOS)	7 ChemFET	Han et al. (2015)
Milk	Monitoring of quality and storage time	Voltammetric	4 working electrodes (Au, Ag, Pt and Pd)	Wei et al. (2013)
	Freshness assessment	Potentiometric	pH probe	Tang & Zulkafli (2013)
Cheese (Ceddar)	Aging and protein/fat content discrimination	Potentiometric (Astree, AlphaMOS)	7 ChemFET	Lipkowitz et al. (2018)

content, microbial count and sensory scores were built by two NN regression techniques, generalized regression neural network (GRNN) and back propagation neural network (BPNN).

The latest version of the same e-nose (PEN3) has been used in combination with headspace-gas chromatography-ion mobility spectrometry (HS-GC-IMS) to study the volatiles of pork meat stored at 4 °C for 21 days and at − 2 °C for 28 days in modified atmosphere-packaged and air-packaged (Bassey et al., 2022a). The work reported the effectiveness of the system in determining the aromatic fingerprint evolution during storage, while the GC-IMS separated the volatiles liable for the characteristic flavor.

In the study by Ramirez Soriano, Gómez, Iranzo, & Briones, (2018), the FOODSniffer® was applied on refrigerated pork meat for shelf life assessment. The three-color responses of this e-nose (green - fresh; orange - cook well; red - spoiled) were highly correlated with the sensory attributes, total biogenic amine content and microbiological count, demonstrating that this simple and cheap device can be applied by producers and consumers for meat quality evaluation.

Wojnowski, Majchrzak, Dymerski, Gębicki, and Namieśnik, (2017b) applied the HERACLES e-nose and an e-nose prototype, with six MOS sensors and two photoionization detectors (PID), for the determination of chicken meat shelf life. A sensory panel evaluated the aroma and the appearance of the samples up to 7 days of refrigerated storage. Heracles was applied to detect changes in the aromatic profile holistically, as fingerprint, and for the qualitative identification of volatiles in sample headspace. The e-nose prototype was used as dedicated device to obtain rapid and trustworthy results when combined with chemometric analysis on the collected signals.

Among the homemade e-noses, specifically developed to be applied on meat, a mobile e-nose (MoLen), using MOS sensors in a wireless sensor network, has been proposed for beef quality detection (Wijaya & Sarno, 2015); likewise, Hasan, Ejaz, Ejaz, and Kim, (2012) developed an eight-MOS sensors e-nose for monitoring beef and fish freshness. Two groups of samples were analyzed with the aim of identifying the decayed item. Among chemometric strategies (ANN, SVM and kNN) applied to identify product decay, kNN demonstrated to be the more reliable in terms of performance.

(Grassi et al., 2019) developed a portable four-MOS sensors e-nose (Mastersense), for the assessment of meat and fish freshness. A cloud platform was developed for the storage of the collected data. This device was applied on refrigerated beef, poultry, plaice, and salmon; whereas the TVC was used to classify sample freshness according to a traffic light system. kNN and PLS-DA classifications exceded 83.3% of sensitivity and specificity, demonstrating the Mastersense's ability to correctly assess the sample freshness.

All these studies are important examples of the applicability of e-nose to evaluate the shelf life of meat; at the same time the role of chemometrics for the development of novel devices and for ensuring the reliability of the results is clearly highlighted.

Freshness assessment is even more critical for fish as it is crucial to ensure consumer safety. However, the commonly used methods to evaluate fish quality, including microbial, physico-chemical and sensory analyses (Cheng, Sun, Zeng, & Liu, 2015), are destructive, expensive and require skilled personnel; therefore, e-nose has been proposed as a rapid and non-destructive device for detecting fish volatiles which, in many of the reviewed works, have been correlated with specific indicators of fish spoilage.

In the work of Jia et al. (2012), the commercial FOX 4000 (Alpha MOS, Toulouse, France) e-nose with eighteen-MOS sensors was applied to assess the freshness of salmon fillets during storage at −2, 0, 4 and 10 °C. The volatile evolution was correlated with TBA, TVB-N, total aerobic bacteria count and sensory quality. A PCA-radial basis function neural network model was applied to predict the freshness of the analyzed samples.

Andre, Facure, Mercante, and Correa (2022), developed an impedimetric e-nose to detect ammonia and volatile amines resulting from the decomposition of proteins in fish during storage. Seven sensors, combining inorganic nanofibers, obtained by electrospinning, with conducting polymers (polyaniline, polystyrene sulfonate), were applied. This device demonstrated good performance for the discrimination of volatile amines.

An eight-MOS sensors e-nose was applied to detect tuna contaminated with *Pseudomonas aeruginosa*, one of the most common microorganisms causing fish spoilage by producing trimethylamine. A SVM model classified the contaminated fish with an accuracy of 99% (Astuti et al., 2023).

In a recent work, Grassi, Benedetti, Magnani, Pianezzola, and Buratti (2022), proposed a specific and portable e-nose system, composed by four-MOS sensors, a PID and two electrochemical cells (ECs), for the freshness detection of refrigerated seafood products (sole, red mullet and cuttlefish). The K-means method was applied to cluster samples into three classes (unspoiled, acceptable and spoiled), then kNN and PLS-DA models were developed to classify the seafood products according to their freshness and regardless the species. The prediction ability of the kNN model provided 100% overall precision.

Remaining in the field of fish products, some works have been published to evaluate the freshness of shrimps (Srinivasan, Robinson, Geevaretnam, & Rayappan, 2020; Du, Chai, Guo, & Lu, 2015; Jiang, Li, Zheng, Lin, & Hui, 2016) which easily deteriorate during transportation and storage due to their high protein and moisture content, potentially resulting in threats to human health (Duc et al., 2009). In particular, Srinivasana, Robinson, Geevaretnam, & Rayappan, (2020), estimated the quality of Pacific white shrimp using a homemade e-nose (Shrimp-Nose) consisting of six MOS sensors. Shrimp samples were kept at 29 °C and at 2 °C and measurements were performed at different times. Supporting indices - pH variation, TVB-N, texture analysis, TVC, sensory score and surface black spots formation (melanosis) - were evaluated. PCA, decision tree, kNN and soft-max regression were implemented on collected data and Shrimp-Nose measurements were found in accordance with the results of analytical indices.

The aroma of milk and dairy products greatly influence the consumer preferences and depend on many factors related to the animal, the heat treatments, the starters, and the microbial and chemical contaminations. These factors make it difficult to define unique criteria for classifying the quality and the spoilage status of dairy products. In this context, the e-nose can be considered a rapid method to ensure high-quality standard and integrity of milk and dairy products (Yakubu et al., 2022).

During the milk storage, some bacteria might cause spoilage by producing off-flavoring volatile compounds, such as acetone, butanone, pentanal, and ethanol (Rashid et al., 2019). Consequently, the e-nose assessment of volatiles in the headspace of milk may be useful to predict shelf life.

Using the commercial e-nose Cyranose320, Ehsan, Al-Attabi, Al-Habsi, Claereboudt, and Rahman (2021) estimated the shelf life of pasteurized milk stored for 56 h at 25 °C and for 15 days at 4 °C. E-nose data were elaborated by PCA and LDA and a clear shift of the samples, also evidenced by the microbial count, was identified after 24 h at 25 °C and 12 days at 4 °C.

Cheese shelf life has an impact on its sensory properties (taste, odor and appearance); e-nose evaluation of volatile compounds produced during aging can be useful to evaluate cheese quality and to monitor its shelf life.

In the work of Ghasemi-Varnamkhasti, Mohammad-Razdari, Yoosefian, Izadi, and Siadat (2019), a homemade five-MOS sensor e-nose, was applied to discriminate French cheeses produced with cow, goat and sheep milk, and to classify samples according to their storage period. For data elaboration, PCA, LDA, SVM, PLS, and ANN methods were applied; ANN classified the different types of cheese with high accuracy, LDA performed well in classifying cheese samples according to their storage time, and PLS predicted well the odor pattern.

Egg is another perishable product that can rapidly loose its quality during storage. The deterioration is due to chemical, nutritional, and functional changes related to temperature, humidity, storage time and hen age (Akter, Kasim, Omar, & Sazili, 2014; Tabidi, 2011; Chung, & Lee, 2014). In egg the concentration of volatiles increases during storage, therefore e-nose could be a useful tool to detect its freshness and quality (Adamiec, Dolezal, Mikova, & Davidek, 2002). In two recent works, two commercial e-noses have been applied to evaluate egg shelf life. In the work of Li, Zhu, Jiang, & Wang, (2017), the PEN2 e-nose was applied to predict egg storage time and yolk index. Yimenu, Kim, & Kim (2017) investigated the ability of HERACLES e-nose to evaluate the shelf life, the Haugh unites and the sensory scores of eggs stored at 20 °C for 20 days. Discriminant factor analysis was used to discriminate eggs according to their storage time; whereas models to predict storage time, Haugh units and sensory scores were developed by PLS.

4.3. E-tongue

E-tongue can play an important role in determining the quality and freshness of foods with many possible applications according to the selected sensors.

Table 2b shows some recent applications of the e-tongue for shelf life assessment of meat, fish and dairy products. Considering the information reported in Table 2b potentiometric and voltammetric sensors have been applied in all the examined works, mainly due to their low cost and large availability on the market. Furthermore, voltammetric sensors are generally characterized by low detection limit, high selectivity and sensitivity, while potentiometric sensors ensure fast response, good reproducibility and selectivity to different compounds (Bratov, Abramova, & Ipatov, 2010).

Considering the voltammetric systems, Apetrei, Rodriguez-Mendez, Apetrei, and de Saja (2013) developed an e-tongue consisting of screen-printed carbon electrodes on which polypyrrole, doped with electroactive materials, was deposited. The device was used to evaluate the biogenic amines in Pontic shad (Alosa pontica). A PLS-DA model was built to classify fish according to the days of storage. In a more recent work, Apetrei and Apetrei (2016) applied screen printed carbon electrodes, modified with bisphthalocyanine and polypyrrole, for the detection of amino compounds in beef samples. The modified electrodes showed excellent analytical properties towards ammonia and putrescine with a very low detection limit. The e-tongue developed using the two types of electrodes was applied to monitor beef freshness and PLS-DA was effective in discriminating and classifying beef samples according to their storage time.

Ruiz-Rico et al. (2013) applied a voltammetric e-tongue for the shelf life evaluation of fresh cod fillets in cold storage. The e-tongue system was composed by eight metallic sensors grouped in two arrays made up of noble and non-noble metals. Cod fillets were stored for up to seven days and physico-chemical and microbial analyses were performed every day, together with e-tongue measurements. PCA results demonstrated the e-tongue ability to cluster samples based on their storage time, in accordance with physico-chemical and microbial results.

With the aim of monitoring the quality of unsealed pasteurized milk, Wei, Wang, and Zhang (2013) developed a homemade voltammetric e-tongue, equipped with four working electrodes to which two potential waveforms were applied. The samples were measured during 72 h of storage and PCA and CA were used to cluster the milk samples. TBC and viscosity were also evaluated and PLS regression and least squares-SVM (LS-SVM) were applied for their prediction. The LS-SVM showed better results with R^2 of 0.986 and 0.999 for the prediction of viscosity and TBC, respectively.

In all the examined works a good correlation of the chemical and microbial parameters with voltammetric e-tongue data was found, demonstrating that this device could be a useful tool for shelf life evaluation.

Considering the potentiometric systems, Gil et al. (2011) developed a homemade e-tongue, equipped with metal (Au, Ag, Cu, Pb, Zn) and graphite electrodes. The device was applied to evaluate the evolution of some physico-chemical, microbial, and biochemical parameters, on refrigerated pork loin during storage. Elapsed post-mortem time was defined by ANN analysis, whereas PLS models well correlated the e-tongue data with measured deterioration indexes (pH, microbial count, and nucleoside concentration).

An e-tongue prototype, built from a pH sensor along with a graphical-user-interface, was applied to measure fresh and spoiled samples of pasteurized and non-pasteurized milk (Tang & Zulkafli, 2013). The experimental results showed the failure of pH value in measuring milk freshness; indeed, additional sensors were required to improve the performance of the device.

The commercial Astree e-tongue, combined with linear and non-linear multivariate algorithms, was applied to evaluate fish (*Parabramis pekinensis)* spoilage during cold storage. For qualitative analysis, data were processed by LDA and SVM and the best classification results were obtained by SVM. For quantitative prediction e-tongue data were correlated to TVB-N and TVC values by PLS and support vector regression (SVR) (Han, Huang, Teye, & Gu, 2015).

In the work of Lipkowitz, Ross, Diako, and Smith (2018), Astree e-tongue and sensory analysis were applied to follow changes in tastes and flavors of on Cheddar cheeses with different protein-fat ratios (PFR), during aging. PCA was performed to cluster cheeses by aging time and PFR whereas PLS regression models were built to predict the sensory attributes by e-tongue data.

The applications of potentiometric systems generally showed reliable results, especially when the commercial device has been used. Further work should be done in the field of tailored potentiometric systems.

4.4. Combined applications

It is noteworthy that joint analysis of data acquired by the e-sensing system can provide complementary information and more complete view of considered samples (Di Rosa, Leone, Cheli, & Chiofalo, 2017; Calvini & Pigani, 2022).

Some works in the literature apply different e-sensing systems even if the collected data are separately processed and not jointly analyzed (Haddi et al., 2015; Bassey et al., 2022b; Tudor Kalit, Marković, Kalit, Vahčić, Havranek, 2014; Ghasemi-Varnamkhasti, Apetrei, Lozano, & Anyogu, 2018).

In combining e-sensing systems, data fusion is the most important step and can be applied at three different levels: low level (LL); mid-level (ML) and high-level (HL) (Calvini & Pigani, 2022) (Fig. 4).

In LL data fusion, data obtained from the e-sensing devices are merged in a unique matrix subjected to multivariate statistical analysis. In ML data fusion, data from e-sensing devices are analyzed separately to extract or select the relevant variables, which are then combined to get the fused dataset used to build the model. In HL data fusion, data from e-sensing devices are analyzed and a model is built from each device, then all model results are merged (Kiani, Minaei, & Ghasemi-Varnamkhasti, 2016b).

Although data fusion is very promising for food quality assessment

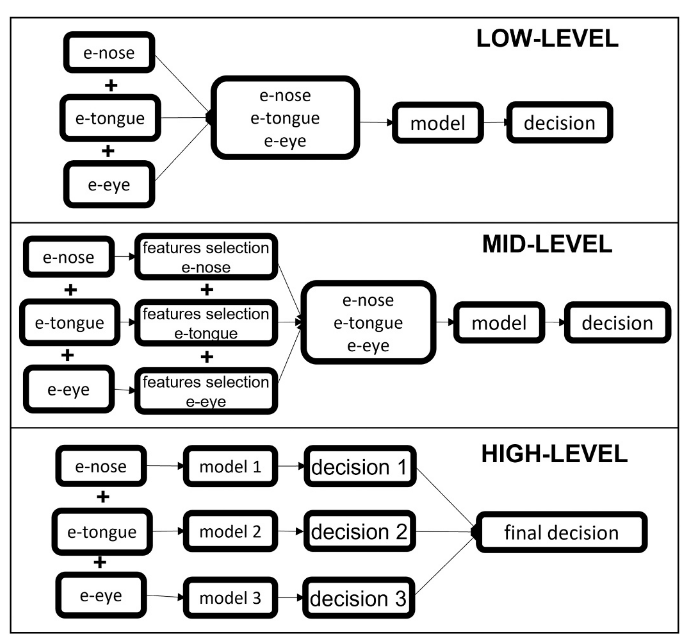

Fig. 4. Schematic representation of data fusion levels.

(Kiani, Minaei, & Ghasemi-Varnamkhasti, 2016b), few papers examined the combined applications of e-sensing for shelf life assessment of fresh food of animal origin.

In two works, the combined application of e-nose and e-tongue was attempted to predict fish freshness (Shi et al. 2018b; Han, Huang, Teye, Gu, & Gu, 2014). In particular, Han et al. (2014) evaluated the freshness of *Pseudosciaena Crocea* fish by combining an e-nose with nine-MOS sensors and a commercial e-tongue (Astree). As first, e-nose and e-tongue data were separately processed by PCA, then three-layer radial basis function neural network models were built for qualitative discrimination of freshness, by considering e-nose principal components (PCs), e-tongue PCs and their combination. The highest discrimination rate was obtained when the two systems were combined. For quantitative determination, a SVM model was built to correlate the merged e-nose and e-tongue data and the TVC values (R in prediction: 0.91).

Bougrini et al. (2014) combined a hybrid e-nose, consisting of two sensor arrays, and a voltammetric e-tongue for the classification of pasteurized milk samples, based on cold storage time. For this purpose, a ML data fusion approach was used, and the variable selection was performed for each data source before their combination and elaboration. SVM method, applied to the new data subset, provided 100% accuracy in recognizing the storage time of pasteurized milk.

A comprehensive method to evaluate the freshness of pork and chicken meat by fusing e-nose, e-eye and artificial tactile (AT) systems was developed by Weng et al., 2020. Odor measurements were conducted by a homemade e-nose with six MOS sensors; color was evaluated by an e-eye system using three-color spaces (RGB, HSI and CIELab); a testing machine was used to mimic human hand in touching meats and feeling their rubbery state. The TVB-N assay was performed to define meat freshness and used as reference to validate the proposed method. PCA and SVM were applied to data of each single device and after their fusion. Results showed that, compared to a single device, the data fusion greatly improved the freshness assessment of meat products. Additionally, PLS analysis was applied to build TVB-N prediction models by merging data from the three systems; for the pork meat the root mean square error in prediction (RMSEP) and the R^2 were 1.21 and 0.91, respectively; for chicken meat the RMSEP and the R^2 were 0.98, and 0.94, respectively.

In the study by Huang, Zhao, Chen, and Zhang (2014), color, chemical composition and volatile compounds of pork meat samples were acquired during spoilage by e-eye, near infrared spectroscopy, and e-nose. The characteristic variables were selected from each system by PCA and submitted to a ML data fusion approach. BP-ANN model well performed in prediction of TVB-N content with a RMSEP of 2.73 mg/100 g and an R^2 of 0.95.

In the work by Li et al. (2023), four prediction methods - ANN, random forest-regression (RFR), extreme gradient boosting (XGBoost) and SVR - were used to jointly elaborate e-nose, e-tongue, and colorimetric data collected from horse mackerel (*Trachurus japonicus*) fish samples during storage. In this study it was found that the evolution of biochemical indices (K value, TBA value, carbonyl content and Ca^{2+}-ATPase activity) was in good relationship with the evolution of volatile compounds, tastes and color parameters, evaluated by the three e-sensing devices. Compared to the independent e-sensing data, the PCA applied on the fused data set ensured a better representation of samples with a total explained variance of about 95%, considering the first four PCs. Furthermore, the quantitative analyses showed that ANN, RFR and XGBoost performed well in the prediction of biochemical indices with R^2 higher than 0.92, 0.93 and 0.88, respectively.

5. Conclusion and future trends

According to the reviewed studies, e-sensing systems show great potential for fresh food shelf life assessment. Although these systems are very promising due to their inherent characteristics, there are some drawbacks to be considered for their routine use.

Visual inspection by colorimeters gives an idea of color changes in selected spots, thus being far from the characterization of the whole food surface. This can be overcome using e-eye, which measure color, texture and morphological characteristics with high accuracy and sensitivity. Even if the market is often oriented to consumer-friendly devices (such as the mobile phones' camera), it should be noticed that the use of imaging system, without the proper knowledge of environmental effects, mainly illumination and distance, can lead to misinformation. On the contrary, the implementation at industrial level, where operating condition can be highly controlled, is highly prompt.

The e-nose has the advantage of quick analysis (few minutes), but the sample preparation is very challenging since the time required for the development of the headspace depends on the sample type and size, and on the container used. Moreover, some e-noses require high operating temperatures (250–500 °C) and are very sensitive to humidity and pressure. Sensor drift is another critical aspect for e-nose loss of performance, caused by sensor aging and contamination.

For e-tongue, the main disadvantages are the sample pretreatment (particularly for solid foods) and the relatively short lifetime of sensors due to absorption of contaminating molecules on their surface.

Another significant drawback is that traditional methods are still the reference for product freshness determination. The reasons are the lack of standardization in terms of analytical procedure, performance assessment, and result reporting. This makes e-sensing techniques recommended for screening purpose or for internal method. The harmonization of analytical guidelines, data handling, and performance criteria will settle the basis for e-sensing recognition as standardized methods for the determination of fresh food freshness. The way is still long, but it is worth to investigate further applications, not only in the laboratories but also at market or industrial level, to fully validate e-sensing potentials.

CRediT authorship contribution statement

Silvia Grassi: Conceptualization; Methodology; Supervision; Writing – original draft; Writing – review & editing. **Simona Benedetti**: Conceptualization; Writing – original draft. **Ernestina Casiraghi:** Writing – review & editing. **Susanna Buratti:** Conceptualization; Writing – original draft.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

No data was used for the research described in the article.

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