ISSN (Online) : 2278-1021
ISSN (Print) : 2319-5940

International Journal of Advanced Research in Computer and Communication Engineering
Vol. 3, Issue 5, May 2014

Neuro-Soft Computing Approach For The Design of Near-Optimal Classifier For Quality Assessment of Food Product

Ms. Yashshree Chavan[1], Prof. Abhijeet Shinde[2]

Student of Master of Engineering, Digital Electronics, D.B.N.C.O.E.T., Yavatmal, India[1]

Assistant Professor, Electronics & Telecommunication, D.B.N.C.O.E.T., Yavatmal, India[2]

Abstract: This paper gives the best neural network classifier for quality assessment of food product. We are using Back propagation network, learning vector quantization & Radial basis function for this purpose, and finally best network will be chosen for the quality Assessment.

Keywords: Neural network, Sensors, BPNN, Radial Basis Function

I. INTRODUCTION

Electronic noses (E-Nose) have been developed as systems for the automated detection and classification of odours, vapours, and gases. Electronic Nose is a smart instrument that is designed to detect and discriminate among complex odours using an array of sensors. The array of sensors consists of a number of broadly tuned (non-specific) sensors that are treated with a variety of odour sensitive biological or chemical materials. This instrument provides a rapid, simple and non-invasive sampling technique, for the detection and identification of a range of volatile compounds. The key function of an electronic nose is to mimic human olfactory system.

The human nose is still consideration the primary tool employed in industry to characterize the odour of a variety of consumer products. E-Nose is a device that identifies the specific components of an odour and analyses its chemical makeup to identify it [1]. To humans, the sensation of flavour is due to three main chemoreceptor systems. These are gestation (sense of taste by tongue), olfaction (sense of smell by nose) and trigeminal (sense of irritation of trigeminal receptors). The sense of taste is used to detect certain non-volatile chemicals, which enter the mouth. The sense of smell is used to detect certain volatile compounds. Receptors for the trigeminal sense are located in the mucous membranes and in the skin. They respond to certain volatile Chemicals and it is thought to be especially important in the detection of irritants and chemically reactive species. In the perception of flavour all three chemoreceptor systems are involved but olfaction plays by far the greatest role.

The proposed research aims at design of near-optimal classifier using neural networks for quality analysis of food or dairy products using E-Nose. The data generated by E-Nose are non-linear and overlapping in the feature space. This justifies the applicability of Nero-Soft Computing Approach for the input data classification in food or dairy product industry. The proposed research aims at the design of near-optimal classifier for quality analysis/ assessment of food or dairy products using E-Nose.

A. *Aims and Objectives*

E-Nose is a new and promising technology which aimed to rapidly becoming a valuable tool for the organoleptic evaluation of food parameters related to taste and smell and could replace human sensory panels in quality control applications, wherethe objective, rapid and syntheticevalua tion of the aroma of many specimens is required. The proposed system aims at providing, real-time, knowledge of odour being produced by E-Nose to assess the quality of food or dairy products.

E-Nose consists of a sampling system (for a reproducible collection of the mixture), an array of sensors (which is the heart of the system), electronic circuitry and data analysis software [1]. E-Nose using arrays of chemical sensors can be divided into three categories according to the type of sensitive material used: inorganic crystalline materials (e.g. semiconductors, as in MOS-FET structures, and metal oxides); organic materials and polymers; biologically derived materials. Comparatively to classical techniques (e.g. the combination of gas chromatography and mass spectroscopy (GC-MS)), E-Nose are simpler and more accurate devices. They recognize a fingerprint that is global information, of the samples to be classified [3,4].
An essential objective of this research work is to ensure that the technology would be robust, sufficiently sensitive, and able to identify and quantify odors from food or dairy products. An odour stimulus generates a characteristic fingerprint (or smell-print) from the sensor array. Patterns, or finger-prints, from known odours are then used to construct a database and train a pattern recognition system so that unknown odours can subsequently be classified, i.e. identified. Thus E-Noses comprise of mechanical components to collect and transport odours to the sensor array as well as electronic circuitry to digitize and store the sensor responses for signal processing.

Generally speaking, electronic noses are faster to respond, easier to use and relatively cheaper in comparison with conventional analytical techniques, such as gas chromatography/mass spectroscopy and flame ionization

ISSN (Online) : 2278-1021
ISSN (Print) : 2319-5940
International Journal of Advanced Research in Computer and Communication Engineering
Vol. 3, Issue 5, May 2014

detection, so that they have wide applications in environmental monitoring [5, 6] , food and beverage industry , medical diagnosis [7], public security [8] , odour classification of grains [9] and others.

Dealing with E-Nose signals is still crucial for artificial olfaction to reliably recognize various odors due to time variance of the signals. Aim of this research work is to develop Neural Network based Near-Optimal Classifier to assess the quality food or dairy product, such as, tea or basmati rice or milk using E-Nose.

Existing method to check the quality of these products is done by Human Tester. For example tea quality/grade is decided on the basis of decision given by Tea Tester who is a human being. There is a lot of error, deviation in the measurement by human being. To avoid this optimum classifier system based on electronic nose using neural network could be designed which would more reliable and accurate [28, 29].

B. Scope and Limitation

Using Electronic-nose we can sense a smell and with a technology called Digital scent technology it is possible to sense, transmit and receive smell through internet, like smelling a perfume online before buying them, sent scented E-cards through scent enabled websites, and to experience the burning smell of rubber in your favourite TV games etc. As a multidisciplinary research, most studies on electronic noses focused on the sensitivities of the chemical sensor array and the pattern recognition methods to process the signals obtained from the sensor array. With the development of functional material technology, signals can be obtained via various sensors, such as metal oxide semiconductor, optical, con-ducting polymer (CP), quartz crystal microbalance and surface acoustic wave sensors [10] . Some pattern recognition methods have been introduced into electronic noses [11, 12]. Neural networks are usually considered to be one of the most promising methods to solve this complex and non-linear problem, because they can cope with nonlinear problems and handle noise or drift better than conventional statistical approaches. So many neural networks to process signals from sensor arrays are reported, such as back propagation trained neural network [13] , radial basis function neural network, learning vector quantization neural network.

There are few disadvantages to the E-Nose technology which includes the price. The cost of an E-Nose is very high which the main hurdle in doing the research work. Another disadvantage has been the delay between successive tests, the time delay ranging between 2 to 10 minutes during which time; the sensor is to be washed by a reactivating agent, which is applied to the array so as to remove the odorant mixture from the surface and bulk of the sensors active material [26].

II. LITERATURE SURVEY

Ritaban Dutta, and Ritabrata Dutta [14] has presented in research on Electronic Nose based ENT bacteria identification in hospital environment is a classical and challenging problem of classification. An electronic nose (e-nose), comprising a hybrid array of 12 tin oxide sensors (SnO_2) and 6 conducting polymer sensors has been used to identify three species of bacteria, *Escherichia coli* (*E. coli*), *Staphylococcus aureus* (*S. aureus*), and *Pseudomonas aeruginosa* (*P. aeruginosa*) responsible for ear nose and throat (ENT) infections when collected as swab sample from infected patients and kept in ISO agar solution in the hospital environment.

S. Ampuero and J.O. Bosset [15] have proposed the model for Electronic Nose. Most of the reported applicability studies of electronic noses to different aspects of quality assessment in dairy products show satisfactory results. Published literature reports the classification of dairy products by sample type with MOS sensors; by ageing with MOS, CP and MS-based instruments; by geographic origin with an MS-electronic nose; by processing stage with CP sensors. A successful model for milk shelf-life prediction was implemented with a MOS system. The identification and classification of different types of quality-deterioration have also been published: different off-odours in milk with an MS-based tool, lower quality of casein samples with MOS sensors, identification of microbial contamination in milk with CP, MS, etc. Nevertheless, in most cases the results will have to be confirmed on a larger scale to make sure that the classifications obtained are still valid with a larger intra-group variability, which is generally found in the case of natural products.

Simona Benedetti *et. al.* [16] have suggested a model of Electronic Nose for honey classification. Seventy samples of honey of different geographical and botanical origin were analyzed with an electronic nose. The instrument, equipped with 10 Metal Oxide Semiconductor Field Effect Transistors (MOSFET) and 12 Metal Oxide Semiconductor (MOS) sensors, was used to generate a pattern of the volatile compounds present in the honey samples. The sensor responses were evaluated by Principal Component Analysis (PCA) and Artificial Neural Network (ANN). Good results were obtained in the classification of honey samples by using a neural network model based on a multilayer perceptron that learned using a back propagation algorithm. The methodology is simple, rapid and results suggest that the electronic nose could be a useful tool for the characterization and control of honey.

Huichun Yu and JunWang [17] made investigation to evaluate the capacity of electronic nose to classfiy the tea quality grade. In their experiment the volume of vial and headspace generated time were considered corresponding to the 5 g. tea samples. The four tea groups were measured and response values at four different collection times were conducteed by PCA, LDA and ANN. The method of ANN was performed and 90 % of the total tea samples were classified correctly by using the back-propogation neural network.

Jun Fu *et. al.* [18] developed a model in which the concept of Electronic Noise is used for pattern recognition. In this paper, a biologically inspired neural network, based on anatomical and electroencephalographic studies of biological olfactory systems, is applied to pattern recognition in electronic noses. Classifying six VOCs commonly presented in the headspace of Chinese rice wine, its performance to eliminate the concentration influence and counteract sensor drift is examined and compared with the simple nonparametric algorithm and the well-known BP-NN. The neural network has a good performance in classification of six VOCs of different concentrations, even for the patterns obtained 1 month later than what was used for training. Its flexibility and robust fault tolerance are quite suitable for electronic nose applications, subjecting to the problems associated with the susceptibility to concentration influence and sensor drift.

As per Federica Cheli *et. al.* [19] proposed that it is possible to differentiate and classify maize samples contaminated and non-contaminated with aflatoxins by using an electronic nose equipped with 10 MOS sensors. Despite the small number of samples, the electronic nose was able to detect a clear difference in volatile profile of maize in the presence and absence of aflatoxins using PCA analysis. By the use of LDA a correct classification of maize contaminated and non-contaminated with aflatoxins was achieved.

Results indicate that electronic nose may be successfully applied as rapid and non-destructive method for screening of commodities contaminated with fungal toxins, in order to select samples that must undergo further accurate quantitative 1analysis. Further improvements of the model are needed in order to eliminate or minimize the component in the model not directly related to aflatoxins concentration, to evaluate the potentiality of classification below/above legal limits and maybe to develop robust regression models for prediction of aflatoxin content in maize samples.

J. Brezmes *et. al.*[20] made investigated on the use of a concentration chamber in the E-Nose has also proven to be very useful; signals are stronger because fruit vapors are accumulated during a long period of time and many pieces can be measured together. More-over, since group measurements can be done, our proto-type can be easily adapted to practical applications where single piece measurements are not cost-effective. The results obtained prove that our Electronic Nose monitors peach and pear ripeness successfully. Measurements with apples were not as good and further research will be done in order to increase the accuracy with this particular fruit.

W.A. Collier *et. al.* [21] proposed a model in which an electronic nose can be used to discriminate among four milk samples, among four yoghurt samples, and among four cultured and non-cultured dairy products with a high degree of success if the measurements on the samples were all made in a single experiment. It has also been demonstrated that a ‘‘single-electrode’’ array can be used to make these discriminations. More rigorous control of manufacturing conditions of arrays or preparation steps could ensure that the sensing surfaces are more reproducible, enabling classification of samples based on previously stored databases of training sets.

III. METHODOLOGY

The demand of E-nose in food or dairy industry is growing because of its versatility and ease of operation of these instruments make them appropriate for fast and accurate analysis of various products or for monitoring the quality in the production process. The study has shown that commercial E-Nose can be used for the evaluation of various products in these industries. The uses of E-Nose can successfully distinguished quality of products such as tea, coffee, honey, basmati rice etc. The E-Nose can also be used to know the pollution of the gases emitted by various industries

The special features of neural networks such as capability to learn from examples, adaptations, parallelism, robustness to noise, and fault tolerance have opened their application to various fields of engineering, science, economics, etc. In all types of artificial neural networks, the basic structure consists of a number of interconnected processing units, called neurons. The calculations that each neuron performs, along with the way that the neurons are interconnected, determine a particular neural network type.

The advantage of neural classifiers over linear classifiers is that they can reduce misclassifications among the neighborhood classes as shown in following Fig. 1. The use of neural networks in this work is therefore proposed due to its learning ability, and capacity for solving nonlinear and complicated problems.

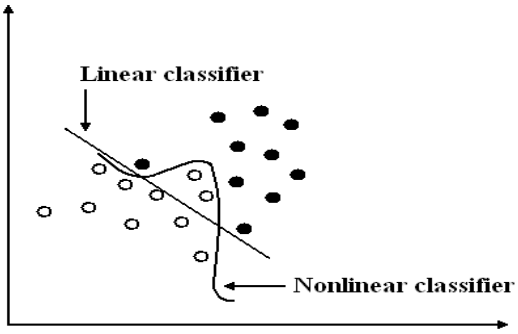

Fig. 1 Neural networks based classifier verses linear classifier

The main objective of our research is to classify the quality of food or dairy product available in the market by employing an efficient near-optimal neural network based classifier using E-Nose. Pattern recognition is an important part of E-Nose technology would be done using neural networks. The main problem associated with neural network is long processing time and large training sample required. The main advantages using this algorithm are learning may be fast and parallel computing is possible, weight analysis is easier for modular network, better generalization performance. The design of neural network is done using MATLAB.

Implementation Scheme in various phases**:**
1) Study of the sensors chosen for classification.
2) Nonlinear parameter identification of the selected sensors.

International Journal of Advanced Research in Computer and Communication Engineering
Vol. 3, Issue 5, May 2014
ISSN (Online) : 2278-1021
ISSN (Print) : 2319-5940

3) Development of a basic neural network based model for sensor data classification.
4) Development different possible efficient neural network models for that, and their comparison.
5) Determination of best possible neural network model from the various efficient models implemented. In this research, it is proposed to use different neural network structures such as Back propagation network, Radial basis function, learning vector quantization neural network for modeling of different intelligent sensors undertaken. The generalization performance of different models will be validated meticulously on the basis of the following important parameters:

- MSE on train, cross-validation and test data
- NMSE on train, cross-validation and test data
- Correlation coefficient for train, cross-validation and test data
- % Error for train, cross-validation and test data
- We have taken three different samples of cheese like 1st day cheese, 90th day cheese & 180th day cheese sample. And compared the performance parameters that we have obtained for individual sample to determine the best possible neural network model.

IV. RESULTS

We have used three neural networks for assessment of quality of cheese product. We compared performance parameters i.e. MSE, NMSE, % error & correlation coefficient of these neural network. The results that we have obtained are:

TABLE I
RESULTS FOR 1ST DAY CHEESE SAMPLE

Parameters	BPNN	RBF	LVQ
MSE	0.0501	6.1500	6.2124
NMSE	0.0503	0.0577	0.0582
% Error	0.01	0.06	0.100
Correlation Coefficient	1.00	1.00	1.00

TABLE II
RESULTS FOR 90TH DAY CHEESE SAMPLE

Parameters	BPNN	RBF	LVQ
MSE	0.0745	6.1901	6.3801
NMSE	0.0505	0.0560	0.0603
% Error	0.6796	0.6934	0.3433
Correlation Coefficient	0.9761	0.9761	0.9761

TABLE III
RESULTS FOR 180TH DAY CHEESE SAMPLE

Parameters	BPNN	RBF	LVQ
MSE	0.1510	6.1941	6.3915
NMSE	0.0503	0.0579	0.0607
% Error	0.9028	0.9212	1.5276
Correlation Coefficient	0.9254	0.9254	0.9254

Now following graphs will give clear comparison of performance parameters of all three networks,

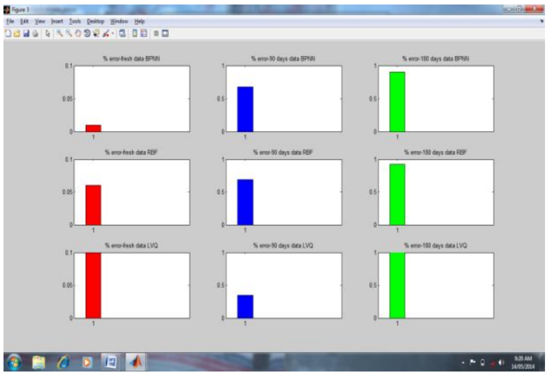

Fig 2. Result of comparison of MSE of BPNN, RBF & LVQ of 1st day cheese sample

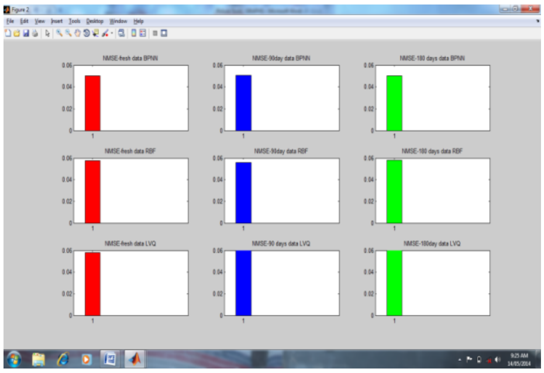

Fig 3. Result of comparison of NMSE of BPNN, RBF & LVQ of 90th day cheese sample

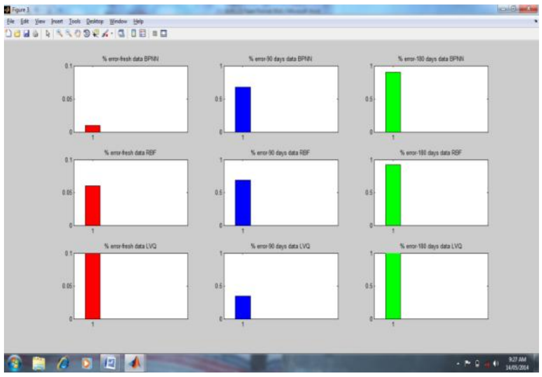

Fig 4. Result of comparison of % error of BPNN, RBF & LVQ of 180th day cheese sample

From these results that we have obtained the values of all four parameter, the BPNN performs well as compared to RBF & LVQ neural network.

ISSN (Online) : 2278-1021
ISSN (Print) : 2319-5940

V. CONCLUSION

There is no universal sensor system that can solve all odor analysis problems. Instead there is a need to employ intelligent application-specific sensor systems that are appropriate to the application. This means building in intelligence through the development of suitable sensor structures, sensor materials and pattern recognition methods. New pattern recognition methods would make use of the transient information in the sensor signal to enhance the identification ability of the system. This requires the use of dynamic models, for the sensor system, which can account for the drift in sensor parameters.

Finally, we can conclude that to assess the quality of cheese the best results are given by Back Propagation Neural Network as compared to RBF & LVQ neural network. BPNN can be used for quality assessment of cheese.

REFERENCES

[1] Esmaeil MAHMOUDI, "Electronic Nose Technology and its Applications", J. Sensors & Transducers, vol 107, no. 8, pp. 17-25, Aug 2009.

[2] Francesco Masulli, Matteo Pardo, Giorgio Sberveglieri, and Giorgio Valentini, "Boosting and classification of electronic nose data", Proceedings of the Third International Workshop on Multiple Classifier Systems , MCS 2002 , Pages 262-271.

[3] Gardner, J.; Bartlett, P.N., "Electronic Nose. Principles and Applications", Oxford University Press: Oxford, UK, 1999.

[4] Diana Hodgins, Derek Simmonds, "Electronic Nose and its applications to the manufacture of food products", J. Automat Chem , vol 17, no.5, pp. 179-185, 1995.

[5] K.C. Persaud, P. Wareham, A.M. Pisanelli, E. Scorsone, "Electronic nose a new monitoring device for environmental applications", J. Chemical Senses vol.30, no 1, pp. 252-253, 2005.

[6] R.E. Baby, M. Cabezas, E.N. Walsoe de Reca, "Electronic nose: a useful tool for monitoring environmental contamination", Sensors and Actuators B, vol 69, no.3, pp. 214-218, Oct 2000.

[7] J.W. Gardner, H.W. Shin, E.L. Hines, "An electronic nose system to diagnose illness", Sens. Actuators B, vol 70, no. 1-3, pp. 19-24, Nov 2000.

[8] J. Yinon, "Detection of explosive by electronic noses", Anal. Chem., vol 75, no.5, pp. 98A-105A, Mar 2003.

[9] T. Borjesson, T. Eklov, A. Jonsson, H. Sundgren, J. Schnurer, "Electronic Nose for odour classification of grains", Cereal Chem., vol 73, no. 4, pp. 457-461, 1996.

[10] D. James, S.M. Scott, Z. Ali, W.T. O'Hare, "Chemical sensors for electronic nose systems", Microchim. Acta , vol 149, pp. 1–17, 2005.

[11] E.L. Hines, E. Llobet, J.W., Gardner, "Electronic noses: a review of signal processing techniques", IEE Proc., Circuit Device Syst., vol.146, no. 6, pp. 297–310, Dec.1999.

[12] R. Gutierrez-Osuna, "Pattern analysis for machine olfaction: a review", IEEE Sensors Journal, vol 2, no. 3, pp. 189–202, 2002.

[13] A.K. Srivastava, "Detection of volatile organic compounds using SnO_2 gas-sensor array and artificial neural network", Sens. Actuators B, vol. 96, no. 1-2, pp. 24-37, 2003.

[14] Ritaban Dutta, and Ritabrata Dutta, "Intelligent Bayes Classifier for ENT infection classification in hospital environment", Biomedical Engineering Online, Volume 5.< http://WWW.biomedical-engineering- nline.com/content/5/1/65>

[15] S. Ampuero, J.O. Bosset, "The electronic nose applied to dairy products: a review", Sens. Actuators B, vol. 94, pp. 1-12, 2003.

[16] Simona Benedetti, Saverio Mannino, Anna Gloria Sabatini, Gian Luigi Marcazzan, "Electronic nose and neural network use for the classification of honey", Apidologie, Vol. 35, No. 4, pp. 397-402, 2004.

[17] Huichun Yu, JunWang, "Discriminationof LongJinggreen-tea gradeby electronic nose", Sensors and Actuators B, vol 122, pp.134-140, 2007.

[18] 18. Jun Fu, Guang Li, Yuqi Qin, Walter J. Freeman, "A pattern recognition method for electronic noses based on an olfactory neural network", Sens. Actuators, B, vol 125, no. 2, pp. 489-497, 2007.

[19] Federica Cheli, Anna Campagnoli, Luciano Pinotti, Giovanni Savoini, Vittorio Dell'Orto, "Electronic nose for determination of aflatoxins in maize", Biotechnol. Agron. Soc. Environ, vol.13, pp. 39-43, 2009.

[20] J. Brezmes, E. Llobet, X. Vilanova, G. Saiz, X. Correig, "Fruit ripeness monitoring using an Electronic Nose", Sens. Actuators B, vol 69, no. 3, pp. 223-229, 2000.

[21] W.A. Collier, D.B. Baird, Z.A. Park-Ng, N. More, A.L. Hart, "Discrimination among milks and cultured dairy products using screen-printed electrochemical arrays and an electronic nose", Sens. Actuators B, vol. 92, no. 1-2, pp. 232-239, 2003.

[22] S.Capone, M. Epifani, F. Quaranta, P. Siciliano, A. Taurino, L. Vasanelli, "Monitoring of rancidity of milk by means of an electronic nose and a dynamic PCA analysis," Sens. Actuators , B, vol 78, no. 1-3, pp. 174-179, 2001.

[23] Graham E. Searle, Julian W. Gardner, "System Identification of Electronic Nose Data From Cyanobacteria Experiments", IEEE Sensors Journal, Vol 2, Issue 3, , pp. 218-229, June 2002.

[24] Vassilis S. Kodogiannis, John N. Lygouras, Andrzej Tarczynski, and Hardial S. Chowdrey, "Artificial odor discrimination system using electronic nose and neural networks for the identification of urinary tract infection", IEEE Trans. Information Technology in Biomedicine, vol 12, no. 6, pp. 707-713, Nov. 2008.

[25] Marco Trincavelli, Silvia Coradeschi, Amy Loutfi, Bo S oderquist, and Per Thunberg, "Direct identification of bacteria in blood culture samples using an electronic nose", IEEE Trans. Biomedical Engineering, vol. **57**, no. 12, pp. 2884 – 2890, 2010.

[26] Fructuoso Ma. L.L. , Llobet E. , Vilanova X. , Recasens I. , Orts J. , Saiz G. , Correig X. , " Evaluation of electronic nose to assess fruit ripeness", IEEE Sensors Journal,Vol 5, no. 1, pp. 97-108, Feb. 2005.

[27] Keller P., "Electronic noses and their applications", IEEE Northcon/Technical Applications Conference (TAC'95) ,

[28] Sberveglieri G., "Coffee analysis with an electronic nose", IEEE Transactions on Instrumentation and Measurement, vol. 51, Issue 6, pp. 1334-1339, Dec 2006,

[29] Bandyopadhyay R., Bhuyan M., Tudu B. , Ghosh D., Jana A., "Electronic nose for black tea classification and Correlation of measurement with 'Tea Taster' marks", IEEE Transactions on Instrumentation and Measurement, Vol 57, no.7, pp.1334-1339, July 2008.