Electronic Noses Application to Food Analysis Using Metal Oxide Sensors: A Review

Syeda Erfana Zohora, A. M.Khan, A. K. Srivastava, Nisar Hundewale

Abstract--Electronic noses employs different types of electronic gas sensors that have partial specificity and an appropriate pattern recognition techniques capable of recognizing simple and complex odors. This paper focuses on use of electronic noses that use metal oxide gas sensors. In this paper,we present the quality assessment applications to food and beverages, that includes determination of freshness and identification of spoilage, polluted, contaminated , unhygienic or adulteration in the food. The applications of electronic noses to a wide collection of food and beverages are considered, that consists of fruits, milk and dairy products, fresh vegetables, eggs, meat, fish, grains, alcoholic drinks and non-alcoholic drinks.

Index Terms—Electronic nose, E-nose, Food analysis, Metal oxide sensors.

I. INTRODUCTION

The main components of electronic nose system is a large array of chemical sensors with associated signal conditioning (pre-processing) and pattern recognition techniques (PARC). Such an artificial gas sensing system is known as 'Electronics Nose (ENOSE)'. The electronic nose strives to mimic human smell processing with an aim to detect the presence of odor/gas at very low concentrations and also to discriminate between them. Very encouraging results have been reported in the past by employing electronic nose for the classification and characterization of foodstuffs such as beverage [1], wine [2], [3], coffee [4], and milk [5]. Detection of volatile organic compounds (VOCs) using non-selective sensor requires an array of multiplexed sensors followed by pattern recognition approach. Volatile organic compounds (VOCs) presented to the sensor array produces a model or prototype which is the characteristic of the vapor. Data analysis and pattern recognition (PARC) are the fundamental components of any sensor array system. There are a range of PARC techniques available which can be classified in three types. The choice of the first way depends on existing data and the type of result that is required. A second way of analysing E-nose signals is by means of multivariate analysis. Multivariate analysis generally involves data reduction. It reduces high dimensionality in a multivariate problem where variables are partly correlated, allowing the information to be displayed in a smaller dimension. There are many multivariate analysis techniques such as fourier transform technique[6] , linear discriminant analysis (LDA)[7], transformed cluster analysis (TCA)[8], *etc.* A third type of class is based on artificial neural network (ANN) techniques which apart from being massively parallel in nature, are also capable of handling nonlinear transduction properties. BP trained ANN, genetically trained ANN [9], radial basis function neural networks [10], adaptive resonance theory [11], self-organizing networks [12] and the combination of fuzzy concept and neural networks [13] have been applied to odor/gas classification problems.The ANN is based on the cognitive process of the human brain [14,15].

The sensing systems based on metal oxide sensors (MOS) reached the food industry more than a decade ago and it was presented as a non-critical technique for food odor analysis that could contend with panel test. Gas sensors based on the chemical sensitivity of metal oxide semi-conductors sensors (MOS), are readily available. They have been more extensively used to make arrays for odor measurement than any other type of gas sensors [14]. Although the oxides of many metals show gas sensitivity under healthy conditions, the most widely used material is tin dioxide (SnO_2) doped with a small amount of a catalytic metal such as palladium or platinum. By varying the selection of catalyst and working conditions, tin dioxide resistive sensors have been developed for a group of applications. Materials with enhanced performance with respect to relative humidity differences have been found by observed testing. Titanium-substituted chromium oxide (CTO) is an example of such a material. Other available oxide-based gas sensors include zinc oxide (ZnO), titanium dioxide (TiO_2) and tungsten oxide (WO_3) [16]. This review article focuses on the use of MOS-based electronic noses for food applications, the scientific limitations for some applications and the different methods carried out to resolve them. The complexity that have been attempted to solve with MOS-based electronic noses are those that are associated to quality control, monitoring process, aging, geographical sources, adulteration, contamination and spoilage of food.

II. METAL OXIDE SENSORS TO FOOD APPLICATIONS

A. Milk and Dairy Products

It is in the area of milk and other dairy products that there has been wide research in assessing electronic noses for monitoring the quality of these products. Areas of research have varied from recognizing adulteration or contamination of milk to establishing the environmental changes of the cheese. Liquid milk is an crucial nutritional food for infants. Adulteration of milk

Manuscript Received on Nov 5 , 2013.
S.E.Zohora, College of Computers & Information Technology, Taif University, Taif, KSA.
A.M.Khan, Mangalore University, Mangalore, India
A.K.Srivastava, LightField Corporation Philadelphia, PA, USA

with water is a subject of serious concern because of the poorer nutritional value provided to the consumers. The dairy industry employs a range of quality tests which contains the determination of fat and total solids by chemical or physical analyses, assessment of residues, identification of bacterial calculation, determination of freezing point, protein, *etc.* [17]. However, most of these measurements are expensive and time consuming since milk samples need to be taken to a laboratory for testing. Yu *et al.* [18] examined the adulteration of milk using an E-nose (PEN2, Germany) containing ten different metal oxide semiconductor sensors. Whole milk, reformed milk powder and whole milk adulterated with different proportions of water or reconstituted milk powder were followed in storage for 7 days at 20 ºC. In this study, the E-nose was able to distinguish skim milk contaminated with different volumes of water and reconstituted milk, and also able to classify 100% skim milk samples between 1 and 4 days of storage. However it was not able to distinguish samples between 5 and 7 days of shelf life. Another area associated to milk quality and safety is the identification of contaminants, including aflatoxins in milk. Benedetti *et al.* [19] studied the feasibility of using a sensor array system, comprising 12 MOS and 12 MOSFET sensors, to identify the presence of aflatoxin M1 (AFM1).

The E-nose classification was in complete agreement with aflatoxin M1 substance measured by an ELISA procedure. An added advantage of this method is that it can be applied to quick screening for AFM1 contamination in random samples taken at many places. Samples which are identified as contaminated in the screening process can then be sent for further characterization using quantitative analytical methods, or else rejected to avoid contamination of the entire lot [19]. Factors which are known to the development of oxidized off-flavor in milk products include the contamination of milk with copper, iron, rust and chlorine, or exposure to sunlight as well as excessive incorporation of air. Other off-flavors in milk may be derived from excessive heating which can especially cause certain proteins (such as whey proteins) to burn. Whey proteins are a rich source of sulfide bonds which can form sulfhydryl compounds which can then contribute to off-flavor [20]. Great efforts have been dedicated to the optimization of ultra high temperature (UHT) milk processing in order to evade this effect. One study using an E-nose comprising of MOSFET, MOS and quartz microbalance (QMB) sensors found that it could distinguish as little as 10% boiled milk in pure UHT milk whereas a sensory panel, in contrast, could not distinguish proportions of UHT below 30% [21]. QMB are sensors made of tiny discs, usually quartz, coated with materials such as chromatographic stationary phases that are chemically and thermally stable. When an alternating electrical potential is applied at room temperature, the crystal vibrates at a very steady frequency, defined by its mechanical properties. Upon contact to a vapor, the coating adsorbs certain molecules which increases the mass of the sensing layer and hence, decreases the resonance frequency of the crystal. One of most important steps in manufacturing dairy products is the quality control of the starting material. Chemical analysis of flavors in dairy products is often complicated due to the heterogeneous nature of milk. Furthermore, the headspace of milk typically represents a complex mixture of organic volatiles at varying concentrations and at high relative humidity. Profiling the volatile components in milk and dairy products is usually performed by dynamic or static headspace, "purge and trap" techniques, etc with measurement by gas chromatography-mass spectrometry (GC-MS) [22]. E-noses can also detect milk volatile compounds and are able to monitor the aging of milk [23,24]. An E-nose with five different SnO2 thin films, prepared using sol-gel technology, was used to measure the development of rancidity in UHT and pasteurized milk during 8 and 3 days, respectively. The sensors could distinguish between both types of milk as well as determine the degree of rancidity of milks (Figure 2). Labreche *et al.* [25] obtained similar results with an E-nose housing 18 MOS sensors (FOX 4000, France). The E-nose detected significant changes in headspace during milk aging. The authors claimed that there was a high correlation between bacterial counts and the sensor responses.

B. Meat

Meat is an best development medium for several groups of pathogenic bacteria. Evaluation of meat safety and quality is usually based on microbial cultures. Bacterial strain identification requires a number of different growth conditions and biochemical tests with overnight or large incubation periods and skilled personnel, which means that testing may not be frequently performed. Other methods of identifying meat safety involve quantifying volatile compounds associated with the growth of microorganisms on meat but these are also time consuming [26-28]. Winquist *et al.* [29] evaluated beef freshly ground using ten metal oxide semi-conductor field-effect transistor sensors (MOSFETs) with thin catalytic active metals like Pt, Ir and Pd, and four SnO2 based Taguchi type sensors (Figaro Engineering Inc, Japan). Compared to MOS sensors, MOSFETs depend on a change of electrostatic potential and they are based on the modulation of charge concentration by a MOS capacitance between a body electrode and a gate electrode located above the body and insulated from all other device areas by a gate dielectric layer which in the case of a MOSFET is an oxide, such as silicon dioxide [30]. A carbon dioxide detector based on infrared ray absorption (Rieken Keiki Co,Japan) was also included in the array. The array of sensors was able to decide the type of meat and predict the storage time as well. When the carbon dioxide monitor was omitted the performance in predicting storage time decreased. Carbon dioxide concentration is an important parameter to consider for predicting shelf life storage of meat products. Balasubramanian *et al.* [31] evaluated the changes in the headspace of vacuum packaged beef strip sides vaccinated with *Salmonella typhimurium* using a metal oxide based electronic nose. The E-nose housed seven thick film SnO2 MOS sensors (Figaro Engineering Inc, Japan). Microbiological measures as a standard method to determine spoilage level included *Salmonella* counts and total aerobic counts. Vernat-Rossi *et al.* [32] studied the ability of six tin oxide semi-conductors (FOX 2000, France) to discriminate cured products (dry sausages of various origins or cured hams of different qualities) and also to identify the existence of pathogenic bacterial strains. Using these sensors it was feasible to classify 98% of the bacterial strains, 94% of the dry sausages and 87% of cured hams into their respective groups. Although most applications of metal oxide semi-conductors based sensors in meat have been focused on quick methods for detecting spoilage by bacterial contamination, some work has also been conducted to determine the presence of off-flavors in meat.

C. Fish

Freshness is the mainly important concern for fish quality. Traditionally, fish quality evaluation has been based on organoleptic tests. This type of testing is subjective even when performed by experienced and well-trained personnel. Gas chromatography has revealed that many volatile compounds are released from degrading fish, some of which can be used as indicators of spoilage. Electronic nose are suitable instruments for measuring fish freshness since a large number of volatile compounds are related to "offness" [33]. Olafsdottir *et al.* [34] employed six MOS sensors ("FishNose", AlphaMOS-France) to evaluate cold smoked Atlantic salmon and compared the results with sensory analysis and microbial counts. In this research salmon were obtained from smokehouses in Norway, Iceland and Germany and stored in different packing for up to four weeks. Samples were also presented to chemical analysis including total fat, salt content, water content and chloride content. Partial least square regression modeling, with gas sensors as predictors and sensory attributes as response variables, showed that there is a general correlation between gas sensors and "off-odor" and "sweet/sour" odor attributes. However, the correlation with the chemical parameters was low which meant that they could not be used to calibrate the "FishNose". With respect to microbial analysis, one sensor type, "PA/2", showed a very similar pattern to the total viable microbial counts. This work demonstrated that an E-nose could be used for speedy quality control and freshness evaluation of smoked salmon products related to microbially produced volatile compounds. The same E-nose was later used to control processing of smoked salmon in a production plant [35]. It was necessary to correct the sensor reading in this case due to the varying ambient air conditions at the plant. Sardines have also been the subject of research with the metal oxide semi-conductor sensors. El Barbri *et al.* [36] developed a simple electronic nose based on available metal oxide sensors in order to supervise the freshness of sardines stored at 4ºC. Other supervised techniques were applied successfully corroborating the usefulness of the sensors to classify samples. The same authors [37] later incorporated a dedicated real-time data acquisition system based on a microcontroller and portable computer in order to miniaturize the device.

D. Eggs

One of the major concerns of the egg industry is the organized determination of egg freshness, because some consumers identify variability in freshness as lack of quality [38]. The modern poultry industry is not satisfied with the traditional system for the handling and processing of eggs, which is based on visual inspection of eggs, mainly because it is time consuming and is not error-free. The industry is therefore interested in evaluating alternative ways that can be used to measure quality parameters more quickly. The main quality parameters of interest are: freshness, weight and shape, state of the eggshell, size of air cell, albumen and yolk quality, the ratio of albumen weight to egg weight (Haugh unit) and eggshell thickness [39]. An alternative approach for determining the state of freshness of eggs is to identify the organic volatiles emitted by eggs with an E-nose. Methyl sulfide compounds are good candidates for freshness determination because they are directly related to deterioration and awareness of unacceptable odors in whole eggs [40]. Dutta *et al.* [39] used four tinoxide odor sensors (Figaro Engineering Inc, Japan) to classify eggs non-destructively. Three different freshness methods were identified using principal component analysis which was in good agreement with the three categories of egg freshness determined from the 'use by date' of the egg samples. Ninety-five percent classification accuracy was achieved using a radial basis function network. Suman *et al.* [41] evaluated the performance of an E-nose based on metal oxide semi-conductors with classical chemical and sensory methods for quality control of manufactured egg products. A trained sensory panel evaluated egg samples against the descriptors 'strong egg odor', 'slightly pungent' and 'pungent'.Lactic acid and succinic acid in the egg products were decided enzymatically while microbiological analyses included total viable mesophilic bacteria and Enterobacteriaceae counts. The researchers employed a destructive method to evaluate freshness of eggs with E-nose where fresh egg products were spiked and homogenized with different percentages of degraded eggs to obtain different degradation levels. The E-nose demonstrated a high degree of discrimination of samples analyzed during their degradation process compared to chemical and microbiological tests.

E. Fruits

The flavour of fruits and vegetables are either produced during ripening or upon tissue disruption, which happens after maceration, blending or homogenization. Many volatile compounds are naturally formed by enzymes found in the intact tissue of fruits and vegetables. They begin from secondary metabolites with various biosynthetic pathways. The characteristic aroma of fruits is an significant factor in their overall approval by the consumer. For many years human senses have been the primary "instrument" that has been used to determine fruit quality. More recently, techniques such as gas chromatography-mass spectrometry(GC-MS) have been used to characterize the volatile profiles of fruits and vegetables. However, it is neither feasible nor practical to use techniques such as GC-MS or sensory panel to assess cultivars or product found at storage stations. Gomez *et al.* [42] evaluated the capacity of ten metal oxide semi-conductor sensors (PEN2, Germany) to monitor the change in volatile production during tomato ripening. The E-nose was able to discriminate among different ripeness stages ("unripe", "half-ripe", "fully-ripe" and "overripe") with LDA showing 100% correct classification of samples. In the same way, an EOS835 E-nose with six thin film MOS sensors was tested for its ability to verify microbial contamination in canned peeled tomatoes [43]. Tomatoes were artificially contaminated with different microbial flora and analyzed by electronic nose, and the E-nose was able to detect contamination at early stages depending on the type of contamination (e.g. *Saccharomyces cerevisiae* and *Escherichia coli*) as well as classify spoiled tomato samples with high fidelity. Other fruits including blueberries, melons, snake fruit and mandarins have been evaluated

Published By
Blue Eyes Intelligence Engineering
& Sciences Publication

by MOS-based electronic noses either to predict the optimal harvest day (OHD) or to monitor shelf life. Blueberry is a highly perishable fruit that must be processed properly and with care otherwise it can develop damage such as cracks, leaks, soft spoilage, which will be apparent to the consumer. Simon *et al.* [44] were able to detect 5% soft and damaged blueberry fruit in packaged containers with just two tin oxide gas sensors and could also distinguish four of five fruit ripeness classes. The sensor responses correlated well with other quality indicators like berry firmness, pH titratable acidity, and color. These workers also detected differences among ten cultivars. In a similar study on snake fruit, three out of 18 MOS-based E-nose (FOX 4000, France) were found able to discriminate among maturity levels [45]. For mandarins however, a sensor array of ten different metal oxide semi-conductor sensors (PEN2, Germany) was not effective in separating mandarins based on different storage times [46]. In contrast, though the same E-nose could detect differences in mandarins picked on different dates and also evaluate mandarin quality attributes such as firmness, soluble solids content and acidity [47]. In a different study with melons and using another E-nose, MOS sensor responses were found to be highly correlated with the sugar content of melon samples harvested at different stages, demonstrating that it could be used to predict the OHD [48,49]. OHD is also of importance in those fruits which are used for further processing, like winegrapes. Berna *et al.* [50] suggested that a MOS based-E-nose (FOX 3000,France) may be a useful practical tool to estimate the time to ripeness of grapes.

F. Alcoholic Drinks

While metal oxide semi-conductors are possibly the most extensively used of the E-nose sensors, they have still some important drawbacks when applied to alcoholic drinks. MOS responses depend logarithmically on the absorption of analyte gases. In the occurrence of very high concentrations of analyte, such as ethanol in alcoholic beverages, sensors become saturated and mask the responses to other volatile compounds. Consequently, samples tend to be differentiated on the center of variations in ethanol content rather than the other volatile compounds which are responsible for the aroma [51]. Several approaches have been developed to reduce ethanol content and increase concentration of other volatile compounds before E-nose analysis. These include: the use of a chromatographic column between the headspace sampler and the sensor array to eliminate ethanol [52], and a purge and trap step to remove water and ethanol [53]. Other techniques include solid phase micro-extraction (SPME) [54], pervaporation [55,56] or dynamic headspace sampling using resin [57]. Other researchers have effectively dried wine samples on nylon membranes prior to E-nose analysis [58-61]. Beer samples cause an additional problem due to the super-saturation of CO2 and foam formation when the samples are heated for headspace sampling. Different methods have been tested to liberate CO2 such as NaCl addition at low temperature [62], nitrogen sparging [63] or simple agitation [64]. Current approaches to assess wines include sensory analysis but, because of its high cost, E-noses have been estimated as an alternative. Penza *et al.* [65] tested three red, three white and three rosé wines from different Italian denominations of origin and vintages using a multisensor array that incorporated four metal oxide (WO3) semi-conductor thin film sensors. Static headspace sampling (SHS) was used to sample the volatile compounds above the wine sample. Although SHS, as recognized by the authors [65], is very sensitive to volatile compounds like ethanol and barely able to identify trace compounds, it is also a simple, fast and reproducible sampling method that can be used with an automated extraction process. Furthermore, it is also low-cost and a solvent free method. Neural network classification of the E-nose data correctly predicted 100% of the white wines, 77.8% of the red wines but only 33.3% of rosé wines. Other researchers [66] used SHS followed by dynamic headspace to classify Spanish wines according to their geographic origin. Multivariate statistical analysis demonstrated that all the tested wines were different. Buratti *et al.* [67] used ten metal oxide semi-conductors type chemical sensor (PEN2, Germany) and an enrichment desorption unit to trap and thermally desorb wine samples into the E-nose. The sorbent material was Tenax®-TA polymer and the wine samples arrived from two northern Italian regions. LDA applied to a larger data set (*i.e.*, chemical analysis, E-nose, Etongue and color measurements) accurately classified 100% of wines into their region. The error rate using only E-nose responses was not disclosed. Berna *et al.* [61] compared E-nose (12 MOS sensors, FOX 3000) SPME measurements after drying wine samples on a nylon membrane with SHS for predicting the regional origins of 34 Sauvignon Blanc wines. GC-MS was also used to examine all wine samples. After training the E-nose based on GC-MS grouping of wines, the average error of prediction was 6.5% with SPME compared with 24% using SHS.Di Natale *et al.* [68, 69] used four MOS sensors to classify wines having the same geographic origin but coming from different vineyards. The E-nose was found superior to the standard chemical analysis usually executed by the wineries. Aging of wines and beers permits desirable flavors and aromas to develop and off-flavor notes to diminish. Volatile chemicals are an important constituent of wine and beer flavor and it is advantageous to monitor them through aging. Garcia *et al.* [54] analyzed wines of the same range and geographical origin that differed in age after fermentation (young wines, aged for a year, aged for 18 months and aged for 24 months). They compared two sampling systems, SHS and dynamic headspace with purge and trap, with a 16 MOS sensor array. With SHS sampling 80% of the wines were correctly classified while with purge and trap, a technique more efficient in decreasing moisture and ethanol content in the headspace, the success rate was 95%. More recently, Villanueva *et al.* [70] used 20 MOS sensors combined with SPME to discriminate wines aged for 3 and 6 months in oak barrels. The E-nose evidently distinguished between aging times and was in good agreement with chemical analysis and sensory panel evaluations. McKellar *et al.* [58] attempted to establish the influence of aging time on the development of aroma characteristics of a commercial beer ("Sleeman Cream Ale") with an E-nose (FOX 3000, France). SHS was the sampling method of choice. The E-nose was able to distinguish beer samples into different groups with those aged up to 12 or 14 days separated from samples aged longer than 14 days. These findings were confirmed by GC-MS. Aging beer for longer than 5 to 7 days shows to have no important advantage in eliminating fermentation odors. The authors concluded that reducing the time required in the aging tank would reduce costs to the brewer. Classification of alcoholic drinks by McKellar *et al.* [59] used a MOS based-E-nose (FOX 3000, France) for the classification of eight fruit wines (blueberry, cherry, raspberry, blackcurrant, elderberry, cranberry, apple and peach) and four grape wines (red, Chardonnay, Riesling and ice wine), and each category of wine obtained from a minimum of five Ontario wineries. The wine samples were dried onto membrane filters to remove ethanol. Each of the 12 different wine varieties could be divided according to winery. The E-nose appeared to be distinguishing volatile patterns that were characteristic of each winery or the wine-making procedure. However, the E-nose was less able to separate the 12 varieties of wines from each other, in part owing to the variation among wineries. Although the E-nose failed to find dissimilarities between fruit wines, the same type of E-nose (FOX 2000, France) seems to be more efficient to discriminate between other alcoholic beverages like tequila, whisky, vodka, wine and beer as found by Ragazzo-Sanchez *et al.* [71].The authors used gas chromatogram (GC) to remove ethanol and dehydrate headspace beverages with the remaining volatile compounds collected by reverting the gas using column 'back-flush' and introduced in the injector port of the E-nose.

G. Non-Alcoholic Beverages

Tea and coffee are the most popular beverages which have been the subject to research using electronic noses, mainly in the assessment of the quality grades of these products. Because of the complexity of the organic compounds present in both raw materials, E-noses are suitable for continuous real time monitoring of odor. Tea grade is conventionally classified by a trained human panel. In total, 24 non-overlapping flavor terms have been recognized out of 40 generally used flavor observations [72]. Dutta *et al.* [73] assessed an E-nose for its appropriateness in monitoring the quality of five Assam tea samples manufactured under different processing situations in India. Tea sample variations were based on drying of the product, fermentation and the final oven fired process. Four tin oxide sensors (Figaro Eng. Inc, Japan) were used to assess headspace of liquid tea samples. MOS sensors were competent to discriminate five different categories of tea, indicating that the instrument was capable to discriminate between flavors of teas manufactured under different processing conditions. A probabilistic neural network used with the E-nose responses provided 100% accuracy in classification of the tea samples. Yu *et al.* [74] studied the applicability of an electronic nose for assessing the same group of tea with different quality grades. Tea samples had five grades (different prices) picked from the same area and prepared as tea leaf or tea beverage or tea remains. Like tea, coffee quality is assessed by coffee tasters, largely on the basis of its aroma and flavor. The highest quality beans command a considerable quality when the product is sold. Coffee volatiles are various and varied in their aroma quality, potency and concentration. Most of the volatiles are derived from non-volatile components of the raw bean, and formed during roasting to produce a complex aroma mixture. Green coffee beans are generally considered as having no pleasant aroma or flavor but do own a large number of volatiles, most of which increase in concentration during coffee roasting even though there is a minority which tend to degrade [75]. Aishima *et al.* [76] focused on the ability of six MOS sensors to discriminate coffee beans and instant coffee. They found, after cluster analysis applied to the normalized responses, a clear separation between coffee beans and instant coffees. Gardner *et al.* [75] employed an array of 12 tin oxide sensors to evaluate three commercial coffees (covering two different blends and two roasted varieties) as well as one coffee sample which was subjected to a range of six roasting times. It appeared that tin oxide gas sensors were suitable for discriminating between both the blend and roasting level of coffee, proving the potential of E-noses for on-line quantitative process control in the coffee industry. Other application of E-noses to coffees include the study of Pardo *et al.* [77] who evaluated a system consisting of four SnO2 thin film sensors, of which two were pure SnO2, another doped with gold and the last one doped with platinum, to distinguish between coffee blends. Twelve types of coffees were evaluated in the form of espresso extract and each were sampled at three points in preparation: as beans, ground powder and liquid. Only two sensors were needed to correctly classify 100% of the bean samples. In the case of ground coffee, a supervised drift compensation algorithm was developed and best classification rate was achieved. On the other hand, liquid coffee samples were not successfully classified; which the authors attribute to the difficulty in assuring reproducible sampling conditions. In later work Pardo *et al.* [78] used the same system with an extra SnO2 sensor doped with palladium in order to evaluate two groups of coffees. The first group comprised six single coffee varieties and an Italian certified espresso blend while the second group of coffees consisted of seven blends. The E-nose results were then compared with sensory analysis of the final product; *i.e.*, cups of espresso, with the panel judging ten quantitative descriptors and four qualitative descriptors. Although the authors focused on the investigation of sampling conditions and feature selection for improving classification performance, the results showed that EOS835 was suitable to monitor coffee blends during the seasoning process. Only two sensors performed adequately for this application.

III. CONCLUSIONS

The approaching applications in odor assessment by electronic noses in the food locality are various; they have been used for quality control, monitoring process, aging, determination of geographical origin, adulteration, contamination and spoilage. In most cases classification of samples obtained a good classification rate, but, before these particular applications can become a reality, *i.e.*, these laboratory-based assessments are moved into the industry, a number of challenges still need to be met; these are to correctly review various characteristics of electronic nose presentation, including drift, humidity influence, redundancy of sensors, selectivity and signal to noise ratio. Although new sensor materials and designs, and improvement of algorithms that can be applied for each sensor, are being accounted, the major drawback of currently available MOS sensors remains their authorization and selectivity. Sensors with poor selectivity change adversely the discriminating authority of the array. Additionally, with the technology developed so far, it is unrealistic to envisage a universal electronic nose that is able to cope with every odor type as accurate data processing and, sometimes instrumentation, must be developed for each application.

REFERENCES

1. P. Ciosek, Z. Brzozka, and W. Wroblewski, "Classification of beverages using a reduced sensor array," *Sens. Actuators B*, vol. 103, pp.76–83, 2004.
2. J. Lozano, J. P. Santos, M. Aleixandre, I. Sayago, J. Gutierrez, and M. C. Horrillo, "Identification of typical wine aromas by means of an electronic nose," *IEEE Sensors J.*, vol. 6, pp. 173–178, Feb. 2006.
3. M. Aleixandre, J. Lozano, J. Guiterrez, I. Sayago, M. J. Fernandez, and M. C. Horrillo, "Portable e-nose to classify different kinds of wine," *Sens. Actuators B*, vol. 131, pp. 71–76, 2008.
4. M. Pardo, G. Niederjaufnes, G. Benussi, E. Comini, G. Faglia, G. Sberveglieri, M. Holmberg, and I. Lundstorm, "Data preprocessing enhances the classification of different brands of Espresso coffee with an electronic nose," *Sens. Actuators B*, vol. 69, pp. 397–403, 2000.
5. K. Brudzewska, S. Osowiki, and T. Markiewicz, "Classification of milk by means of an electronic nose and SVM neural network," *Sens. Actuators B*, vol. 98, pp. 291–298, 2004.
6. W. M. Sears and K. Colbow, "Selective thermally cycled gas sensing using fast Fourier transform techniques," *Sens. Actuators B*, vol. 2, pp.283–289, 1990.
7. J. W. Gardner,H. V. Shurmer, and T. T. Tan, "Application of electronic nose to the discrimination of coffees," *Sens. Actuators B*, vol. 6, pp.71–75, 1992.
8. M. S. Nayak, "Transformed cluster analysis: An approach to the identification of gases/odors using integrated gas sensor array," *Sens. Actuators B*, vol. 12, pp. 103–110, 1993.
9. A. K. Srivastava, K. K. Shukla, and S. K. Srivastava, "Exploring neurogenetic processing of electronic nose data," *Microelectronics J.*, vol.29, pp. 921–931, 1998.
10. F. C. Chen and M. H. Lin, "On the learning and convergence of the radial basis networks," in *Proc. IEEE Conf. Neural Networks*, San Fransisco, CA, Mar. 28, 1993, pp. 983–988.
11. K. K. Shukla, R. R. Das, and R. Dwivedi, "Adaptive resonance neural classifier for identification of gas/odors using an integrated gas sensor array," *Sens. Actuators B*, vol. 50, pp. 194–203, 1998.
12. S. Marco, A. Ortego, A. Pardo, and J. Samitier, "Gas identification with tin oxide sensor array and self-organizing map: Adaptive correction of sensor drifts," *IEEE Trans. Instrum. Measurment*, vol. 47, pp. 316–320, 1998.
13. R. R. Das, K. K. Shukla, R. Dwivedi, and A. R. Srivastava, "Discrimination of individual gas/odor using responses of integrated thick film tin oxide sensor and fuzzy-neuro concept," *Microelectronics J.*, vol. 30, pp. 793–800, 1999.
14. Syeda Erfana Zohora; Dr.A.M.Khan; Dr.Nisar Hundewale; Electronic Noses Principles And Its Applications;International Journal of Imaging Science and Engineering; Volume 6 No 1 Apr 2012.
15. Gardner, J.; Bartlett, P.N. *Electronic Nose. Principles and Applications*; Oxford University,Press: Oxford, UK, 1999.
16. Syeda Erfana Zohora; A.M.Khan; Nisar Hundewale; Chemical Sensors Employed In Electronic Noses: A Review; Proceedings of the Second International Conference on Advances in Computing and Information Technology (ACITY-2012); July 13-15,2012 Chennai; India-Volume 3; **Springer**-Verlag Berlin Heidelberg (2012),page 177-184; Accepted & Published.
17. Fox, P.F. *Advanced Dairy Chemistry*; Chapman & Hall: London, UK/New York, NY, USA,1992.
18. Yu, H.C.; Wang, J.; Xu, Y. Identification of Adulterated Milk Using Electronic Nose. *Sens.Mater.* 2007, *19*, 275-285.
19. Benedetti, S.; Bonomi, F.; Iametti, S.; Mannino, S.; Cosio, M.S. Detection of aflatoxin M1 in ewe milk by using an electronic nose. In *Proceedings of the 2nd Central European Meeting 5th Croatian Congress of Food Technologists, Biotechnologists and Nutritionists*, Opatija, Croatia,October 17–20, 2004; pp. 101-105
20. Ampuero, S.; Bosset, J.O. The Electronic nose applied to dairy products: a review. *Sens.Actuat.B* 2003,*94*,1-12.
21. Mulville, T. UHT the nose knows. *Food Manufact.* March 2000**,** 27-28.
22. Mariaca, R.; Bosset, J.O. Instrumental analysis of volatile (flavour) compounds in milk and dairy products. *Lait* 1997, *77*, 13-40.
23. Capone, S.; Epifani, M.; Quaranta, F.; Siciliano, P.; Taurino, A.; Vasanelli, L. Monitoring of rancidity of milk by means of an electronic nose and a dynamic PCA analysis. *Sens. Actuat. B* 2001, *78*, 174-179.
24. Capone, S.; Siciliano, P.; Quaranta, F.; Rella, R.; Epifani, M.; Vasanelli, L. Analysis of vapours and foods by means of an electronic nose based on a sol-gel metal oxide sensors array. *Sens. Actuat. B* 2000, *69*, 230-235.
25. Labreche, S.; Bazzo, S.; Cade, S.; Chanie, E. Shelf life determination by electronic nose:application to milk. *Sens. Actuat. B* 2005, *106*, 199-206.
26. Dainty, R.H.; Edwards, R.A.; Hibbard, C.M. Time course of volatile compound formation during refrigerated storage of naturally contaminated beef in air. *J. Appl. Bacteriol.* 1985, *59*, 303-309.
27. Mayr, D.; Hartungen, E.; Mark, T.; Margesin, R.; Schinner, F. Determination of the spoilage status of meat by aroma detection using proton-transfer-reaction mass-spectrometry. In Proceedings of the 10th Weurman Flavour Research Symposium, Beaune, France, June 25−28, 2002; pp. 757-760.
28. Lindinger, W.; Hansel, A.; Jordan, A. On-line monitoring of volatile organic compounds at pptv levels by means of proton-transfer-reaction mass spectrometry (PTR-MM)—medical applications, food control and environmental research. Int. J. Mass Spectrom. 1998, 173, 191-241.
29. Winquist, F.; Hornsten, E.G.; Sundgren, H.; Lundstrom, I. Performance of an electronic nose for quality estimation of ground meat. Meas. Sci. Technol. 1993, 4, 1493-1500.
30. Vilaseca, M.; Coronas, J.; Cirera, A.; Cornet, A.; Morante, J.R.; Santamaria, J. Gas detection With SnO2 sensors modified by zeolite films. Sens. Actuat. B 2007, 124, 99-110.
31. Balasubramanian, S.; Panigrahi, S.; Logue, C.M.; Doetkott, C.; Marchello, M.; Sherwood, J.S. Independent component analysis-processed electronic nose data for predicting Salmonella Typhimurium populations in contaminated beef. Food Control 2008, 19, 236-246.
32. Vernat-Rossi, V.; Garcia, C.; Talon, R.; Denoyer, C.; Berdague, J.L. Rapid discrimination of meat products and bacterial strains using semiconductor gas sensors. Sens. Actuat. B 1996, 37, 43-48.
33. Bene, A.; Hayman, A.; Reynard, E.; Luisier, J.L.; Villettaz, J.C. A new method for the rapid determination of volatile substances: the SPME-direct method—Part II. Determination of the freshness of fish. Sens. Actuat. B 2001, 72, 204-207.
34. Olafsdottir, G.; Chanie, E.; Westad, F.; Jonsdottir, R.; Thalmann, C.R.; Bazzo, S.; Labreche, S.;Marcq, P.; Lundby, F.; Haugen, J.E. Prediction of microbial and sensory quality of cold smoked atlantic salmon (Salmo Salar) by electronic nose. J. Food Sci. 2005, 70, S563-S574.
35. Haugen, J.E.; Chanie, E.; Westad, F.; Jonsdottir, R.; Bazzo, S.; Labreche, S.; Marcq, P.; Lundby, F.; Olafsdottir, G. Rapid control of smoked Atlantic salmon (Salmo salar) quality by electronic nose: Correlation with classical evaluation methods. Sens. Actuat. B 2006, 116, 72-77.
36. El Barbri, N.; Amari, A.; Vinaixa, M.; Bouchikhi, B.; Correig, X.; Llobet, E. Building of a metal oxide gas sensor-based electronic nose to assess the freshness of sardines under cold storage.Sens.Actuat.B 2007,128,235-244.
37. El Barbri, N.; Llobet, E.; El Bari, N.; Correig, X.; Bouchikhi, B. Application of a portable electronic nose system to assess the freshness of moroccan sardines. Mat. Sci. Eng. C-Bio S. 2008, 28, 666-670.
38. Wang, Y.W.; Wang, J.; Zhou, B.; Lu, Q.J. Monitoring storage time and quality attribute of egg based on electronic nose. Anal. Chim. Acta 2009, 650, 183-188.
39. Dutta, R.; Hines, E.L.; Gardner, J.W.; Udrea, D.D.; Boilot, P. Non-destructive egg freshness determination: an electronic nose based approach. Meas. Sci. Technol. 2003, 14, 190-198.
40. Brown, M.L.; Holbrook, D.M.; Hoerning, E.F.; Legendre, M.G.; Stangelo, A.J. Volatile indicators of deterioration in liquid egg products. Poult. Sci. 1986, 65, 1925-1933.
41. Suman, M.; Riani, G.; Dalcanale, E. MOS-based artificial olfactory system for the assessment of egg products freshness. Sens. Actuat. B 2007, 125, 40-47.
42. Gomez, A.H.; Hu, G.X.; Wang, J.; Pereira, A.G. Evaluation of tomato maturity by electronic nose. Comput. Electron. Agri. 2006, 54, 44-52.
43. Concina, I.; Falasconi, M.; Gobbi, E.; Bianchi, F.; Musci, M.; Mattarozzi, M.; Pardo, M.;Mangia, A.; Careri, M.; Sberveglieri, G. Early detection of microbial contamination in processed tomatoes by electronic nose. Food Control 2009, 20, 873-880.
44. Simon, J.E.; Hetzroni, A.; Bordelon, B.; Miles, G.E.;

Charles, D.J. Electronic sensing of aromatic volatiles for quality sorting of blueberries. J. Food Sci. 1996, 61, 967-970.
45. Supriyadi; Shimazu, K.; Susuki, M.; Yoshida, K.; Muto, T.; Fujita, A.; Tomita, N.; Watanabe, N.Maturity discrimination of snake fruit (Salacca edulis Reinw.) cv. Pondoh based on volatiles analysis using an electronic nose device equipped with a sensor array and fingerprint mass spectrometry. Flavour Frag. J. 2004, 19, 44-50.
46. Gomez, A.H.; Wang, J.; Hu, G.X.; Pereira, A.G. Discrimination of storage shelf-life for mandarin by electronic nose technique. Lwt-Food Sci. Technol. 2007, 40, 681-689.
47. Gomez, A.H.; Wang, J.; Pereira, A.G. Mandarin ripeness monitoring and quality attribute evaluation using an electronic nose technique. Trans. ASABE 2007, 50, 2137-2142.
48. Steinmetz, V.; Crochon, M.; Talou, T.; Bourrounet, B. Sensor fusion for fruit quality assessment:application to melons. In Proceedings of International Conference on Harvest and Postharvest Technologies for Fresh Fruits and Vegetables, Guanajuato, Gto, Mexico, February 20–24, 1995;pp. 488-496.
49. Steinmetz, V.; Sevila, F.; Bellon-Maurel, V. A Methodology for sensor fusion design:Application to fruit quality assessment. *J. Agr. Eng. Res.* 1999, *74*, 21-31.
50. Berna, A.Z.; Trowell, T.; Clifford D.; Stone, G.; Lovell, D. Fast aroma analysis of Cabernet Sauvignon and Riesling grapes using an electronic nose. *Am. J. Enol. Vitic.* 2007, *58*, 416A-417A.
51. Marti, M.; Boque, R.; Busto, O.; Guasch, J. Electronic noses in the quality control of alcoholic beverages. *Trends Anal. Chem.* 2005, *24*, 57-66.
52. Herbele, I.; Liebminger, A.; Weimar, U.; Gopel, W. Optimised sensor arrays with chromatographic preseparation: characterisation of alcoholic beverages. *Sens. Actuat. B* **2000**,*68*, 53-57.
53. Garcia, M.; Aleixandre, M.; Gutierrez, J.; Horrillo, M. Electronic nose for wine discrimination.*Sens. Actuat. B* 2006, *113*, 911-916.
54. Aishima, T. Discrimination of liquor aromas by pattern-recognition analysis of responses from a gas sensor array. *Anal. Chim. Acta* 1991, *243*, 293-300.
55. Schafer, T.; Serrano-Santos, M.; Rocchi, S.; Fuoco, R. Pervaporation membrane separation process for enhancing the selectivity of an artificial olfactory system ("electronic nose"). *Anal.Bioanal. Chem.* **2006**, *384*, 860-866.
56. Pinheiro, C.; Rodrigues, C.; Schafer, T.; Crespo, J. Monitoring the aroma production during wine-must fermentation with an electronic nose. *Biotechnol. Bioeng.* 2002, *77*, 632-640.
57. Guadarrama, A.; Fernandez, J.; Iniguez, M.; Souto, J.; Saja, J. Array of conducting polymer sensors for the characterisation of wines. *Anal. Chim. Acta* 2000, *411*, 193-200.
58. McKellar, R.; Young, J.; Johnston, A.; Knight, K.; Lu, X.; Buttenham, S. Use of the electronic nose and gas chromatography-mass spectrometry to determine the optimum time for aging beer.*Master Brewers Assoc. Amer.* 2002, *39*, 99-105.
59. McKellar, R.; Rupasinghe, H.; Lu, X.; Knight, K. The electronic nose as a tool for the classification of fruit and grape wines from different Ontario wines. *J. Sci. Food. Agric.* 2005,*85*, 2391-2396.
60. Berna, A.Z.; Trowell, S.; Cynkar, W.; Cozzolino, D. Comparison of metal oxide-based electronic nose and mass spectrometry-based electronic nose for the prediction of red wine spoilage. *J.Agric. Food Chem.* 2008, *56*, 3238-3244.
61. Berna, A.Z.; Trowell, S.; Clifford, D.; Cynkar, W.; Cozzolino, D. Geographical origin of Sauvignon Blanc wines predicted by mass spectrometry and metal oxide based electronic nose.*Anal. Chim. Acta* 2009, *648*, 146-152.
62. Pinho, O.; Ferreira, I.; Santos, L. Method optimization by solid-phase microextraction in combination with gas chromatography with mass spectrometry for analysis of beer volatile fraction. *J. Chromatogr. A* 2006, *1121*, 145-153.
63. Pearce, T.C.; Gardner, J.W.; Friel, S.; Bartlett, P.N.; Blair, N. Electronic nose for monitoring the flavor of beers. *Analyst* 1993, *118*, 371-377.
64. Sakuma, S.; Amano, H.; Ohkochi, M. Identification of off-flavor compounds in beer. *J. Am. Soc.Brew. Chem.* **2000**, *58*, 26-29.
65. Penza, M.; Cassano, G. Chemometric characterization of Italian wines by thin-film multisensors array and artificial neural networks. *Food Chem.* 2004, *86*, 283-296.
66. Santos, J.; Arroyo, T.; Aleixandre, M.; Lozano, J.; Sayago, I.; Garcia, M.; Fernandez, M.; Ares, L.; Gutierrez, J.; Cabellos, J.; Gil, M.; Horrillo, M. A comparative study of sensor array and GC-MS: application to Madrid wines characterisation. *Sens. Actuat. B* 2004, *102*, 299-307.
67. Buratti, S.; Benedetti, S.; Scampicchio, M.; Pangerod, E. Characterization and classification of Italian Barbera wines by using an electronic nose and an amperometric electronic tongue. *Anal.Chim. Acta* 2004, *525*, 133-139.
68. Di Natale, C.; Davide, F.A.M.; D'Amico, A.; Nelli, P. An electronic nose for the recogition of the vineyard of a red wine.*Sens.Actuat. B* 1996,*33*,83-88.
69. Di Natale, C.; D'Amico, A. The electronic nose: a new instrument for wine analysis. *Ital. Food Bever. Tech.* 1998, *14*, 17-19.
70. Villanueva, S.; Guadarrama, A.; Rodriguez-Mendez, M.L.; De Saja, J.A. Use of an array of metal oxide sensors coupled with solid phase microextraction for characterisation of wines study of the role of the carrier gas. *Sens. Actuat. B* 2008, *132*, 125-133.
71. Ragazzo-Sanchez, J.A.; Chalier, P.; Chevalier, D.; Ghommidh, C. Electronic nose discrimination of aroma compounds in alcoholised solutions. *Sens. Actuat. B* 2006, *114*, 665-673.
72. Bhuyan, M.; Borah, S. Use of electronic nose in tea industry. In *Proceedings of International Conference on Energy, Automation and Information Technology*, Kharagpur, India, December 2001; pp. 848-853.
73. Dutta, R.; Hines, E.L.; Gardner, J.W.; Kashwan, K.R.; Bhuyan, A. Tea quality prediction using a tin oxide-based electronic nose: an artificial intelligence approach. *Sens. Actuat. B* 2003, *94*, 228-237.
74. Yu, H.; Wang, J.; Xiao, H.; Liu, M. Quality grade identification of green tea using the eigenvalues of PCA based on the E-nose signals. *Sens. Actuat. B* 2009, *140*, 378-382.
75. Gardner, J.W.; Shurmer, H.V.; Tan, T.T. Application of an electronic nose to the discrimination of coffees. *Sens.Actuat. B* 1992, *6*, 71-75.
76. Aishima, T. Aroma discrimination by pattern-recognition analysis of responses from semiconductor gas sensor array. *J. Agric. Food Chem.* 1991, *39*, 752-756.
77. Pardo, M.; Niederjaufner, G.; Benussi, G.; Comini, E.; Faglia, G.; Sberveglieri, G.; Holmberg,M.; Lundstrom, I. Data preprocessing enhances the classification of different brands of espresso coffee with an electronic nose. *Sens. Actuat. B* 2000, *69*, 397-403.
78. Pardo, M.; Sberveglieri, G. Coffee analysis with an electronic nose. *IEEE T. Instrum. Meas.*2002, *51*, 1334-1339.

AUTHOR PROFILE

Syeda Erfana Zohora received her B.E. Degree in Computer Science & Engineering from Mysore University, Karnataka, India & M.S. in Software Systems from BITS, Pilani, Rajasthan. She is pursuing her Ph.D Degree from Mangalore University, Mangalore and currently working in the College of Computers and Information Technology, Taif University, Taif, KSA. Her research interest are Artificial Neural Networks, Support Vector Machine and Genetic Algorithms.

A.M.Khan received his Ph.D degree in Electronics from Mangalore University, Mangalore, Karnataka, India. He is presently working as a Professor in the Electronics Dept., Mangalore University, Mangalore.. His research interest are Artificial Neural Networks , Machine Learning and Digital Image Processing.

A.K.Srivastava received his Ph.D degree in 1999 from Banaras Hindu University, India. He is presently working as Chief Technology Officer, LightField Corporation Philadelphia, PA, USA. His research interest are Artificial Neural Networks, Genetic Algorithms, Nano Sensors.

Nisar Hundewale received his Ph.D degree in 2007 from Georgia State University, USA. He is presently working as Assistant Professor in the College of Computers and Information Technology, Taif University Taif, SA. His research interest are Machine Learning, Bioinformatics and Algorithms.