E-nose application to food industry production

José Chilo, José Pelegri-Sebastia, Maria Cupane and Tomás Sogorb

Food companies worldwide must constantly engage in product development to stay competitive, cover existing markets, explore new markets, and meet key consumer requirements. This ongoing development places high demands on achieving quality at all levels, particularly in terms of food safety, integrity, quality, nutrition, and other health effects. Food product research is required to convert the initial product idea into a formulation for upscaling production with ensured significant results. Sensory evaluation is an effective component of the whole process. It is especially important in the last step in the development of new products to ensure product acceptance. In that stage, measurements of product aroma play an important role in ensuring that consumer expectations are satisfied. To this end, the electronic noses (e-nose) can be useful tools to achieve this purpose. The e-nose is a combination of various sensors used to detect gases by generating signals for an analysis system. Our research group has investigated the scent factor in some foodstuff and attempted to develop e-noses based on low-cost technology and compact size. In this paper, we present a summary of our research to date on applications of e-noses in the food industry.

INTRODUCTION

Managing aroma properties in food production plays a vital role in assessing the product to ensure its acceptability. Moreover, it can be a component of product design by utilizing consumer expectations before a product is completed. At the end of the production process, the product must be acceptable to the consumer.

The aromatic properties of foodstuff depend on many chemicals that give to the food character and unique qualities. Reliably identifying and measuring the optimum flavor and its characteristics are ongoing critical tasks in the development of new products. So-called "odor experts" have typically been responsible for this challenging task. However, the individual judgments of these experts inevitably include subjective factors of personal preferences. To avoid this subjectivity, the electronic nose (e-nose) can instead be used.

Measurements made with the e-nose are objective, reproducible, reliable, and relatively inexpensive. E-nose interpretation is simple, fast, and can be performed in real time. As with the human nose, the e-nose "learns" by experience and improves its capabilities. It is designed to analyze, recognize, and identify very low levels (parts per billion) of volatile chemicals. The technology is based on absorption and desorption of volatile chemicals traversing a sensor array. This translates the specific changes in electrical resistance—measurable at each sensor element—when sensors are exposed to different flavors and odors.

Recent researches had confirmed the possibility of developing e-noses for new product development in the food industry. Ortega et al. [1], for example, performed an e-nose analysis to understand the factors critical to Internet connectivity processes in the olive oil industry. Other approaches have focused on analyzing the primary raw material used in the given food; i.e., water. Accordingly, it has been possible to classify the quality of this important raw material with a good approximation [2-3]. Other studies have focused on classification processes to determine if the food is contaminated or fresh, such as chicken or fish [4-7]. Classification of some liquids, such as beer, alcohol and sesame oil, has been undertaken in other studies with good results [8-10]. Moreover, the authors of [11-16] have classified other products, such as black tea, coffee beans, green coffee, instant coffee, and rice varieties.

In fact, many researchers have investigated the above issues and strived to develop e-noses. However, many challenges remain in this research area, such as developing e-noses specifically for the food industry. Some researchers have used commercial e-noses, which have only a few sensors and are typically developed with their own classification software. Furthermore, commercial e-noses are for general-purpose applications and are relatively expensive. Similarly, some researchers have developed e-noses that have a maximum of eight sensors and use only simple classification algorithms, such as principal component analysis (PCA). However, food production processes require sensitive, rapid, and reliable e-noses for real-time monitoring. Multisensory e-noses and complex classification algorithms are necessary for this kind of application.

SENSORS AND E-NOSES

Analysis of volatile components in the food industry employs two conventional techniques: conventional gas chromatography coupled with mass spectrometry (GC-MS) and quality sensory panel analysis. However, these two approaches are very time- and labor-intensive and expensive. Moreover, they are limited in terms of developing new products. The e-nose, on the other hand, may be a viable alternative to these techniques.

In the present study, we employed semiconductor-type gas sensors. This type of sensor is most commonly used in research on electronic olfaction systems on account of their high sensitivity to the presence of various organic volatiles. Furthermore, these sensors are easy to install in a system and have low manufacturing costs. Through the rapid development of electronics over the last two years, various types of inexpensive sensors have emerged. To mention a few, we have

Figaro gas sensors (TGS2610-C00, TGS2610-D00, TGS2611-C00, TGS2600-B00, TGS2620-C00, TGS2602-B00), MQ gas sensors (MQ-2, MQ-3, MQ-303A, MQ-4, MQ-5, MQ-216, MQ-6, MQ-306A, MQ-7, MQ-309A, MQ-8) and other series that have appeared on the market, such as the MG, MC, ME and MD series.

Gas sensors are solid-state sensors composed of a sintered metal oxide that detects gases through an increase in electrical conductivity when reducing gases are adsorbed on the sensor's surface. A simple electrical circuit shown in Fig. 1 can convert the change in conductivity to an output signal that corresponds to the gas concentration. The sensor requires two voltage inputs: heater voltage (V_{Heater}) and circuit voltage (V_{sensor}). The heater voltage (V_{Heater}) is applied to the integrated heater to maintain the sensing element at a specific temperature, which is optimal for sensing. Circuit voltage (V_{sensor}) is applied to allow measurement of voltage (V_{out}) across a load resistor (R_L), which is connected in series with the sensor.

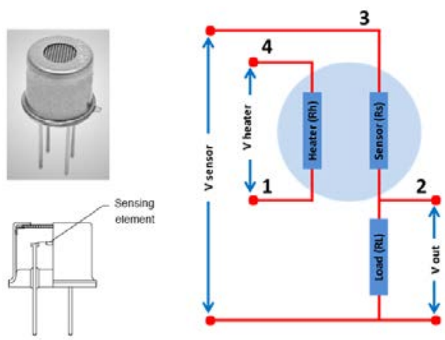

Fig. 1. Basic measuring circuit.

As shown in Fig. 2, our proposed e-nose employs 32 Figaro gas sensors [17-18]. Its olfactory system is based on the assumption that normal variations in these sensors combined with the selected operating temperature results in a wide range of responses to volatile organic compounds.

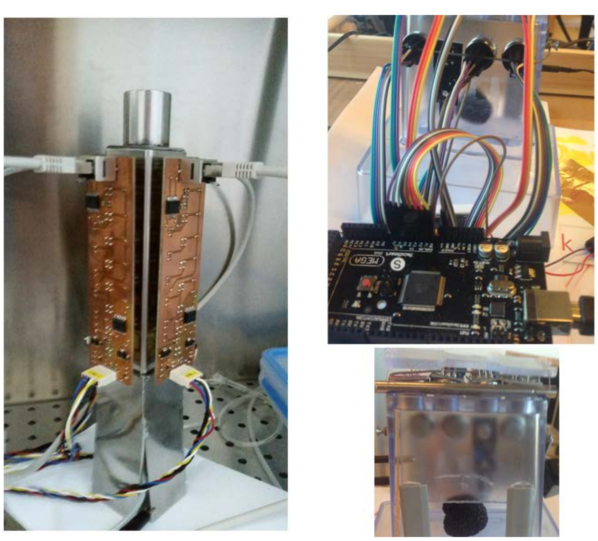

Fig. 2. Left: Proposed e-nose with 32 Figaro sensors; top right: rear portion of the e-nose with eight MQ sensors connected to an Arduino; bottom right: front portion with a truffle sample.

The complete system is shown in Fig. 3. It consists of two parts: an electrical part and a prechamber, which is the component for the sample preprocessing. The system electrical design is comprised of eight identical electronic boards with four sensors in each of them. For data acquisition, an ADC from National Instruments (NI USB-6218, 16 Bits, 250 kS/s) is used. The NI USB-6218 has 32 analog inputs for data collection from the 32 sensors.

The first part of the prechamber has a clean air pump. The air flow is manually adjusted using a small valve. The air flow is split into two streams, one that passes through the sample chamber and then to the electrovalve, and one that directly flows to the electrovalve. The electrovalve is automatically controlled by the interface. In this process, air passes through the system to clean it for a predetermined time interval. It then flows through the sample chamber for another fixed time interval.

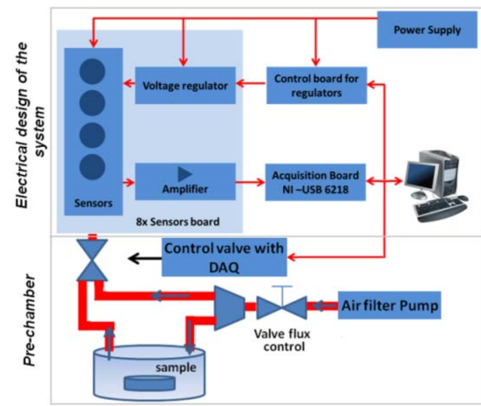

Fig. 3. Complete system, including the electrical design and prechamber.

The authors recently designed a prototype e-nose in which MQ sensors are used and an Arduino is employed for data acquisition. Figure 1 shows the rear part where the sensors are connected to an Arduino and the front part where the sample is collocated.

In this case, we strived to design an e-nose for use in the food industry. The sample is placed in a device at some distance from the sensor. When the measurement begins, the sample is moved close to the sensors.

FEATURE EXTRACTION AND CLASSIFICATION

Two different techniques are employed to extract the data features. Figure 4 depicts the features of the first method: transient slope, saturation slope, and late saturation [19-20]. From experimental results, we conclude that more information can be obtained about the substance itself than just the level response by calculating the sensor responses to different substances. These responses are the increasing time at the start of the measurements and the decreasing time at the end of the measurements.

The features of the second method are spectral entropy, the Hurst exponent, detrended fluctuation analysis, Hjorth mobility and complexity, Petrosian fractal dimension, approximate entropy, Hjorth fractal dimension, Fisher information, and singular value decomposition entropy [21].

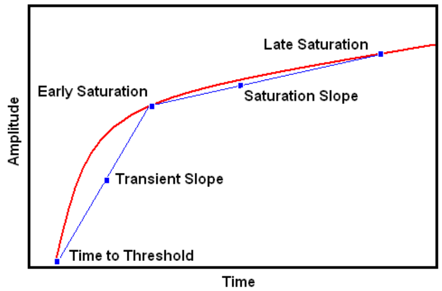

Fig. 4. Classification features used in the first proposed method.

We use PCA to visualize the similarities and differences among the various measurements in the dataset using the extracted features. For classification, artificial neural networks are one of the most popular pattern recognition technique used for e-noses, as presented in [22]. We use the classification algorithms of the Waikato Environment for Knowledge Analysis (WEKA) [23]. WEKA is an open-source data mining toolbox (written in Java) developed by Ian Witten's group at the University of Waikato. It provides tools for all tasks typically performed in data mining, including numerous algorithms for preprocessing, classification, regression, and clustering.

EXPERIMENTAL RESULTS

In the last few years, the authors have focused efforts on developing the e-nose. Our third-generation e-nose has shown impressive properties. In this work, we have applied algorithms for pattern recognition as well as conducted evaluations of sensors new to the market that have the most current acquisition systems. We tested our e-nose in a variety of applications, including those in medical, environmental, security, and food industries. We herein present results relevant to the food industry.

a) Classification of apple and pear

The e-nose shown in Fig. 1 was tested with two types of fruits: pear and apple. The output of the sensors consisted of 32 independent analog voltages. Each one varied with time and odor. Then we have analyzed the pear and apple samples with WEKA classification algorithms. Table I lists the results for 40 runs (20 pears and 20 apples) from our experiment.

TABLE I. CLASSIFICATION RESULTS WITH WEKA

Classification Algorithm	**Pear**	**Apple**	**Total (%) Correctly Classified**
Bayes Network	37/39	38/40	94
RBF Network	38/39	36/40	93
SimpleLogistic	39/39	38/40	97
SMO	39/39	39/40	99
IB1	39/39	40/40	100
KStar	39/39	38/40	97
VFI	34/39	36/40	89
ADTree	39/39	36/40	95
NNge	39/39	38/40	97
PART	38/39	36/40	94

Additionally, we used PCA to visualize the similarities and differences among the various measurements in the dataset using the transient slope feature. Figure 5 shows the resulting data plot in the PC1-PC2-PC3 plane for the pear and apple.

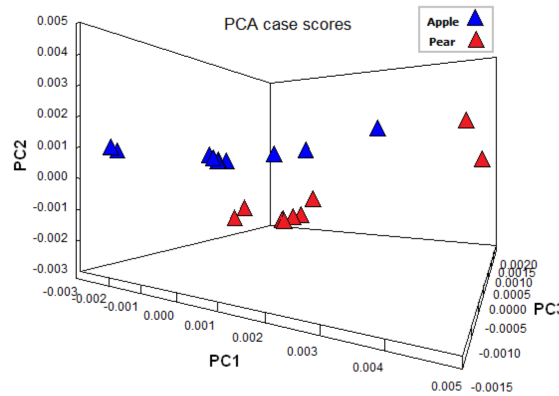

Fig. 5. PCA using the transient slope feature.

As shown in the table I and Fig. 5, the proposed e-nose can easily distinguish between pears and apples. It should be noted that the samples were actual pieces of the fresh fruits.

b) Off-flavor of drinking water

Most waterborne bacteria are common and not dangerous to human health; however, they are responsible for some of the most problematic odor contaminations in potable water. One genus of bacteria commonly found in water supply networks is *Pseudomonas*. These bacteria are relatively ubiquitous on account of their simple nutritional requirements and ability to utilize many different organic compounds as energy sources [24]. In fact, they can increase sulfur and selenium content, which results in off-odors usually described by associations to wet cloth, cockles, butane, rubber, or rotten eggs. In our work, we simulated a microbial contamination using different molecules that have an offensive odor, such as the above secondary metabolism products [25]. To analyze the sample headspaces, we employed the e-nose with 32 sensors, as shown in Fig. 1.

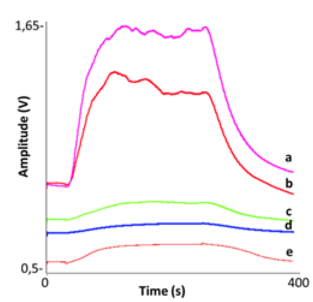

Fig. 6. Typical response of the TGS-2600 sensor to different substances dissolved in water: a) mixture of sulfur compounds; b) geosmin; c) dimethyl disulfide; d) sulphuretted; e) control.

To test the sensibility of the e-nose we employed molecules at two different concentration, parts per billion (ppb) and parts per trillion (ppt). For each analysis 3 measurements were performed with 4 repetitions, with a delay of 5 seconds among each repetition. Figure 6 shows that the e-nose can effectively discriminate between the control and treated water samples. Only the responses from one sensor are shown.

For further analysis, we used three different data analysis methods of discrimination, as illustrated in Fig. 7. This work showed a high rate of sensitivity and selectivity of the e-nose that is able to distinguish among the different molecules and between the different concentrations. The accuracy of the results is closely related to the statistic test: for low concentration the probability model showed the best classification, while for higher concentration the three tests provided the same level of correctly classification.

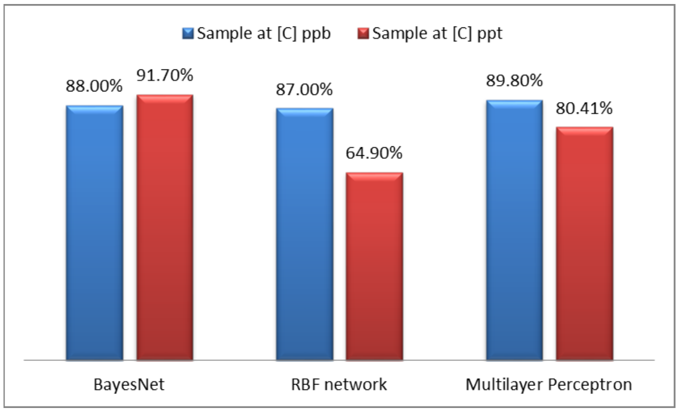

Fig. 7. Comparison of different statistical treatments of the data based on the percentage of correctly classified instances.

c) Orange aroma

In the food industry, oranges are processed after harvesting. The first step of the production chain is the cleaning with water and some chemical products. Then they are processed through the packing line, transported and properly stored until the distribution to the final consumers.

In this work, we analyzed the flavor of oranges submitted to different postharvest treatments. Four types of samples were chosen: a control sample group, a sample of fruits collected after washing the oranges with chemicals, a sample collected after treatment with ethylene, and a sample collected after waxing process.

The samples were analyzed in four different periods of storage: 24 to 48 h after harvest (T0), after four weeks at 4°C (T1), after eight weeks at 4°C (T2), and after an additional week in a normal environment at 20°C while simulating the conditions in which the consumer eats the fruits (T4). For each sample were performed 5 measurements with 5 repetitions each, with a delay of 10 seconds among each repetition. The results are presented in Table II. As shown in the table, the e-nose system was able to reveal that orange juice flavor changes even when fruits are stored under refrigerated conditions.

TABLE II. CLASSIFICATION RESULTS WITH WEKA

	T0	**T1**	**T2**	**T3**
Bayes Network	92.5	100	97.5	87.5
Naive Bayes	95.0	100	97.5	93.7
MLP	95.0	100	98.7	87.5
RBF Network	97.5	100	98.75	92.5
J48	88.7	96.2	91.2	85.0
IB1	97.5	100	97.5	90.0

d) Truffle classification

Some of the most important objectives of food production are to achieve a high level of quality and produce uniform raw materials. These objectives are applicable to truffles. The truffle is a type of mushroom that grows underground. It is used as a spice and is considered a delicacy. Consequently, it is an expensive raw material. Truffles can be found using trained “truffle dogs” and “truffle pigs.” One of the most significant problems for the truffle industry is the systematic determination of ripeness at harvest. Truffles must have a specific level of maturity; otherwise, they are perceived by the consumer as having a poor quality. To determine if a truffle is ripe, we developed a prototype for the truffle industry with only eight inexpensive MQ sensors, as shown in Fig. 1.

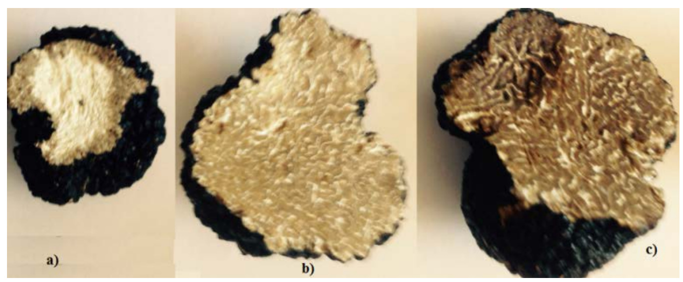

Fig. 8. a) Unripe truffle; b) ripe truffle; c) overly ripe truffle.

As shown in Fig. 8, it is possible to visually distinguish different types of truffle maturity. To achieve this, however, the truffle must be turned to the right side, which can cause problems when using image processing for classification. The proposed e-nose leverages the truffle smell and calculates the exact degree of maturity to determine the ripeness. This approach is different from conventional methods of tasting the truffle. Once the e-nose has “learned” the characteristics of an optimally ripe truffle, a specialized smell operator is not necessary; rather, the e-nose will provide results in seconds with good accuracy.

The results using the e-nose are presented in Fig. 9.

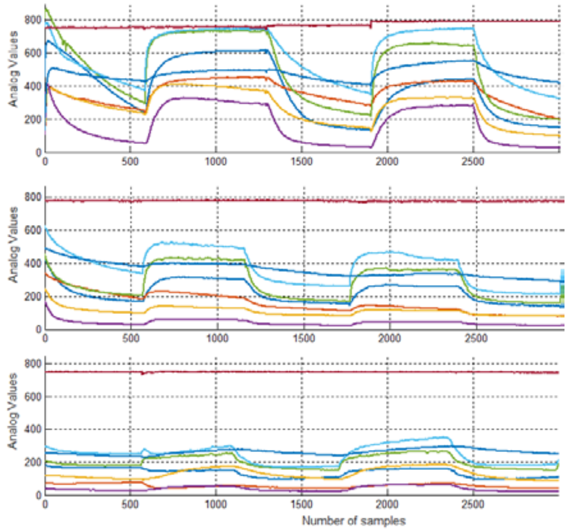

Fig. 9. Response from 8 MQ sensors, top: unripe truffle; center: ripe truffle; bottom: overly ripe truffle.

CONCLUSIONS

The technology of e-noses has emerged in recent years. However, to date, this technology has been too expensive and complicated for the mass market. To address this issue, we developed e-noses and tested them in various medical, environment, safety, and food industry applications. In this paper, we overviewed the portion of our e-nose work that focused on food sector applications.

In food production, the proposed e-nose can detect if the product is spoiled or fresh; moreover, it can classify different types of products. The proposed e-nose can be further developed for more advanced food industry applications by including many more sensors and employing an advanced signal processing algorithm for classification.

REFERENCES

[1] J. Beltran Ortega, J. Gamez Garcia and J. Gomez Ortega, "Precision of volatile compound analysis in extra virgin olive oil: The influence of MOS electronic nose acquisition factors," in *Industrial Technology, IEEE International Conference*, pp.1482-1487, 17-19 March 2015.

[2] K.N.A.K. Adnan, N. Yusuf, H.N. Maamor, F.N.A. Rashid, S.W.M. Ismail, R. Thriumani, A. Zakaria, L.M. Kamarudin, A.Y.M. Shakaff, M.N. Jaafar and M.N. Ahmad, "Water quality classification and monitoring using e-nose and e-tongue in aquaculture farming," in *Electronic Design (ICED), 2014 2nd International Conference*, pp.343-346, 19-21 Aug. 2014.

[3] E. Nunez Carmona, V. Sberveglieri and A. Pulvirenti, "Detection of microorganisms in water and different food matrix by Electronic Nose," in *Sensing Technology (ICST), 2013 Seventh International Conference on* , pp.699-703, 3-5 Dec. 2013.

[4] P. Chongthanaphisut, T. Seesaard and T. Kerdcharoen, "Monitoring of microbial canned food spoilage and contamination based on e-nose for smart home," in *ECTI-CON, 12th International Conference*, pp.1-5, 24-27 June 2015.

[5] G. Sberveglieri, G. Zambotti, M. Falasconi, E. Gobbi and V. Sberveglieri, "MOX-NW Electronic Nose for detection of food microbial contamination," in *SENSORS, 2014 IEEE* , pp.1376-1379, 2-5 Nov. 2014.

[6] K. Timsorn, C. Wongchoosuk, P. Wattuya, S. Promdaen and S. Sittichat, "Discrimination of chicken freshness using electronic nose combined with PCA and ANN," in *Electrical Engineering/Electronics, Computer, Telecommunications and Information Technology (ECTI-CON), 2014 11th International Conference*, pp.1-4, 14-17 May 2014.

[7] S. Guney and A. Atasoy, "Fish freshness assessment by using electronic nose," in *Telecommunications and Signal Processing (TSP), 2013 36th International Conference*, pp.742-746, 2-4 July 2013.

[8] M. Siadat, E. Losson, M. Ghasemi-Varnamkhasti and S.S. Mohtasebi, "Application of electronic nose to beer recognition using supervised artificial neural networks," in *Control, Decision and Information Technologies (CoDIT), 2014 International Conference*, pp.640-645, 3-5 Nov. 2014.

[9] S. Siyang, T. Seesaard, P. Lorwongtragool and T. Kerdcharoen, "E-nose based on metallo-tetraphenylporphyrin/ SWNT-COOH for alcohol detection," in *Electron Devices and Solid-State Circuits (EDSSC), 2013 IEEE International Conference*, pp.1-2, 3-5 June 2013.

[10] M. Lihui, G. Yongyang, S. Hui, Q. Mingjun, Z. Ting and H. Xiaohua, "Rapid Detection of Sesame Oil Flavoring Based on the Gas Sensor Array," in *Measuring Technology and Mechatronics Automation (ICMTMA), 2013 Fifth International Conference*, pp.841-844, 16-17 Jan. 2013.

[11] N. Bhattacharyya, R. Bandyopadhyay, M. Bhuyan, B. Tudu, D. Ghosh and A. Jana, "Electronic Nose for Black Tea Classification and Correlation of Measurements With “Tea Taster” Marks," in *Instrumentation and Measurement, IEEE Transactions on* , vol.57, no.7, pp.1313-1321, July 2008.

[12] B. Tudu, A. Metla, B. Das, N. Bhattacharyya, A. Jana,Ghosh and R. Bandyopadhyay, "Towards Versatile Electronic Nose Pattern Classifier for Black Tea Quality Evaluation: An Incremental Fuzzy Approach," in *Instrumentation and Measurement, IEEE Transactions on* , vol.58, no.9, pp.3069-3078, Sept. 2009.

[13] K. Brudzewski, O. Stainslaw and A. Dwulit, "Recognition of Coffee Using Differential Electronic Nose," in *Instrumentation and Measurement, IEEE Transactions on* , vol.61, no.6, pp.1803-1810, June 2012.

[14] V. Sberveglieri, P. Fava, A. Pulvirenti, I. Concina and M. Falasconi, "New methods for the early detection of fungal contamination on green coffee beans by an Electronic Nose," in *Sensing Technology (ICST), 2012 Sixth International Conference*, pp.414-417, 18-21 Dec. 2012.

[15] T. Thepudom, N. Sricharoenchai and T. Kerdcharoen, "Classification of instant coffee odors by electronic nose toward quality control of production," in *Electrical Engineering/Electronics, Computer, Telecommunications and Information Technology (ECTI-CON), 2013 10th International Conference*, pp.1-4, 15-17 May 2013.

[16] Y. Huichun, M. Miaojuan and Yin Yong, "The research on the application of electronic nose in discriminate the rice varieties," in *Advanced Mechatronic Systems (ICAMechS), 2013 International Conference*, pp.449-454, 25-27 Sept. 2013.

[17] A. Del Cueto Belchi, D. Carcia Rodriguez, N. Rothfeffer, J. Pelegri Sebastiá and J. Chilo, “Multi-sensor olfactory system: using temperature modulation”, IEEE International Instrumentation and Measurement Technology Conference, pp. 1139-1141, May 2012.

[18] A. Del Cueto, N. Rothpfeffer, J. Pelegri-Sebastiá, J. Chilo, D. Garcia and T. Sogorb, “Sensor Characterization for Multisensor Odor-Discrimination System”. Sensors and Actuator A: Physical, vol. 191, pp. 68-72, Mar. 2013.

[19] J. Waldemark, T. Roppel, M. Padgett, D. Wilson and Th. Lindblad, “Neural network and PCA for determining region of interest in sensory data pre-processing”, Virtual Intelligence/Dynamic Neural Network Workshop, vol. 3728, pp. 396-405, 1998.

[20] M. Kermit, Å. J. Eide, Th. Lindblad and K. Agehed, “Intelligent machine olfaction”, IASTED, Tokio, Japan, pp. 25-27, 2002.

[21] F. S. Bao, Y.-L. Li, J.-M. Gao, and J. Hu, “Performance of dynamic features in classifying scalp epileptic interictal and normal EEG,” in Proceedings of 32nd International Conference of IEEE Engineering in Medicine and Biology Society (EMBC '10), 2010.

[22] L. Zhang and F. Tian, "Performance Study of Multilayer Perceptrons in a Low-Cost Electronic Nose," in *Instrumentation and Measurement, IEEE Transactions on* , vol.63, no.7, pp.1670-1679, July 2014.

[23] I.H. Witten and E. Frank, “Data mining: Practical Machine Learning Tools and Techniques”, 2nd Edition, *Morgan Kaufmann Publishers*, San Mateo, CA, 2005.

[24] M. Madigan, J. Martinko, D. Stahl, D. Clark “Brock Biology of Microorganisms”, Cumminds, San Francisco, 2012.

[25] M. Cupane, J. Pelegrí Sebastiá, V. Guarrasi, J. Chilo and T. Sogorb, “ Electronic Nose to detect off-flavor of drinking water” , XXII Congresso Nazionale Società Italiana di Biofísica Pura e Applicata (SIBPA 2014), pp. 61, Sept 2014.