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Food Analysis Using Artificial Senses

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ABSTRACT: Nowadays, consumers are paying great attention to the characteristics of food such as smell, taste, and appearance. This motivates scientists to imitate human senses using devices known as electronic senses. These include electronic noses, electronic tongues, and computer vision. Thanks to the utilization of various sensors and methods of signal analysis, artificial senses are widely applied in food analysis for process monitoring and determining the quality and authenticity of foods. This paper summarizes achievements in the field of artificial senses. It includes a brief history of these systems, descriptions of most commonly used sensors (conductometric, potentiometric, amperometic/voltammetric, impedimetric, colorimetric, piezoelectric), data analysis methods (for example, artificial neural network (ANN), principal component analysis (PCA), model CIE $L^*a^*b^*$), and application of artificial senses to food analysis, in particular quality control, authenticity and falsification assessment, and monitoring of production processes.

KEYWORDS: *artificial senses, electronic nose, electronic tongue, computer vision, sensors, data analysis methods, food analysis*

INTRODUCTION

A quality control system is used at each step of the production process to ensure quality and food safety as well as to meet the expectations and needs of consumers.[1,2] The quality of products is determined on the basis of sensory evaluation, chemical composition, physical properties, the level of microbiological and toxic contamination, and the ways in which products are stored, packed, and labeled. Over the past decade, quality control systems such as Hazard Analysis and Critical Control Points (HACCP) and ISO 9000 certificates have emerged. Implementation of the HACCP system ensures food safety as well as the identification and evaluation of the scale of health risks to consumers.[3,4] ISO 9000 standards have been used as a basis for formulating quality management systems in a wide spectrum of organizations. These norms contain the requirements related to the implementation, improvement, and control of systems.[5] The primary method for evaluating the quality of food products is sensory analysis, which is based on the use of human senses. The smell, taste, and appearance of products is evaluated by a group of properly trained persons. Because sensory evaluation is a subjective method, gas chromatography coupled to a mass spectrometer (GC-MS) or olfactometer (GC-O) is additionally used to control the quality of food products. In recent years, comprehensive two-dimensional gas chromatography coupled to a time-of-flight mass spectrometer (GC×GC-TOFMS) has been used with increasing frequency.[6,7]

Consumers pay attention to the smell, taste, and appearance of a product; therefore, scientists have researched for long time how to substitute human sensory organs with so-called artificial senses. The latter require less time to perform sensory analysis compared to chromatographic techniques.[8] This paper is a summary of the achievements in the field of artificial senses, which include electronic noses, electronic tongues, and systems of computer vision. It includes the historical development of artificial senses; the structure and principles of operation of an electronic nose, electronic tongue, and systems of computer vision; a description of the most commonly used sensors (conductometric (CP, MOS, MOSFET), potentiometric, amperometic/voltammetric, impedimetric, piezoelectric (QMB), colorimetric, electronic noses based on gas chromatography and mass spectrometry, biosensors); CCD and CMOS arrays in still cameras; data analysis methods (ANN, kNN, HCA, CA, DFA, PCA, SVM, PLS, PCR, SIMCA, ANOVA, LDA, FDA, QDA, MLR, CDA, CCA) and models (RGB, CIE XYZ, CIE $L^*a^*b^*$, CIE $L^*u^*v^*$, HSV, HSL, HIS); and analysis of image properties and application of artificial senses to food analysis (milk, dairy products, meat products, fish, shellfish, fruit, vegetables, oils, sauces, vinegars, spices, grains, grain products, teas, coffees, herbal infusions, nonalcoholic and alcoholic beverages, and others), in particular, food process monitoring, evaluation of food freshness, testing the shelf life of food, authentication of food, and stability testing of food.

ARTIFICIAL SENSES

Historical Development of Artificial Senses. The development of electronic senses was begun to create devices that mimic the senses of smell, taste, and sight. The history of electronic tongues and noses starts in the beginning of the 20th century. Then the ion exchange theory was developed, which has resulted in the construction of glass membrane electrodes used for measuring pH.[9] The first electrochemical sensor, consisting of a microelectrode and a simple platinum wire, was described by Hartman in 1954.[10,11] In 1960, a Japanese inventor, Taguchi (Figaro), constructed a sensor that has been applied in household alarm systems for detecting gas leaks.[12] The first mechanical instrument mimicking smell was

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elaborated by Moncrief in 1961; he worked on material coatings that would enable discrimination between simple and complex aromas such as polychloride vinyl, gelatin, and plant fat. Moncrief proved that the electronic system containing an array of six sensors with different coatings is capable of detecting a large number of odors.[13,14] In 1964, Wilkens and Hartman developed another system for artificial smell detection, which was based on electrochemical reactions taking place on the electrodes as a result of stimulation with odorants. Wilkens and Hartman concluded that transformation of the sensor output in response to the chemical reaction is possible; in other words, the transformation of a chemical signal into an electrical signal is possible.[7,11] In the following 20 years, new sensors were designed, including MOSFET (metal oxide semiconductor field-effect transistor), BAW (bulk acoustic wave), ion exchange membrane, potentiometric biosensor, ISFET (ion sensitive field-effect transistor), PdMOS (palladium metal oxide semicoductor), and SAW (surface acoustic wave). In 1982, at the University of Manchester, Persaud and Dodd constructed the first electronic nose, which consisted of three metal oxide sensors and was capable of identifying 20 odorants. A detailed definition of an electronic nose was introduced by Gardner in 1988.[15] In 1985, Otto and Thomas presented the first system for liquid phase analysis by using a multisensor array.[16] Seven years later, at the University of Kyusho, the taste sensor was constructed by Toko; it consisted of ion-selective lipid membranes immobilized in PCV polymer.[17,18] In 1995, as a result of cooperation between Russia and Italy, the concept of an electronic tongue was presented; it was based on an inorganic chalgogenide glass sensor, which enables both qualitative and quantitative analysis.[19]

The history of the computer system for image analysis started in the 1960s. In 1964, Minsky began to realize the project that involved coupling a camera to a computer as well as the interpretation of the obtained image.[20] Five years later, Boyle and Smith received the Noble Prize for developing the CCD (charge coupled device) array used to register images in a videophone.[21] In 1970, attempts to better understand the methods for image edge extraction were made, which has resulted in the construction of 3D images.[22] At the same time, such algorithms as line labeling, articulated body model, and optical flow became popular. In 1982, David Marr proposed three levels of information (image) processing, that is, computational theory, representations and algorithms, and hardware implementation.[23] Since 1980 the research has focused on sophisticated mathematical techniques for the segmentation and modeling of shapes and contours. This phenomenon has given rise to the analysis of moving objects, the so-called tracking, which is presently applied on production lines. In 1989, the CMOS (complementary metal oxide semiconductor) array was developed, having principles of operation that are similar to those of the CCD array.[24,25]

Structure and the Principles of Operation of an Electronic Nose. An electronic nose is the analytical device used for the fast detection and identification of mixtures of odorants, which mimics the principles of operation of human smell. Specific chemical sensors are used in the device, which generates a characteristic odor profile, a so-called fingerprint, in response to the interaction with a gaseous mixture; identification of the mixture components is made by comparing the obtained odor profile with odor standards.[26] The electronic nose is similar to the human nose because it is based on the same principles of operation. The volatile components in the investigated sample are analyzed by chemical sensors that mimic olfactory cells present in the nose. Then the signal is sent to the data recognition system, which simulates brain functions.[17,27]

Usually, an electronic nose is composed of a set of sensors, electronic components, pumps, a flowmeter, and software, which is necessary for data processing and statistical analysis.[7] A sample dispensing system is the first element of the device. Sampling can be conducted in different ways, for example, by collecting a headspace sample, by using diffusion methods, and via prior sample enrichment. Commercially available electronic noses have two or more separate chambers, that is, a sample dispensing chamber and a sensor chamber. Temperature and humidity are measured in each chamber to determine the influence of these two factors on the conducted analysis. The sample dispensing chamber should be made of nonflammable and nonreactive materials to avoid the effect of "wall memory"; it should also be adjusted to the sample size.[28] Moreover, a thermostat is required to increase the amount of volatile components in the headspace for the volatile fraction analysis. Air or an inert gas in introduced into the sample chamber. A special system of pumps and tubes made of plastic or stainless steel delivers the gas together with the volatile sample components to the chamber where the second element of the electronic nose, that is, a set of sensors is located.[29] The sample injection step should be preceded by passing the clean and dry air through both chambers. Such a procedure should stabilize the signal at the baseline level and purge the remnants of sample that had been analyzed earlier.[30,31] Due to the contact between odorants and the active material, the electric properties of sensors change; for example, the conductivity changes, which results in an electric signal.[32] The strength of the response signal depends on the type and concentration of odorant. It is important to stabilize the sensors by heating them for two or three days prior to measurement. The time required to receive a sensor output is called a response time, whereas the time required for a sensor to return to baseline after a response is defined as a recovery time[33] (Figure 1). Depending on the application of an electronic nose, different numbers and types of sensors are used.

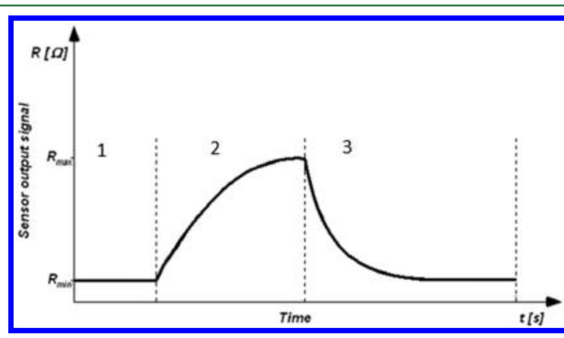

Figure 1. Response characteristics of a semiconductor-based electronic nose: R_{min}, baseline; R_{max}, resistance; 1, gas flow; 2, response time; 3, recovery time.

Structure and Principles of Operation of an Electronic Tongue. An electronic tongue, also known as an artificial tongue, or taste sensor, is the analytical device mainly used to classify the tastes of various chemical substances in liquid phase samples. Its mode of operation is based on the human sense of taste (Figure 2). An electronic tongue can be used to identify, classify, and analyze in a qualitative and quantitative way the

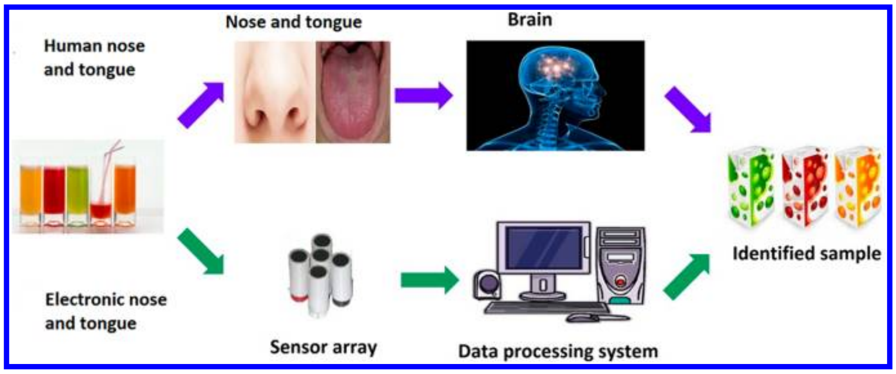

Figure 2. Comparison of the principles of operation of the senses of taste and smell and electronic tongue and electronic nose.

multicomponent mixtures by applying a fingerprint method, that is, by comparing the mixture profiles with those of standards.[31,32] An electronic tongue consists of three elements, that is, the sample-dispensing chamber or automatic sample dispenser (it is not necessary), an array of sensors of different selectivities, and software for data processing (image recognition system, which mimics brain functions).[34] The analysis of liquid phase samples is performed directly; solid phase samples have to be dissolved prior to analysis. An artificial tongue is most commonly used to evaluate food and pharmaceutical products.[35]

An electronic tongue consists of two chambers; the first chamber is used to analyze the sample, whereas the second one cleans the array of sensors after each analysis. A thermostat enables continuous monitoring of the sample temperature during analysis, which results in the repeatability of measurements. Two mechanized flow analysis techniques are used in artificial tongues, that is, flow injection analysis (FIA) and sequential injection analysis (SIA). The first-generation equipment (FIA), designed by Ruzik and Hanser in 1975, consists of a pump, injection valve, solenoid, and detector. In 1995, Ruzick and Marshal elaborated the second-generation apparatus (SIA) consisting of a single-channel duct, two-way pump, solenoid, multiposition valve, and flow sensor. Both techniques are commonly used; however, SIA has more advantages, including the capability to perform a larger number of analyses and a significantly lower use of reagents. The mechanized sample injection allows for decreasing analysis time and improving repeatability. The injected sample reaches the array of chemical sensors.[34] These sensors are characterized by low selectivity and generate information about a wide concentration range of different substances present in the mixture. The sensor response, which is a function of the concentration of components in the liquid, is presented via image recognition module. The signal from the chemical sensors is transformed into a data matrix. The identification and classification are based on a comparison of standard images and the image of the analyzed sample.[36] Depending on the application of an electronic tongue, sensors with different modes of operation are used.

Structure and Principles of Operation of Computer Image Processing. Computer image analysis system, called, "computer vision", includes subjects such as acquisition, processing, and analysis of images.[37] The main reason for creating the system was to understand the mode of operation of human vision. In general, the computer system consists of five elements, that is, lighting, a camera (in the case of an analog camera, a frame grabber is necessary, which allows for analog-to-digital signal conversion), a computer with software, and a high-resolution monitor[38,39] (Figure 3). The application of an

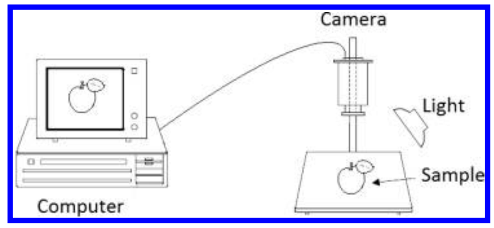

Figure 3. Schematic structure of an image analysis system.

image analysis system is very broad, particularly in the food industry. It is a fast, precise, and noninvasive way of evaluating the product quality already at the production step. Moreover, the system enables detection of imperfections, for example, in meat structure, and the onset of food deterioration, which are both invisible to the human eye.[40]

As in the case of the human eye, the operation of vision systems 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 (LED), quartz halogen lamps, metal halide lamps (applied in microscopy), and high-pressure sodium lamps (best suited for lighting large industrial buildings) are also used. However, due to more uniform and intensive light at specific wavelengths, fluorescent lamps are the most popular. There are two types of lamp arrangements, that is, a circular system used with flat samples and a scattered system for lighting ball-shaped samples. An X-ray tube is used to perform a detailed evaluation of the quality and ripeness of food products; the penetration of X-rays depends on the emitted energy, absorption coefficient, and density and thickness of the analyzed objects.[41] On the other hand, fluorescent spectroscopy is applied to monitor stress in plants.[42] Another part of the image analysis system is a still camera, movie camera, or scanner; its purpose is to record a photograph of a given object. There are two types of cameras, that is, analog and digital cameras, which are equipped with CCD or CMOS sensor arrays.[43] In an analog camera, the recorded image is transformed into the analog signal and then transferred to a frame grabber (in the form of a card), 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.[38,41]

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■ SENSORS USED IN ELECTRONIC SENSES

Sensors are the most important element of electronic senses; their task is to collect information about the parameters measured.[27,29,43] During this process, the input signal, which occurs as some form of energy, is transformed into the output signal in a different energy form, for example, electric, magnetic, chemical, thermal, or radiation energy.[44] Sensors are divided into five groups: piezoelectric; electrochemical (potentiometric, voltammetric, amperometric, conductometric, and impedimetric) and colorimetric sensors; biosensors; and sensors based on gas chromatography and mass spectrometry.[7,34,36,45]

Conductometric Sensors. The mode of operation of a conductometric sensor is based on the changes in conductivity. These changes result from the interactions with the volatile odorants, which leads to the changes in the sensor's electrical resistance; the underlying mechanism differs depending on the material used. Despite the fact that various materials are used, the construction and distribution of specific elements in conductometric sensors are, in principle, the same. There are three types of conductometric sensors that are most commonly used in electronic noses; they are conductive polymer (CP) sensors, metal oxide semiconductors (MOS), and metal oxide semiconductor field-effect transistors (MOSFET). In addition, the conductometric sensors are divided into cold and hot sensors, the latter being capable of performing at higher temperatures.[7,30] Publications on the use of conductometric sensors in an electronic tongue are very scarce.[46]

The advantages of CP sensors are a low price and fast response, whereas susceptibility to humidity is the main disadvantage.[32] These sensors have been used in an electronic nose to, among others, identify stages of wine fermentation,[47] monitor decomposition in Atlantic salmon during its storage at different temperatures,[48,49] and detect spoiled vacuum-packed beef.[50] Cyranose 320, Aroma Scan A32/50S, and Bloodhound BH114 are commercially available electronic noses that employ CP sensors. MOS sensors are also inexpensive, stable, easy to use, and highly sensitive.[7,48] They require a high working temperature, which is a disadvantage.[51] These sensors are used in electronic noses to monitor red wine spoilage[52] and the dehydration process in tomatoes;[53] for the quality control of Atlantic salmon;[54] to determine the freshness of meat;[55] to classify fruits on the basis of their ripeness;[56,57] and to detect aflatoxins in corn.[58] The commercially available electronic noses that employ MOS type sensors are, among others, i-PEN, i-PEN3, PEN-2, PEN3, FOX 2000, 3000, 4000, 5000, FishNose (GEMINI), KAMINA, EOS[835], and FF-2A. Compared to the above-mentioned, the MOSET sensors are small and inexpensive; however, their main disadvantage is low sensitivity to ammonia and carbon dioxide and drifting baseline.[13] These sensors have been employed in electronic noses that are used to evaluate the oxidation level of olive oil stored under various conditions;[59] to detect the presence of fungi, bacteria, and ergosterol in grain samples;[60] to monitor fermentation in sausages;[61] and to determine the freshness of shrimp and cod roe.[62] NST 3210, NST 3220, and NST 3320 are the commercial electronic noses that employ MOSET type sensors.

Amperometric/Voltammetric Sensors. Measurements by means of these sensors are based on the electric current reading between the working and reference electrode in an electrochemical cell as a function of analyte concentration.[63] The main disadvantage of such sensors is the lack of selectivity. This type of sensor in electronic noses is used to assign the correct class to wheat samples in accordance with the quality classification,[64] whereas in the electronic tongue it is used to evaluate different conditions under which olive oil is stored,[59] to identify white wines with regard to the type of grape and geographical origin,[65] and to discriminate among various blends of fruit juices.[66] Additionally, similarly to potentiometric sensors, these sensors are used to monitor the aging phase of wine,[67] to monitor beer fermentation,[68] to control the freshness of milk stored at room temperature,[69] to detect chemically adulterated red wine,[70] and to identify rice wine with regard to its age.[71]

Potentiometric Sensors. Potentiometric sensors are based on the voltage measurement at null current, which is usually needed to retain the balance of electrochemical process.[7] Potentiometric sensors have the following positive properties: well-known principles of operation, low cost, ease of commercial production, the possibility of obtaining selective sensors, and the highest degree of similarity with the mechanism of molecular recognition. Their disadvantages are the dependence of the measured value on temperature and adsorption of the solution components onto the electrodes, which influences the changes in potential.[32,34,36] Potentiometric sensors are most frequently found in electronic tongues, which are used to monitor cheese fermentation;[72] to evaluate the impact of micro-oxygenation and oak chip maceration on wine composition, in particular, on the presence of phenol compounds;[73] to monitor changes during beer brewing;[74] and to identify the botanical origin of honey.[75]

Impedimetric Sensors. The principle of operation of impedimetric sensors is based on measuring the impedance at one constant frequency or for a frequency spectrum by means of impedance spectroscopy.[34] They could be employed in an electronic tongue; however, in practice, this happens only sporadically. This sensor was used, for example, to discriminate brands in red wines in an electronic tongue.[76]

Piezoelectric Sensors. The operation of piezoelectric sensors is based on a piezoelectric phenomenon. As a result of sensor exposure to odorants, a change in mass occurs due to the adsorption or absorption of odorants by the sensor, which, in turn, causes changes in the sensor resonance. Consequently, the electric current also changes, which is the output signal. The main advantages of piezoelectric sensors are high sensitivity, real-time measurements, small size, durability, low cost, and the principle of detecting analytes on the basis of the universal change in mass.[77] A quartz crystal microbalance (QMB) is an example of the application of a piezoelectric sensor.[7,29] Piezoelectric sensors are more commonly used in electronic noses (e.g., to determine the optimal time for harvesting apples[78] and to evaluate the quality of tomatoes[79]) than in electronic tongues. It seems, however, that their wider use in electronic tongues is just a question of time.[32]

Colorimetric Sensors. Colorimetric sensors are devices mostly based on the interaction of electromagnetic radiation with matter. Colorimetric sensors can be based on different phenomena such as fluorescence, reflection, and absorbance. These sensors consist of an indicator, detector, and light source, the latter set at a specific wavelength to maximize selectivity. Due to the interaction with an analyte, the properties of an indicator change, which influences the membrane absorbance or fluorescence. The changes are monitored via a detector, which converts the signal from optical into electric form.[32] There is a great variety of colorimetric sensors; therefore, they are characterized by low cost, simple procedure, and high selectivity.[7] Thanks to the use of colorimetric sensors, it is possible to detect substances that are not electrochemically active and therefore cannot be detected by an electrochemical sensor. Colorimetric sensors have some disadvantages that significantly limit their application, for example, sensor durability and output signal distortion.[32] These sensors have been employed in electronic noses to discriminate commercial drinks[80] and in electronic tongues to evaluate the quality of beer brands[81] and discriminate wines with regard to wine age and grape variety.[82]

Electronic Noses Based on Gas Chromatography and Mass Spectrometry. In the electronic nose technology, it is possible to use the technique of fast gas chromatography. A fast gas chromatograph is a stationary device that requires a short time for analyzing samples; it simulates the work of a system consisting of hundreds of orthogonal sensors, which allows for precise separation of volatile components in the investigated sample. There are also electronic noses employing a mass spectrometer;[52,83−85] the mass spectra of particular substances are then used as the output signal from the sensor. However, due to the high cost of such devices, their application is relatively rare.[7,51] A mass spectrometer was used, for example, to predict the shelf life of pasteurized and homogenized low-fat milk in an electronic nose[86,87] and to discriminate bacterial strains and monitor the smell intensity during fermentation of milk and cheeses.[83]

Biosensors. A biosensor consists of a biological measuring element, which is located close to the transducer to achieve high sensitivity to the target analytes (Figure 4).[31] A biosensor-based electronic tongue is often called a bioelectronic tongue. Such a device can be described as an analytical system made of a number of biosensors that are sensitive to particular compounds present in a solution; the system is connected to the properly selected chemometric tool for data processing.[88] Until now, different principles of operation of bioelectonic tongues have been proposed, including voltammetric, amperometric, and potentiometric principle. Biosensor arrays display high selectivity due to enzyme−substrate interactions. Moreover, the biosensor efficiency can be improved by the introduction of electron mediators, which facilitate the transfer of electrons from the enzyme to the electrode.[89] Such sensors have been used to, among others, monitor changes occurring during the aging process in beer.[90]

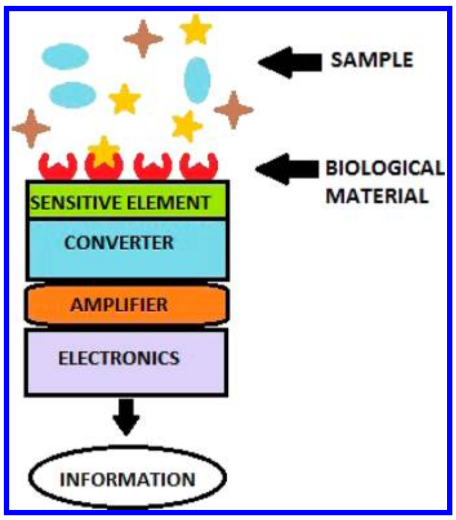

Figure 4. Exemplary structure of a biosensor.

Arrays in Still Cameras. *CCD Array.* A charge coupled device (CCD) array consists of hundreds of thousands of light-sensitive elements, or semiconductor sensors, which are called pixels. The creation and storage of the electric charge originating in the presence of light is one of the sensor's functions. The task of the whole array is to sample the image, be light-sensitive, and store and transport the created charges. CCD sensors are made of light and fragile materials; they can be in the form of diodes and a MOS capacitor stacked in rows. Light, upon reaching the array covered with a crystal silicon plate, ejects electrons from particular pixels. The number of ejected electrons is proportional to light intensity at a given pixel. A CCD array has two working modes, that is, passive and active. In passive mode, different numbers of electrons are gathered depending on light intensity, whereas in active mode the pixel readout takes place, where charges from higher levels are transferred one pixel lower. This process is repeated until all pixels have been read. Next, the content of consecutive rows ends up in the shift register, a so-called output register, where a conversion of charge into a voltage occurs at the output (Figure 5).[41]

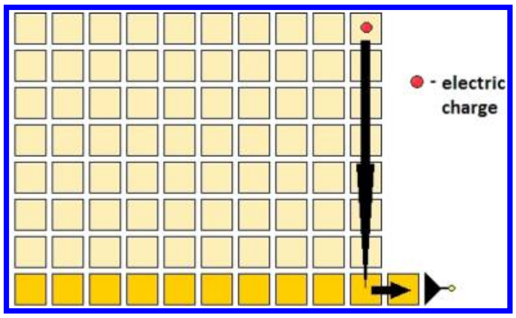

Figure 5. Simplified schematic representation of a CCD array.

Color Sensors. The most commonly used color sensors are a Bayer sensor and a device called 3CCD. The Bayer sensor is employed as an RGB (red, green, blue) filter in CCD sensors of digital cameras. It is a chess board-like grid having a filter pattern that is 50% green, 25% red, and 25% blue. Such an arrangement of colors results from the fact that a human eye is most sensitive to green color. Unfortunately, the filter transmits only a part of the spectrum; therefore, some information does not reach the sensor. Additional information is created by using a demosaicing algorithm. The 3CCD sensor has better color resolution because it contains three independent image sensors and dichroic prisms, which split light into red, green, and blue beams. This sensor is characterized by better light sensitivity as it absorbs the whole beam of light, whereas sensors covered with a Bayer filter absorb only 33%.[41]

CMOS Array. A complementary metal oxide semiconductor (CMOS) array is based on the same principle as a CCD array. Light absorbed by silicon crystals generates electric charges. The CMOS sensors differ from the CCD sensors with regard to distribution and structure (Figure 6). The basic difference is that each so-called active pixel has its own voltage transducer. As a result, the coefficient of a transformation of electric charge to voltage is almost the same for each pixel. Consequently, it is necessary to calibrate the CMOS array with regard to differences between pixels by using digital camera software. Contrary to the CCD array, the CMOS pixels can be read in

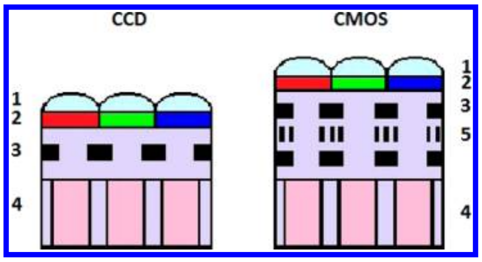

Figure 6. Comparison of the CMOS and CCD arrays: 1, microlenses; 2, color filter; 3, signal transmission path; 4, photodiodes; 5, transistors and amplifiers.

any order. The main advantages of the CMOS array are low energy use and the possibility to miniaturize the camera.[41,91,92]

METHODS OF SIGNAL ANALYSIS USED IN ELECTRONIC SENSES

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. The simplest method is the graphical representation of data in the form of a histogram or circle diagram. Both of these graph types are used to determine the sample components that significantly differ from the others. Another method of signal analysis is based on statistical analysis or multidimensional data analysis. Besides the aforementioned methods, artificial neural networks can also be applied.

Artificial Neural Networks (ANN). An artificial neural network mimics a biological neural network, which collects and transfers signals to the central nervous system, processes the data, and makes specific decisions depending on the identified objects. The basic elements of ANN are artificial neurons. The most important parts of a neuron are the nucleus, dendrites, synapses, axon hillock, and axon. The nucleus is the computing center of the neuron. Dendrites are entrance gates of the neuron through which the input signals enter, whereas a synapse is the end part of dendrites and a so-called exit gate of the neuron. The input signal at a synapse undergoes a preliminary modification; that is, it is either amplified or attenuated. As in a dendrite, the axon is the exit gate from the neuron, whereas the axon hillock is the so-called neuron's exit.

In an axon, the neuron's exit is intertwined with the dendrites of other neurons (i.e., entrances), which enables further transfer of the signal. An artificial neuron has been designed to simulate its biological counterpart. The entrances, or more specifically the signals passing through them, correspond to dendrites. Weights are digital analogues of changes made in the signals at a synapse. The summation function block corresponds to a nucleus, the activation function block corresponds to the axon hillock, and the exit is analogous to the axon. Signal processing by an artificial neuron can be presented in a generalized way as follows. Signals delivered by the entrance gates are multiplied by weights. The multiplied signals are then summed using a summation function block, which results in the signal called a membrane potential. This signal is passed through an activation block, which can be described by different activation functions depending on the requirements. The value of a activation function is the neuron's output signal, which is transferred to the neurons in the next layer. The activation function can have one of three forms: step function (a so-called threshold function), linear function, and nonlinear function. Neurons are usually distributed in layers. The first neuron layer is called an 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 can be present between the input and output layers. Neurons assigned to specific hidden layers process the input information into the output information. Neurons in adjacent layers are connected, which results in a system of paths used for information transfer; these connections can be of a one-way or two-way type. One of the main advantages of neural networks compared to other methods of data processing is the learning process, which enables the proper reaction to signals that have not been foreseen by the constructor. Contrary to mathematical methods and algorithms, a neural network can be used for many different models without significant alterations. The aforementioned advantages are available only when a proper learning algorithm is employed. The most commonly used methods of training ANN include error back-propagation (BPNN) and its modified versions.[93−95] We can identify different types of ANN used in the analysis of data obtained through electronic senses: radial basis function (RBF), counterpropagation−artificial neural network (CP-ANN), generalized regression neural network (GRNN), time delay neural networks (TDNN), probabilistic neural networks (PNN), self-organizing maps (SOM), and neural networks of learning vector quantization (LVQ) type.

***k*-Nearest Neighbor (kNN) Algorithm.** The kNN algorithm belongs to the group of algorithms in which the description of the classifier's target function is not performed during the classifier's training, but at the stage of assigning an object to the specific classes. The underlying principle of the classifier's operation is that the object belonging to a specific class has in its close proximity other objects belonging to the same class. Classification is performed by comparing the fitted object to all objects stored in the training set and then choosing from among them k objects that are most alike. To estimate how similar the two feature vectors are, the Euclidean distance is commonly used; the objects that are separated by the shortest Euclidean distance are considered similar. The object is assigned to the class represented by the highest number of objects from among k selected neighbors. When more than one class is represented by the same number of neighbors, the class consisting of the closest neighbors is chosen. Parameter k is selected experimentally to obtain the best classification for a given data set.[96,97]

Hierarchical Cluster Analysis (HCA): Czekanowski's Method. Czekanowski's method/diagram is mainly used to cluster territorial units into homogeneous regions. The starting point of Czekanowski's method is the matrix of distances between the objects, $D[dii']$, which are defined on the basis of any distance type. The distance measures in the D matrix are divided into similarity classes of objects, and the appropriate graphical symbols are assigned to these classes. In this way, an unorganized Czekanowski's diagram is created, which allows for a visual evaluation of the object classification. Object sorting is performed by organizing the diagram, that is, by rearranging its rows and the corresponding columns to align the graphical symbols that code the shortest possible distances along the main diagonal. As the distance from the main diagonal increases, the symbols corresponding to larger distances appear. The sequence in which objects are organized is defined by the sequence of the corresponding rows (columns).[98]

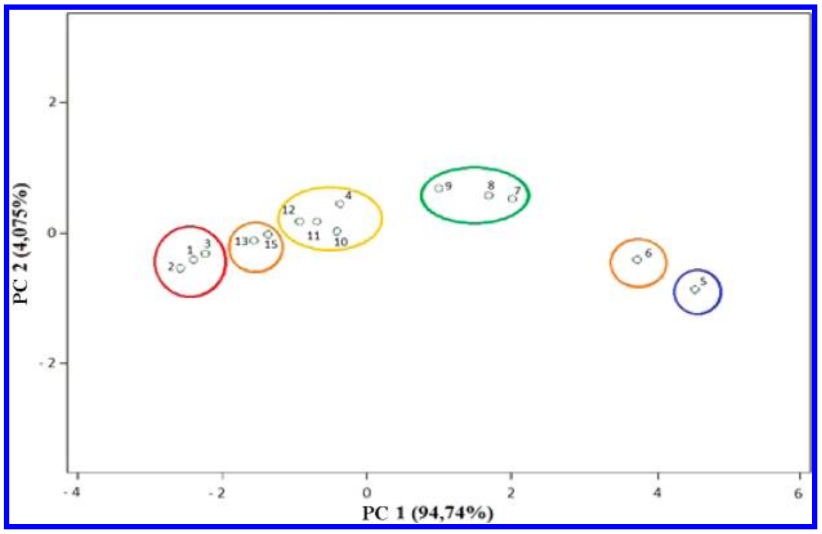

Figure 7. Example of a PCA plot for the varieties of Polish honey.

Cluster Analysis (CA). CA is a method that allows for grouping elements described by more than one feature into relatively homogeneous classes. The most important part of CA is the formation of clusters, that is, the sets of objects for which the similarity between any two objects from the same set is higher than that between any object from the same set and any object not belonging to the set. The clusters do not overlap; that is, none of the objects can belong to more than one class. The clusters are separated by a precisely determined distance, which can be defined in a number of ways. There are two types of clustering methods, that is, hierarchical methods that allow for generating a hierarchy of clusters depending on the distance between the clusters and nonhierarchical methods based on relocating objects from one cluster to another in the search for the most suitable scheme according to the desired criterion. Agglomeration and *k*-means clustering are considered hierarchical and nonhierarchical methods, respectively.[99,100]

Discriminant Function Analysis (DFA). DFA is used when the assumptions of a linear regression are met. The cases are classified into groups using a discriminant prediction equation to examine differences between or among groups. It allows for the rejection of variables that are little related to group distinctions and to determine the fastest way to distinguish groups of elements. Discriminant analysis is carried out in two stages. The first stage, the F test, is used to check whether the discriminant model as a whole is significant. The second step is carried out when the F test shows significance. The individual independent variables are evaluated to see which differ significantly in mean by the group, and they are used to classify the dependent variable.[101]

Principal Component Analysis (PCA). PCA is mainly used to model, compress, and visualize multivariate data (Figure 7). The aim of PCA is to present the data set X, with m objects and n variables, in the form of a product of two new matrices T $(m \times f)$ and P $(n \times f)$, where $f \ll n$; matrices T and P contain the object coordinates and parameters that lie on the first new coordinate (first principal component), which is the direction of maximum variance. The PCA model can be described by the equation

$$X_{[m,n]} = T_{[m,f]}P_{[f,n]}{}^{T} + E_{[m,n]}$$

where E is the matrix of residues for the PCA model with f principal components. The columns of matrices T and P contain the object coordinates and parameters that are assigned to new variables called principal components. The principal components are derived by iteration in such a way as to maximize the data variance. Each consecutive principal component explains the variance that has not been accounted for by the earlier principal components; therefore, the variance assigned to it decreases. Each principal component has an associated value, a so-called eigenvalue, v_i, which is computed by summing the squares of results for a specific principal component. Eigenvalues quantitatively describe the variance associated with the consecutive principal components. Principal components form a new coordinate system in which the Euclidean distances between the objects remain the same; that is, new distances are identical with the original distances in the data space. Each object has coordinates defined by specific results.[102]

Support Vector Machine (SVM). SVM is a mathematical model described by the supervised learning algorithm that is capable of making predictions. Similarly to ANN, the assignment of objects to specific classes by the SVM method is realized with the use of a training set. SVM is a great alternative to ANN because of better classification compared to the latter, for example. 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. The SVM algorithm assumes that a maximum-margin hyperplane separates the two classes of data sets in the best way. The margin is a distance between the hyperplane and the support vectors. The support vectors are hyperplanes that separate two classes of data points and are supported by these data sets. Besides the standard support vector machine, different modifications of this method exist such as support vector regression (SVR) and least-squares support vector regression (LSSVR).[103]

Partial Least Squares (PLS). Partial least squares regression (PLSR) is a technique commonly used in data analysis. PLSR is a variant of PCA; a number of linear combinations of the predictors, which predict the response variable in a satisfactory way and are orthogonal, is sought. In the case of the PLSR method, the new explanatory variables should not only explain the variability of the original data but also be correlated with the response variable. This method is used when one analyzes a relationship between one response variable and many explanatory variables. PLSR is particularly useful when the number of variables is larger than the number of data points. For these reasons, the method is frequently applied in chemometry. The multiple-regression methods, for example, PLS, can also be used to construct discriminant analysis models (PLSDA).[104]

Principal Component Regression (PCR). In PCR the model is composed of principal components instead of the original variables. The principal components are derived via iteration by decomposing the original data matrix X into the result matrix T and the weight matrix P. The role of principal components is to maximize the data variance. In general, a PCR model with f factors that allows for the prediction of dependent variables can be described by the following set of equations:

$$X_{[m,n]} = T_{[m,f]}P^{T}_{[f,n]} + E_{[m,n]}$$

$$Y_{[m,k]} = T_{[m,f]}Q^{T}_{[f,k]} + G_{[m,k]}$$

The coefficients of the regression model Q are estimated by the least-squares method, as follows:

$$Q_{[f,k]} = (T^{T}_{[f,m]}T_{[m,f]})^{-1}T^{T}_{[f,m]}Y_{[m,k]}$$

The principal components used for the construction of the PCR model are orthogonal. This property allows for the calculation of regression coefficients by applying the least-squares method. Moreover, a part of the experimental error of data set X is reduced after a couple of principal components have been chosen. The number of columns in matrix T, that is, the number of principal components used in the constructed model, defines the model's complexity. Matrices E and G contain this part of variance of X and Y, which has not been accounted for by the fitted model.[104]

Soft Independent Modeling of Class Analogies (SIMCA) Classifier. In the SIMCA method, a separate model is constructed for each class, which is based on the principal component approach. Next, a so-called confidence envelope (i.e., a certain volume or hypervolume) is created around the model, which should contain all elements belonging to the specific class with a given probability. For each class, the number of significant principal components in the model is individually chosen in accordance with the commonly used methods. In the case when only one principal component is significant for a given class, the component mean and the vector associated with this component become the model of the class. For two significant components, the model is defined by the location of class center and the plane determined by the component vectors. The remaining models are constructed in a similar way.[97]

Analysis of Variance (ANOVA). ANOVA is a parametric tool that allows for comparing more than two groups that had been categorized on the basis of one variable (one-way ANOVA). The underlying idea is to compare the variance of dependent variables within the groups that had been created on the basis of the values of independent variables. To apply ANOVA, the following assumptions must be fulfilled: the dependent variable is normally distributed; between-group variance is homogeneous; the dependent variable must be measured at least on an interval scale; and the analyzed groups should contain equal numbers of objects.[105,106]

Linear Discriminant Analysis (LDA). The aim of LDA is to construct linear discriminant functions for the samples in the model set that belong to specific groups. The constructed discriminant functions are used to classify new samples. The underlying idea of the method is to reduce the dimension of the data set and, at the same time, retain the value of the T^2 statistic, which is used to evaluate the hypothesis about the equality of means in a multidimensional space. As a result of LDA, a space is created having a dimension that had been reduced to $k - 1$ at best (k is the number of classes). For normal multidimensional distributions of the analyzed data in such a space, the discriminatory features remain intact. To properly apply LDA, a number of assumptions has to be fulfilled, that is, the distribution of objects in each group should be approximately normal; the groups should be linearly separable; variance−covariance matrices of each group should be linearly separable; and the total number of objects has to be at least 3 times larger than the number of variables. There are three variants of LDA, stepwise linear discriminant analysis (SLDA) being an example of one of them.[104,107]

Fisher Discriminant Analysis (FDA). FDA assumes that data vectors occupy p-dimensional space $X \times {}^{1}/_{2}R^{p}$, whereas its aim is to obtain a discrimination rule based on a linear function. For $g = 2$ (g is the number of classes), the rule determines the direction a in X that separates the two training sets in the best possible way and, at the same time, creates a distance measure between the classes that includes a within-group variability. A within-group dispersion should be characterized by appropriate covariance matrices that are based on suitable data. FDA requires that the information about classes, to which new observations are assigned, should be categorized by using the indicators of location and dispersion of g subsets in the training set.[108]

Quadratic Discriminant Analysis (QDA). QDA is also considered a statistical method however, of a more sophisticated type than LDA. In QDA, the data set is subdivided by using quadratic curves. This method is applied when variance−covariance matrices significantly differ. In the case of QDA, the boundaries between the groups are nonlinear.[107,108]

Multiple Linear Regression (MLR). The aim of MLR is to determine the relationships between many independent (explanatory) variables and the dependent (response) variable. In the regression analysis, the parameters of a theoretical model are estimated to reflect the true relationship in the best possible way, as illustrated by the plot of real and theoretical values of the response variable.

The basic regression models assume the existence of linear relationships between the response variable and the explanatory variables.[104]

Complex Data Analysis (CDA). CDA is based on the assumption that data consist of x vectors containing non-negative elements x_1, ..., x_D, which form a specific unity:

$$x_1 + ... + x_D = 1$$

The variables in the aforementioned equation are not independent because they sum to 1; such data are called closed data.

Information contained in the vectors is connected to the relative content of a component. Therefore, the relationships between the components can be expressed in the form of proportions. A transformation of the component vector spaces (simplex) into a Euclidean space can be performed by applying logarithmic transformations. The characteristic feature of a complex data set is that each row in the data matrix corresponds to only one sample, whereas each matrix column corresponds to one component. Moreover, each matrix element is non-negative, and all matrix rows sum to 1 (e.g., proportions) or 100 (e.g., percentage shares).[108]

Canonical Correlation Analysis (CCA). CCA allows one to find points (variables) in the new coordinate system and points (objects) in the same coordinate system.

In this way, a relationship between the variables and objects under observation can be defined. The analysis of relationships between the variables and objects is conducted directly, which is contrary to the indirect analysis via relationships among the variables and factors, as in other factor-based methods. The rows of matrix X, that is, the input data matrix, can be interpreted geometrically as the coordinates of data points of the variables in n-dimensional object space R_n, whereas the matrix columns as the coordinates of points (objects) in m-dimensional variable space R_m. The input variables are made uniform by applying a canonical transformation. The standardization process in CCA aims at homogenizing the columns and rows of the relative frequency matrix. This type of standardization is performed by scaling the coordinates after matrix columns and matrix rows had been standardized.[109]

Color Image Analysis. *RGB Model.* The most popular method of color image analysis is the RGB model based on three components, that is, red (R), green (G), and blue (B). The RGB color space can be depicted in the form of a cube with three perpendicular axes R, G, and B, each with the axis range from 0 to 255,[25,110] as presented in Figure 8.

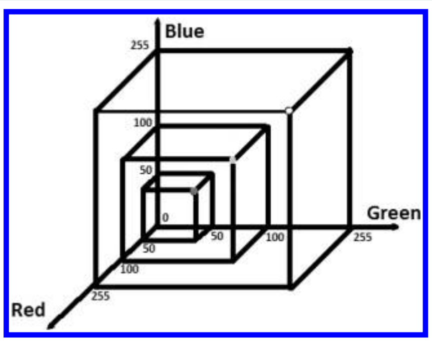

Figure 8. 3D volume of RGB model in a Cartesian coordinate system.

For $R = G = B = 0$, no light is present; therefore, such assignment indicates the color black. In the case when all components assume maximum values, white color is the outcome. Points with different hues of gray color, which lie along the achromatic axis of the RGB cube, are also shown in the figure. The achromatic axis has been defined as a set of points lying on the main diagonal of RGB cube between the points $[R_{min}\ G_{min}\ B_{min}] = [0,0,0]$ and $[R_{max}\ G_{max}\ B_{max}] = [255,255,255]$. The RGB model is called an additive color model because a broad spectrum of colors is obtained by adding beams of primary colors in space.[25,110]

CIE XYZ Model. The CIE XYZ, or CIE 1931 color space, is the first mathematically defined color space model. It is considered a standard and reference point for CIE $L^*a^*b^*$ and CIE $L^*u^*v^*$ color spaces. The abbreviation CIE stands for the International Commission on Illumination (Comission Internationale de I'Eclairage). The tristimulus values XYZ correspond to the percentage shares of primary colors in the RGB model.[111]

*CIE L*a*b* and CIE L*u*v*.* Unfortunately, the CIE XYZ model has numerous flaws, for example, the lack of uniform color perception; that is, similar differences among colors are not separated by the same Euclidean distances in the color space. As a result of mathematical transformation of the CIE XYZ model, two models are produced: CIE $L^*a^*b^*$ and CIE $L^*u^*v^*$.[25,112] Colors in the CIE $L^*a^*b^*$ model are defined by three components: L^*, which is luminance, an achromatic property in the range between black and white; a^*, which is a chromatic component in the range between green and magenta; and b^*, another chromatic component in the range between blue and yellow.[111,112]

Contrary to the CIE L^*a^*b model, the CIE $L^*u^*v^*$ model is characterized by a simpler calculation required to transform the CIE XYZ model, which does not involve so many cube root operations. However, the transformation requires intermediate parameters, u^* and v^*. As in the previous model, the symbol L^* stands for luminance, whereas u^* is a chromatic component in the range between green and red and v^* is a chromatic component in the range between blue and yellow.[111,112]

HSV, HSL, and HSI Models. HSV, HSL, and HSI are other color space models; each letter codes a specific model component, that is, hue, saturation, value, lightness, and intensity. These models are modified versions of the RGB space that more precisely reflect the perception of a human eye and, at the same time, retain the simplicity of calculation.[41,113−115] Figure 9 shows a comparison of the three aforementioned models.

The HSV model has the shape of a pyramid, whereas the HSL and HSI models are a double pyramid and a cylinder, respectively. The HSV model is based on the cube that has resulted from the RGB model. The analogy is also visible in the HSL model. The HSI model has a different shape; saturation is expressed as a distance from the cylinder center, and intensity is defined as the axis height. As all color models, the HSV, HSL, and HSI models have certain flaws, for example, unspecified H value for $S = 0$. In the HSI model, intensity contains information that is tightly connected to the other system components. In the case when intensity is close to 0, the analysis of hue and saturation is pointless because of the possible occurrence of large errors.[113]

Analysis of Image Properties. An image has basic properties such as resolution, dimension, the number of discrete intensity levels for each pixel, color space, and the signal-to-noise ratio.[38,116] The processing of a raw image consists of many graphical operations, which enable the improvement of image quality by removing specific flaws, for example, geometric distortions, inappropriate sharpness, uneven lighting, and camera movement. Image analysis is mostly based on the discrimination between a given object and its background. There are three levels of image processing: low, medium, and high.[38,110] In low-level image processing, simple corrections can be introduced to the image by using geometrical operations such as moving, rotating, and scaling to correlate the image with the coordinate system. The consecutive processes that improve image quality are arithmetic operations; they allow for increasing the contrast and adjusting the brightness to increase the differences between the object and the background.[117] Image filtering is one of the possible operations where the intensity at pixel location is recalculated on the basis of the pixel intensity and the intensity of

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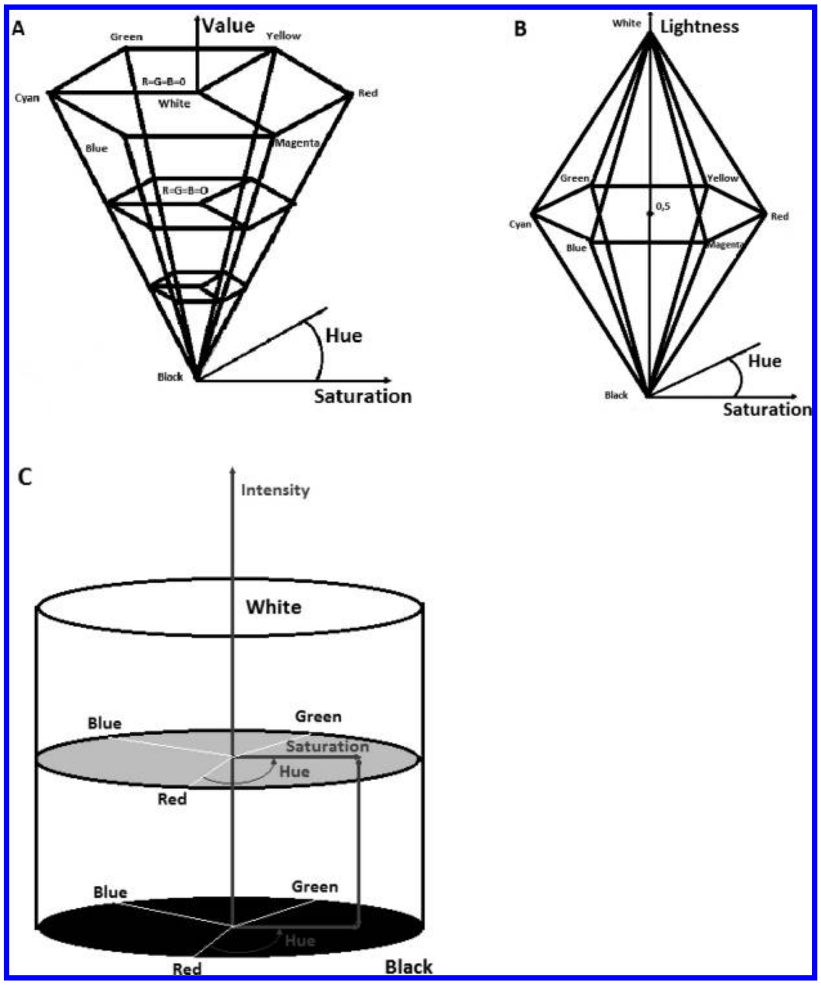

Figure 9. Three color models: (A) HSV; (B) HSL; (C) HSI.

neighboring pixels. Due to the use of filters, it is possible to improve image quality by removing the sensor noise or by correcting the nonuniformly lit image. Moreover, filtering enables the sharpness correction of edges and boundaries between the objects. Segmentation, which is considered a medium-level image processing, is one of the most important methods of image analysis. In this method, the previously filtered image is partitioned into fragments that correspond to specific objects. This allows delineation of image areas that fulfill the homogeneity criterion with regard to color, brightness, and texture.[38,118] A high-level image processing is based on image recognition and interpretation by using statistical classification, neural networks, and fuzzy logic. This stage of image processing supplies information that is necessary for quality control, sorting operations, and object classification on the production lines in food-processing plants.[38,119]

■ APPLICATION OF ARTIFICIAL SENSES TO FOOD ANALYSIS

At first, an electronic nose was used only to analyze the mixtures of volatile air contaminants that had already been detected by olfaction. At present, the application of this device is much broader and includes the analysis of liquids and oxygen-free gas mixtures. The use of electronic nose encompasses environmental monitoring (detection of air pollution, tracking of pollution pathways, and efficiency assessment of wastewater and waste gas treatment), medical sciences (identification of selected diseases, including tumors, based on odorants excreted by the infected cells and organs), the perfume industry (authentication of perfumes), the pharmaceutical industry (production control of medicines), forensic operations, and the food-processing industry.[7]

An electronic tongue is used to analyze liquid samples. This device enables a parallel analysis of multiple components present in the investigated liquid. The artificial tongue is applied in environmental monitoring (detection of contaminants in samples of water and wastewater), medical sciences (detection of pathogens in liquid samples), and the food-processing industry.[120]

On the other hand, computer vision is used in the food-processing industry for quality control. The system is commonly employed on the production lines for sorting and discriminating specific products.

Milk and Dairy Products. Dairy products are a very diverse group due to the fact that they comprise many types of yogurt, cheese, and milk, each of these foods being broadly diversified as well. Dairy products are made in various ways by using a wide spectrum of fermentation techniques, microorganisms, and food additives. This scenario stimulates the search for analytical tools that would allow for the discrimination of products and their quality evaluation. The electronic nose and tongue are used to monitor food processing, evaluate food freshness, authenticate products, and determine the shelf life of foods. This allows for reducing the number of poisonings and allergic reactions in human. The electronic eye is employed to monitor visual changes in cheese during the pizza-baking process.[121]

In the case of food process monitoring, the electronic nose and tongue have been used to monitor fermentation in milk and cheese.[72,83] The application of artificial senses assures product quality at the very start of the food production line.

The monitoring of food freshness and product quality during storage is the foremost application of the electronic nose and tongue.[69,87,122−126] This allows the exclusion of spoiled products from the market as well as the determination of appropriate shelf times and storage conditions for milk and cheese to avoid financial losses by the dairy industry.

Another important application of electronic senses is product authentication. Thanks to this procedure, falsified products are excluded from the market; therefore, consumers can purchase merchandise of quality precisely specified by the manufacturer. In the case of dairy products, the conducted studies were aimed at discriminating the brands of milk and yogurt[127−130] and identifying hydrogen peroxide in cow's milk.[131] The determination of age, geographical origin, type, and maturation level in cheeses is also very important; such studies were conducted on a broad variety of cheeses by means of an electronic nose.[132−139] It is necessary to perform this type of research because the investigated parameters influence the cheese quality and therefore the price of specific cheese varieties.

Meat Products. Chemical analyses of meat products are mainly performed via an electronic nose; the use of an electronic tongue in this case is less suitable because it requires a more complex preparation of samples. On the other hand, an electronic eye can be employed to evaluate the freshness of different meat types,[140−145] the medical condition of meat,[146] and the influence of storage conditions on meat quality to determine an expiration date[147,148] based on color and shape. Computer image analysis was used to evaluate the freshness of beef,[140,142] pork,[141,144,147] and poultry.[144,146] The electronic tongue was applied to analyze ground meat to predict the level of chlorides, nitrates, and nitrites.[149] Actually, it is the electronic nose that has found a broader application in the field of meat product analysis. This device is used to, among others, monitor the curing process in Iberian ham to detect spoilage;[150] this allows exclusion of a production batch that could possibly pose a health risk to consumers. Moreover, the electronic nose is frequently used to detect spoilage, evaluate freshness,[55] and determine the storage time of meat. Until now, the conducted studies were aimed at discriminating between fresh and spoiled meat in samples of beef,[50,151,152] turkey meat,[153] sheep meat,[151] and sausages.[61] Another field of application of electronic senses is the freshness evaluation in meat during storage, which is aimed at determining the optimal storage time and conditions to avoid meat spoilage.[154] On the basis of freshness evaluation studies, different freshness categories of meat products can be defined. Research on the influence of storage time on meat quality was conducted on samples of veal,[155] beef,[156] lamb,[157] and meat products used in pizza production.[158] The meat price depends on the animal species from which meat is produced. Therefore, it is specifically important to avoid falsified or misidentified meat. The electronic nose was used to discriminate llama meat from alpaca meat,[159] identify the meat of Iberian pigs among other pork meat,[160] discriminate among hams and sausages on the basis of their type and quality,[161,162] and discriminate meats on the basis of the meat preparation.[163]

Fish and Shellfish. The electronic senses are employed in the fish-processing industry to mainly evaluate the freshness of fish and shellfish. The electronic nose has been used to perform such analysis in sardines,[164−166] shrimp and cod roe,[62] and Atlantic salmon,[54] whereas the electronic tongue has been used on samples of bream.[167] The electronic eye was employed to analyze the freshness of shrimp,[145,168] sturgeon fillets,[148] and salmon fillets.[143] The duration and conditions of storage have a great influence on the freshness of fish and shellfish. To protect consumers from the purchase of old fish, studies on the relationship between the duration and conditions of storage and product freshness were conducted by means of an electronic nose on cod fillets,[169] fresh and frozen Atlantic salmon,[48,49] tilapia,[170] Argentine hake,[171] and oysters.[172,173] Similar investigations were performed on gilt-head bream[174,175] and tench fillets[176] by employing an electronic tongue; in the case of gilt-head bream, the analysis aimed at predicting the biochemical and chemical parameters of spoilage.[175] Another aspect of the application of artificial senses is discrimination between fish species. The electronic tongue was used to discriminate between freshwater and marine fish species.[177] Similar studies were conducted by using an electronic eye.[176] Moreover, the electronic nose was applied to discriminate shrimp on the basis of the presence of phosphates, sulfates, and bleaching agents due to processing.[178]

Fruits and Vegetables. An electronic nose is mainly used to analyze fruits and vegetables. The application of this device is related to the monitoring of food processing and the evaluation of freshness, shelf life, and authenticity of food. On the other hand, the electronic tongue has been mostly used to classify cultivars (e.g., discrimination between onion and shallot),[179] tomatoes on the basis of various parameters,[180,181] apples,[182] and apricots, the latter being also discriminated on the basis of storage duration.[183] The electronic eye is employed to determine the quality of product by using shape and size parameters;[38,119,184−187] to identify the presence of unwanted objects, for example, twigs and leaves;[119,188] to establish the relationship between storage time and product condition on the basis of color analysis;[189−192] and to identify bruising.[191,193] The following fruits and vegetables have been investigated so far: bananas, apples, pears, oranges, strawberries, broccoli, potatoes, and carrots. The electronic nose was used to monitor dehydration in tomatoes[53] and grapes[194,195] to determine the optimal storage time. Studies aimed at evaluating the freshness of fruits and vegetables were conducted to determine the optimal harvest time (apples[78]), the ripeness level (bananas[56] and mandarins[57]), and quality (tomatoes,[79] tomato puree,[155] peaches,[196,197] and apricots[198]). Some products were analyzed to determine their shelf life and classify the ripeness levels (apples,[199−202] tomatoes,[203−205] peaches,[202,206] mandarins,[207] and pears[202]). The electronic nose has also become a useful tool for discriminating among the varieties of, among others, apricots,[208] mangoes,[209] and apples.[210,211] Yet another application of this device was the determination of selected parameters that influence the quality of fruits and vegetables such as oranges, apples,[212] peaches, nectarines,[213] pears,[214,215] and onions.[216] It has also been confirmed that the e-nose can be used for monitoring diseases in cucumbers, paprika, and tomatoes.[167]

Oils, Sauces, Vinegars, and Spices. Among this group of products, olive oil is most frequently analyzed because attempts to adulterate more expensive olive oil with its cheaper alternative are very common.[217] Therefore, the electronic

Table 1. Examples of the Application of an Electronic Nose to Food Analysis

application	sample	object of investigation	type of e-nose	method of data analysis	ref
food process monitoring	grape wine	discrimination of the sequential stages of fermentation	AromaScan A32S: 32 CP	PCA	47
	Australian red wine	monitoring of wine spoilage caused by yeasts	HP 4440 FOX 3000	PCA, PLS	52, 84
	Iberian ham	determination of the degree of spoilage in ham	tin oxide sensors	PCA, PNN	150
	milk, cheeses	monitoring of the smell intensity during fermentation	SMart Nose: MS	PCA	139, 140
	Cencara tomatoes	monitoring of the dehydration process	Air Sense: 10 MOS	PCA	53
	grapes	monitoring of the dehydration process in postharvest grapes	8 QMB	PCA, ANOVA	194
				CA, DA	195
	black tea	determination of the optimal duration of fermentation	8 MOS	TDNN, SOM,	255
evaluation of food freshness	cod fillets	discrimination of samples based on different storage times	LibraNose FreshSense	PLS	169
	smoked Atlantic salmon (fresh, frozen)	classification of spoilage in samples at different temperatures	FishNose: 6 MOS	PLS, PLSR	49, 54
	fresh tilapia fillets	discrimination of fillets based on storage times	eNose 4000: 12 CP	DFA	170
	Argentine hake	freshness evaluation in samples	MOS	PCA	171
	shrimp, cod roe		MOSFET	PCR, ANN	62
	oysters	predictive modeling of smell changes in shells	EEV model 4000: 12 CP	FDA DFA	172, 173
	sardines	freshness evaluation in sardines	6 MOS	PCA, SVM DFA	164−166
	fat-free milk	predicting the shelf life of different milk	MS	PCA	86, 87
		detection of bacteria and yeasts causing spoilage	BH-114: 14 CP	DFA, PCA	123
	veal, cod	discrimination of samples based on storage time	8 QMB	PCA, SOM	155
	ground beef/beef/sheep meat	detection of spoilage and rancidification	FOX 3000: 12 MOS	PCA, SVM,	151
		determination of changes in lipid ground beef	6 tin oxide sensors	PLS	152
	meat	freshness evaluation in meat in relation to storage time and storage conditions	KAMINA PEN2 FOX 4000	PCA, LDA, BPNN, CDA	55, 156, 157
	turkey meat	detection of rancidification in frozen turkey meat during storage	12 MOS, 10 MOSFET, IR sensor	PLSR, PCA	153
	vacuum-packed beef	detection of spoiled meat	4 MOS, 10 MOSFET	PLSR	50
	meat products used in pizza preparation	evaluation of product quality in relation to storage time	e-nose based on ion mobility	PLSR	158
	sausages	monitoring of the sausage fermentation process	4 MOS, 10 MOSFET	ANN	61
	eggs	determination of egg freshness based on storage time at room temperature	PEN3 4 tin oxide sensors	PCA, BPNN, SOM, ANN	301, 302
	apple juice	quality evaluation of juices	Prometheus: MS-nose	QDA	85
	apples	determination of the optimal harvest time	Libra Nose: QMBs	PCA, PLS, PCR	78
	bananas, mandarin oranges	discrimination of bananas as dependent on ripeness level	MOS, PEN2	PCA, LDA	56, 57
	apricots	use of an e-nose to sort apricots	8 QMB	PLS	198
	peaches	detection of ripeness level in peaches	8 MOS	PCA, LDA	196, 197
	tomato puree, tomatoes	monitoring of the puree spoilage and quality evaluation of tomatoes	8 QMB	PCA, SOM	79, 155
	corn	determination of aflatoxins in corn	PEN2: 10 MOS	PCA, LDA	58
	oats, rye, barley	discrimination of samples in relation to the presence of fungi and bacteria	NST 3210	ANN	60
	bread	discrimination of bread spoilage	Bloodhound BH-114	PCA, DFA, CA	236
	olive oil	detection of rancidification	32 CP	PCA	224
testing the shelf life of food	Pink Lady and Jonagold apples	discrimination of varieties ripeness level, shelf life and storage conditions	21 MOS, 12 QMB, MS LibraNose	PCA, ANN, PLS,	199−201
	tomatoes (*Lycopersicon esculentum* Mill.)	discrimination of ripeness level, shelf life, varieties, prediction of quality characteristics of fruit	LibraNose: 5 QMB, MS, PEN-2: 10 MOS	PCA, LDA, PLS	203−205
	peaches, pears, apples	classification of fruit samples at ripeness levels and varieties	PEN-2, tin oxide sensor	PCA, LDA,	202, 206
	mandarin oranges	testing shelf life during storage	PEN-2: 10 MOS	PCA, LDA	207
	Crescenza cheese	determination of maximum shelf life at different temperatures	NST 3320	PCA, CA, LDA	122
	milk	determining the influence of storage time on milk	FOX 4000	PCA	124, 125
	meat	determination of shelf life	NST 3210	LDA	154

Table 1. continued

application	sample	object of investigation	type of e-nose	method of data analysis	ref
	extra-virgin olive oil	evaluation of oxidation status under different storage conditions	NST 3320	PCA, LDA	59
authentication of food	tequila, whiskey, vodka	discrimination of four types of beverages	FOX 4000	PCA, DFA	268, 269
	Chinese spirits	discrimination of eight types of spirits	PEN3	PCA, CA, LDA	270
	Italian wines	detection of falsification	4 thin-film MOS	PCA, BP/ANN	282
	wines	classification of wine in relation to the botanical and geographical origin, aging process, and method	MOS, SAW MS	PCA, PNN SIMCA, PLS, LDA	273−281
	wines	detection of the falsification	FOX 4000	PCA	283
	beer	identification of beer brand	lab-made: 12 CP	PCA	271
	olive oil	detection of falsification	FOX 3000: 12 MOS	LDA, QDA, ANN	217
	extra-virgin olive oil	discrimination of geographical varieties	NST 3320	PCA, CP-ANN	219,
	plant oils	classification of plant oils	6 MOS	LDA	225
		quality discrimination	zNose	PCA	226
	balsamic vinegar of Modena	authentication	MS	PCA, SIMCA	230
	soy sauce	discrimination between soy sauces	31 CP	CA	227
	sesame seed oil	detection of corn oil in adulterated sesame seed oil	10 MOS	PCA, LDA, PNN	231
	Chinese vinegar	identification of some commercial vinegars	9 MOS	BPANN, kNN, PCA	228
	spices	discrimination of different spices	9 MOS	PCA, ANN	229
	orange juices	discrimination of geographical varieties	FOX 3000	PCA, FDA	264
			FOX 4000	PCA, DFA	265
	citrus juices	discrimination of citrus juices	FOX 3000: 12 MOS	LDA	266
	cola drinks	comparison of different brands	FOX 2000: 6 MOS	CA	256
	commercial beverages	discrimination of beverages	colorimetric sensors	HCA, PCA	80
	cheese	discrimination of geographical varieties and age in cheese	MGD-1 eNose 5000 MS, FOX 2000, CP	ANOVA, PCA, CA	132−136, 138, 139
	Pecorino cheese	discrimination of cheese at different maturation stages	AromaScan: 32 PC	PCA	137
	milk	discrimination between milk brands	7 MOS	PCA	127
			18 MOS		128
	dried sausages, cured ham	discrimination of dried sausages in relation to their origin	FOX 2000: 6 MOS	FDA	162
	ham	discrimination of different types of ham	tin oxide sensors	PCA, PNN	161
	products made of Iberian pigs	discrimination between products made from Iberian pigs and from other pigs	QCM, MOS	LDA	160
	llama and alpaca meat	discrimination of meat from llama and alpaca	BH114	LDA	159
	apricots	discrimination of varieties	FOX 4000	PCA	269
	mango	discrimination of fruit varieties and ripeness	FOX 4000	DFA	209
	apples	discrimination of apple varieties and types	tin oxide gas sensors	PCA, PLS, BP-ANN	211
			8 SAW		210
	honey	discrimination of honey in relation to its geographical and botanical origin	MOS-AOS system, SMart Nose	PCA, DFA	305, 307
	mushrooms	discrimination of lyophilized mushroom	AromaScan A20S	PCA	306
	coffee	discrimination of coffee brands, different quality criteria, and bean ripening time	FOX 4000 lab-made FOX 3000, EOS835	PCA, ANN	45, 220, 240, 241, 243
	green tea	discrimination of the quality classes in Longjing tea	PEN-2: 10 MOS	LDA, PCA,	245
				ANOVA, ANN	244
		identification of coumarin-enriched green tea	FF-2A: 10 MOS	PCA, CA	253
		discrimination of the green tea brands	8 MOS	PCA, ANN	316
	tea	classification of teas characterized by varying quality, regions, and brands	MOS	PCA, SOM, RBF, LDA, PNN	246, 248, 251
	rice	identification of rice varieties	Cyranose-320	PCA, CDA	235
	grains	discrimination of different samples and smell-based classification of grains	NST 3210 FOX 3000	ANN	233, 234
other applications	olive oil	discrimination of quality classes based on qualitative and quantitative information	8 CP	SOM,	221,
			MS	SIMCA, PLS	222,
			FOX 3000	PCA	223
	Cabernet red wine	monitoring of changes in wine aroma after bottle opening	8 QMB	PCA, SOM	154

Table 1. continued

application	sample	object of investigation	type of e-nose	method of data analysis	ref
	oranges, apples, peaches	postharvest quality evaluation	LibraNose: 7 TSM	PCA, PLS, ANN	212, 213
	pears	indicators for predicting quality	8 MOS	MLR, ANN, PLS	214, 215
	onions	determining the influence of edaphic factors on bulb quality	AromaScan A32S	PCA	216
	shrimp	discrimination of shrimp	12 CP	DFA	178

tongue and nose were both used to discriminate among olive oils on the basis of oil geographic origin[218−220] and type and quality.[59,221−223] In the case of olive oil, the conducted studies were also aimed at determining rancidity[224] and the relationship between storage time and oil quality.[59] Also, other plant oils were analyzed via an electronic tongue[89,219] and an electronic nose,[225,226] whereas soy sauces,[227] Chinese vinegars,[228] and selected spices[229] were analyzed by using an e-nose. As mentioned before, in the case of luxury and traditional products, it is of utmost importance to authenticate such merchandise to protect the consumer from purchasing substandard goods. The electronic nose was used to authenticate the balsamic vinegar of Modena[230] and sesame seed oil.[231]

Grains and Grain Products. In the case of grains and grain products, quality evaluation and authentication are important (wheat,[64,232−234] rice,[235] barley and oats,[233,234] and corn[186]); however, the critical issue for consumers is the evaluation of possible health risks of such products by means of electronic senses. Possible health risks are related to grain diseases, which often go unnoticed due to the fact that they are not visible to the naked eye. Mycotoxin contamination of grain, which also includes contamination with aflatoxins, and various diseases caused by fungi and bacteria are such risks. Studies on the subject of disease detection were performed on samples of corn[58] and oats, rye, and barley.[60] The electronic nose was used on samples of bread,[236] whereas an electronic eye was used on samples of rice[237] and corn.[238,239] The artificial senses allowed exclusion of samples that could have caused the development of a disease in consumers.

Teas, Coffees, and Herbal Infusions. Coffees, teas, and herbal infusions are mainly analyzed to distinguish among specific types, quality levels, and brands. This is due to the fact that these products are highly variable. Products of low and high quality are frequently mixed together to lower the overall production costs and then sold as top-quality merchandise. Coffees were discriminated on the basis of the quality,[220] brand,[45,177,240−242] and ripening period,[243] whereas teas were evaluated in relation to quality,[244−247] brand,[248−250] geographical origin,[251,252] and content of flavoring substances such as coumarin[253] and theaflavin.[254] Moreover, the electronic nose was used to monitor the fermentation process in black tea and to determine the optimal time for producing tea with the best flavor.[255]

Nonalcoholic Beverages. The analysis of alcohol-free beverages is among many applications of electronic senses. Until now, studies aimed at identifying brands and quality of such beverages were conducted in, for example, cola type drinks,[256] other commercial beverages,[80] mineral water,[257−260] and fruit juices and fruit juice-based drinks.[66,130,240,257,261,262] The beverages were analyzed by means of an electronic eye to determine the quality of orange juice on the basis of its color and color saturation.[263] Another example of the application of electronic senses is the identification of geographical origin in juices[263−265] as well as discrimination of juices on the basis of fruit type.[266]

Alcoholic Beverages. Alcoholic beverages are among the products that have been most frequently analyzed by means of electronic senses. Process monitoring in alcohol production requires fast analytical tools that can detect substandard products, discriminate among products, and authenticate products in real time. Wine and beer are mostly subjected to such type of monitoring because both beverages undergo fermentation that results in a release of specific compounds influencing the taste and aroma of the final product. The artificial senses monitored the processes of fermentation,[68] brewing,[74] and aging[90] in beer. In the case of wine, these devices were employed to control the aging process, to determine the influence of wooden barrels on aging and maceration,[67,73,267] and to monitor grape fermentation.[47] Authentication of alcohols is aimed not only at detecting adulterated products with substandard characteristics but also at identifying falsified products that can be potentially harmful to the consumer's health. Until now, the electronic nose was used to, among others, discriminate among vodkas,[268,269] spirits,[270] whiskeys,[268,269] wines,[268,269] tequilas,[268,269] beers,[269,271] and sorghum-based drinks.[272] The most widely researched group of alcoholic beverages is wines, which have been discriminated on the basis of geographical origin,[273,274] grape variety,[275] and type of maturation and aging process[276−281] as well as analyzed to detect cases of product adulteration.[282,283] The electronic tongue was applied to detect falsified vodkas,[284] whiskeys,[285] and wines; to determine the amount of ethanol in alcohols;[286] and to discriminate among beers on the basis of beer type[287−290] and quality.[81] Similarly to the electronic nose, the electronic tongue was used to analyze wines in relation to their geographical[65,259,291−294] and botanical origin,[65,71,82,294,295] brand,[293] and product adulteration,[70] as well as discrimination based on flavor, for example, bitterness level[296−298] and age.[82,295,299] The electronic eye was employed to monitor aging in wine on the basis of the color analysis.[300]

Others. Besides the aforementioned applications, the electronic nose has been used to, amont others, evaluate egg freshness,[301,302] discriminate honey on the basis of botanical[303,304] and geographical origin,[305] discriminate lyophilized mushroom species,[306] and detect pathogens in food.[307] The electronic tongue has been applied to discriminate honey on the basis of geographical[308] and botanical origin.[75,308−311] On the other hand, the electronic eye has been used to evaluate the quality of pizza,[312] corn tortillas,[313] potato fries,[314] and popular potato chips[315] on the basis of food appearance.

Examples of the application of e-nose, e-tongue, and computer image processing in food analysis are presented in Tables 1, 2, and 3, respectively.

SUMMARY

Due to growing consumer awareness, the need for safe and high-quality food increases. At present, consumers are willing to

Table 2. Examples of the Application of an Electronic Tongue to Food Analysis

application	sample	object of investigation	type of e-tongue	method of data analysis	ref
food process monitoring	bacterial cultures used in cheese production	monitoring of the fermentation process	30 potentiometric sensors	PLS	72
	milk	monitoring the origin of raw milk	voltammetric sensors	PCA	317
	red wines	monitoring of wine aging	13 voltammetric sensors	PCA, SIMCA	67
		evaluating the influence of micro-oxygenation and oak chip maceration on wine composition	potentiometric sensors	PCA, PLS, ANOVA	73, 267
	beer	variability monitoring of the brewing process	7 potentiometric sensors	PCA, PLS	74
		monitoring of changes during the aging process in beer	3 biosensors	PCA, LDA, RBF, PNN BP-NN	90
		monitoring of the fermentation process	potentiometric and voltammetric sensors	PLS	68
evaluation of food quality and freshness	fillets of farmed gilt-head seabream (*Sparus aurata*)	discrimination of storage time; predicting parameters of spoilage	potentiometric sensors	PCA, ANN, PLS MLR	174, 175
	tench (*Tinca tinca*)	discrimination of storage time	voltammetric sensors	PCA	176
	apricots	discrimination based on postharvest storage time and apricot varieties	7 potentiometric sensors	CDA, PLS	183
	nonalcoholic beverages	quality evaluation of high-fructose corn syrup	7 potentiometric sensors	SIMCA	74
	rice	quality evaluation of milling	potentiometric sensors	PCA	318
	milk	monitoring freshness of milk stored at room temperature	boltammetric sensors	PCA, ANN, CA, PLSR, LS-SVM	69, 126
stability testing of food	extra-virgin olive oil	evaluation of different storage conditions	2 amperometric sensors	LDA	59
authentication	honey	discrimination based on botanical origin	potentiometric sensors	PCA, PLS, ANN, LDA	75, 309
		discrimination based on botanical and geographical origin	6 voltametric sensors, Alpha-Astree	PCA, CA, CCA, ANN	308, 311
	yogurt	discrimination and evaluation of yogurt types	4 voltammetric sensors	PCA, DFA PLSR	129
	fermented milk	discrimination of different types	conductometric, potentiometric, and voltammetric sensors	PCA, ANN	46
	milk	discrimination of milk samples pasteurized in different ways	voltammetric sensors	PCA	130, 131
	alcoholic beverages	fast quality evaluation of alcoholic drinks and identification of brands	20 potentiometric sensors	PLS, LDA, PCA	284
		determination of ethanol content in alcohols from different sources	potentiometric sensors	PCA, SIMCA, PLS, PCR	286
		discrimination between cheap and expensive whiskies	voltammetric sensors	PCA	285
	beer	discrimination of beer based on type and manner of production	voltammetric sensors, potentiometric sensors	PCA, LDA	287
		discrimination of beers based on beer type and bitterness level	18 potentiometric sensors	PCA, CCA	288
			6 voltammetric sensors	CCA	289
		discrimination between alcoholic and nonalcoholic beers and between dark and light beers	potentiometric sensors	PCA, PLS, HCA	81, 319
	red wines	detection of chemical adulteration	voltammetric sensors	PLS, PCA	70
		discrimination of wines based on geographical origin	voltammetric sensors	PCA	291
				ANN, PCA	292
		discrimination of brands in red wines	impedimetric sensors	PCA, ANN	233
	white wines	discrimination based on grape variety and geographical origin	voltammetric sensors	PCA	294

Table 2. continued

application	sample	object of investigation	type of e-tongue	method of data analysis	ref
			amperometric sensors	PCA	65
	wines	discrimination of wines based on geographical origin; discrimination of wines based on vintage, vineyard, and age	potentiometric sensors	PCA, ANN, PLS, SIMCA	293, 295, 299, 320
		discrimination of wines based on aging method and content of polyphenols	voltammetric sensors	PCA, CA, PLS, BP-ANN	71, 296, 297
		discrimination of wines based on age and grape species	colorimetric system and 6 potentiometric sensors	PCA, PLS	82
	beverages	discrimination between beverages of the same type and monitoring of aging in juice	potentiometric sensors	PCA, SOM, LDA, ANN	177, 242, 257
	mineral water	discrimination between high mineralized and low mineralized waters	potentiometric sensors	PCA, PLS, ANN, SOM	259
		discrimination of 13 brands of mineral water	ASTREE 2	PCA, HCA, SIMCA	260
	orange, pear, peach, apricot juices	discrimination of orange juice brands	potentiometric sensors	PLS, PCA, ANN	258, 261, 262
		discrimination of fruit juice brands	voltammetric sensors	PCA	130
	green tea	quality discrimination	7 potentiometric sensors	PCA, ANN	247
	tea, herbal infusions	discrimination of infusions	potentiometric sensors	PCA, PCR	154
		discrimination of green and black teas based on geographical origin	potentiometric sensors	PCA	321
			3 voltammetric sensors	PCA	322
		discrimination of black teas based on tea type and brand	5 voltammetric sensors	PCA, ANN	249
			potentiometric sensors	PCA, CA, LDA	250
		discrimination of black teas based on geographical origin	Alpha Astree II	PCA, PLS, LDA, ANOVA	252
	plant oils	discrimination of edible oils based on oil type and geographical origin	voltammetric sensors	PCA	323
	olive oil	discrimination of extra-virgin olive oil based on geographical origin and bitterness level	amperometric sensors	PCA, ANN	219
			voltammetric sensors	PCA	89
	apples	discrimination between apple varieties	potentiometric sensors	PCA, PLS	66, 182
	tomatoes	discrimination of varieties; determination of savory compounds	2 e-tongues: Alpha Astree and e-tongue with potentiometric	PCA, CDA, PLS, CCA	180, 181
	onions, shallots	discrimination between onion and shallot	21 potentiometric sensors	PCA	179
	fishes	discrimination between freshwater and marine fishes	30 potentiometric sensors	PCA	177
other applications	extra-virgin olive oil	discrimination of samples based on phenolic compunds content	voltammetric sensors	PCA, PLS, PLS-DA	324
	black tea	determination of theaflavin level	5 voltammetric sensors	PCA, ANN	254
	ground meat	prediction of the level of chlorides, nitrates, nitrites	voltammetric sensors	PLS	149

Table 3. Examples of Computer Image Processing in Food Analysis

application	sample	object of investigation	method of data analysis	ref
monitoring of raw food	grain	analysis of morphological features in different grain varieties	DA	325
	wheat grain	analysis of physical properties and identification of varieties		232
	rice	verification of spoiled grains	ANN	237
	bananas	monitoring of changes during the aging process in bananas	*L*,*a*,*b*	192
	Golden Delicious apples	defect detection based on color	image segmentation algorithms	190
	Haunghau pears	identification of pear and pear peduncle shapes	ANN	119
	Iyokan oranges	analysis of shape, structure, and surface roughness	ANN	184
	oranges	identification of twigs and leaves	thinning algorithms	188
	strawberries	shape and size analysis	CIELAB	38
	broccoli	evaluation of ripeness level in broccoli flowers	DFT algorithms	189
	potatoes	discrimination between good and bad potatoes by color	HSI	193
	carrots	classification based on structure	ANN	187
	corncob	shape analysis	DA	186
	mushrooms	identification of discoloration caused by aging and damages		191
	pistachio nuts	classification of pistachio nuts based on the shape and shell opening		326
	pork tenderloin	quality analysis based on color identification	ANN, PLS	141
	poultry fillet	identification of tumors and bruised skin	ANN	146
	beef	detection of color changes in beef samples	CIELAB	142
	shrimp	visual measurement of shape, color, and size		145
monitoring of processed food	corn grain	quality control of spoiled grains		238
		mold identification		239
	raisins	classification of raisins based on the analysis of shape and surface	image analysis algorithms	280
	orange juice	color analysis, i.e., brightness, color saturation		263
	red wine	evaluation of color		327
		measurement of changes during wine aging process by means of e-nose, e-tongue, and e-eye	CIELAB	300
	potato chips	evaluation of color during frying		315
	French-fried potatoes	evaluation of color and texture	algorithms for statistical analysis	314
	pork	analysis of changes in color of freezer-stored meat packed in plastic bags	CIELAB *L*,*a*,*b*	147
	beef steak	color, shape, and structure analysis	ANN	140
	meat	evaluation of color and surface in pork and poultry slices	CIELAB	144
	sturgeon fillets	analysis of changes in color during storage	*L*,*a*,*b* CIELAB	148
	salmon fillets	color classification of salmon based on comparison with SalmonFAN color palette	*L*,*a*,*b*	143
	shrimp	evaluation of color to determine the water content in dehydrated shrimp	*L*,*a*,*b* ANN	168
	corn tortillas	color and shape analysis	*L*,*a*,*b*	313
	pizza	quality control based on color and size	image segmentation algorithms	312
	Cheddar and mozzarella cheese	comparison of cheese properties during cooking and baking	image processing algorithms	39

pay more for products that, beyond any doubt, have better quality and are naturally processed. Therefore, the companies that specialize in the processing, transport, and sale of food are put under increasing pressure to find new solutions that would parallel a sensory evaluation of food products. Sensory analysis is performed by testers; therefore, it is a subjective method that does not always reflects the true condition of a given product. Chromatographic techniques such as comprehensive two-dimensional chromatography coupled with detection by olfactometry require a long analysis time, and they often yield unreliable results mainly due to the complexity of the sample matrix. In the case of companies that process and sort food, time and reliability are the most significant and most valued parameters in relation to food quality evaluation. The equipment used until now is frequently being replaced with electronic senses, which, despite their many faults (e.g., complicated calibration, poor selectivity of sensors, and complicated data analysis), are promising alternatives. At present, electronic noses are widely applied to food evaluation with regard to both liquid and solid phase samples. Sample preparation is simple, and the analysis is noninvasive; therefore, different types of meat (e.g., veal, beef, and poultry) as well as different fruits and vegetables, alcoholic and nonalcoholic beverages, dairy products, etc., can be evaluated by means of an electronic nose. The conducted evaluations are also aimed at authenticating luxury products such as traditional balsamic vinegar of Modena and extra-virgin olive oil, detecting falsified wines, and determining the quality, freshness, and shelf life of food products. An electronic tongue has been used for similar purposes, although this device is mainly applied to evaluate liquid samples, for example, alcoholic and nonalcoholic beverages, oils, vinegars, and milk. It has been mostly used for product authentication and freshness evaluation. A computer image analysis system has found wide application

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in production plants for sorting foods such as fruits, vegetables, meat, and fish and to discriminate packaging in which food is packed. The evaluated features are color, shape, size, morphology, discoloration, and color intensity. These parameters allow for excluding faulty or substandard products. It is an increasing trend to combine all artificial senses into a quality evaluation system that encompasses the evaluation of appearance, taste, and smell and most closely simulates the sensory analysis by testers. At the same time, such a system is much more sensitive, precise, and reliable. Projects dealing with the improvement of electronic senses via the search for better sensors create the opportunity to widen the range of applications of these devices in food analysis.

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Notes

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