www.s2is.org
International Journal on Smart Sensing and Intelligent Systems
ISSN 1178-5608

FRAGRANCE MEASUREMENT OF SCENTED RICE USING ELECTRONIC NOSE

Arun Jana[1], Nabarun Bhattacharyya[1], Rajib Bandyopadhyay[2], Bipan Tudu[2], Subhankar Mukherjee[1], Devdulal Ghosh[1], Jayanta Kumar Roy[1]

[1]Agriculture and Environmental Electronics, C-DAC, Kolkata, India.
[2]Department of Instrumentation and Electronics Engineering, Jadavpur University, Kolkata 700 098, India
Email: arun.jana@cdac.in

Submitted: July 3, 2015 Accepted: Aug 10, 2015 Published: Sep. 1, 2015

Abstract- This article describes about an instrument and method for aroma based quality detection of Basmati and other aromatic rice varieties. It comprises few modules such as odour delivery module, sniffing module, water bath module and computing module. Odour handling module helps to deliver odour to the sensor array; a sniffing unit comprising a sensor array module that includes a eight number of metal oxide semiconductor sensors assembled on a printed circuit board, said printed circuit board fitted into a sensor chamber; a water bath module for preparing rice sample, said water bath module including a heater attachment to facilitate cooking; a computing module to quantify the aroma data acquired by sensors; data acquisition module etc. Principal Component Analysis (PCA) implemented for clustering the data sets acquired from sensor array. Also data generated from sensor array was fed to Probabilistic Neural Network (PNN), Back-propagation Multilayer Perceptron (BPMLP) and Linear Discriminant Analysis (LDA) for identification of different rice varieties. Finally, for aroma quantifying, pure-quadratic response surface methodology model used with mean square error (MSE) 0.0028.

Index term: Aromatic rice, Sensor, Principal Component Analysis, Probabilistic Neural Network, Back-propagation Multilayer Perceptron, Linear Discriminant Analysis, response surface methodology.

1. INTRODUCTION

From ancient, rice occupies prevailing position among cereals of throughout the world and maximum people of the world are dependent on rice as a basic food. Of all the rice varieties, Basmati rice [1] is considered as a best variety throughout the world, due to its gentle texture, pleasant aroma, long and slender grains. And also Basmati rice is not only consumed worldwide but also it is a foreign exchange earner for India as Indian Basmati is exported to several countries and it also gets a premium price in the international market referable its high quality as compared to that produced by other countries.

The quality of rice [2] may be considered from point of view of milling quality, grain quality and cooking characteristics. Rice grain quality are largely determined by the properties of the milling quality, size, shape and appearance; cooking and eating characteristics [3] are influenced by the properties of gelatinization temperature, amylase content, gel consistency test and grain elongation. And finally, the most important quality parameter is an aroma. Most of the high quality preferred varieties in major rice growing countries are aromatic. The Indian Basmati rice is characterized by long slender grains, intermediate amylase, and intermediate gelatinize temperature, high elongation ratio and strong aroma [4-5].

Conventionally, an aroma is tasted by expert human panel called 'judges,' and evaluation of rice is done on the basis of assigning scores as a symbol like '+' for mild scent, '++' for medium scent and '+++' for strong scent to samples of basmati rice depending on the aroma of the sample or human panelist assign score out of 4. Rice quality estimation is mostly commercially oriented, and region specific customer taste and demand are kept in mind by the judges during quality identification. Furthermore, human panel testing is highly subjective with numerous problem like inaccuracy, and non repeatability and is laborious and time consuming due to various human factors like individual variability, decrease in sensitivity due to prolonged exposure, infection and adverse mental state at times. Also there are few instruments like GC/MS, [6-7] HPLC available for aroma measurement. Limitation of these type of system are high cost, time consuming, trained manpower is required to run the system and lot of calibration required for getting accurate result. In these circumstances, an instrument like electronic nose may help in determining the measurement of aroma. A MOS sensor based instrument namely, Electronic nose technology has been successfully employed for the recognition and quality analysis of various food and agro products, viz., wine [8], meat [9], fish [10], tea [11-13] etc.

In this paper, a new instrument namely electronic nose, based aroma categorization of basmati and other aromatic varieties rice was attempted and promising results obtained. An electronic nose has the potential to eliminate problems that are associated with human panel testing, and, if this instrument is standardized for the aroma characterization of basmati rice, it may serve as a very useful gadget for fast, reliable, noninvasive, continuous and real time monitoring of the aroma of basmati rice.

In the present study, an appropriate set of gas sensor of Figaro Engineering Inc. for basmati rice classification were procured. This sensor array comprising eight sensors were used in the customized instrument that was developed for this purpose. Rice samples were collected from Bidhan Chandra Krishi Viswavidyalaya (BCKV), West Bengal, India, and instrument measurements was correlated with the rice judges' assigning score on the basmati and other aromatic rice aroma by a pure-quadratic response surface methodology model to predict the score for unknown aromatic rice samples.

II. MATERIALS AND METHODS

a. Aromatic rice sample description

Following varieties of aromatic rice samples were collected from Bidhan Chandra Krishi Visyavidyalaya (BCKV), Mohanpur, Nadia, West Bengal, India. All the samples were tested by a human panel of rice experts and the aroma scores (1 to 4) for all the samples obtained from them. The numbers of samples collected for each variety along with their scores are shown in the Table 1.

Table 1.

Scores of the rice varieties.

Sl. No.	Name of sample	Average Score
1.	Kaminibhog	1.2
2.	Radhunipagal	2.6
3.	Govindobhog	2.4
4.	Sitabhog	1.8
5.	Tulsimukul	2.2
6.	Tulaipanji	2.4
7.	Radhatilak	2.4
8.	Katharibhog	2.0
9.	Kalogira	2.6

b. Sensor array module:

The most important component of any artificial olfaction system is the sensor array. In many application of electronic nose, the sensors selected are metal oxide semiconductor type because of their sensitivity and stability to the agricultural applications. Sensor selection process was done for aromatic rice sample testing; however, detailed description of sensor selection process is out of scope of the present study. An array consisting of 8 different nonspecific commercial tin oxide semiconductor sensors from Figaro, Japan. TGS-825, TGS-816, TGS-823, TGS-832, TGS-830, TGS-2600, TGS-2620, and TGS-821 were fount adequately sensitivity to the aroma of rice. The sensor requires two voltage inputs: heater voltage (V_H) and circuit voltage (V_C). The heater voltage (V_H) was applied to the integrated heater in order to maintain the sensing element at a specific temperature, which was optimal for sensing. Circuit voltage (V_C) was applied to allow measurement of voltage (V_{out}) across a load resistor (R_L), which was connected in series with the sensor. An array of eight MOS sensors was assembled on a

Printed Circuit Board (PCB). The sensor chamber was made in a funnel shaped structure of teflon and the sensor array printed circuit board (PCB) is tightly fitted into the chamber. The chamber equipped with the inlet passage through Teflon tubing for allowing in volatiles from the sample holder headspace. Also an outlet passage has been provided for purging operations.

c. Odour handling and delivery system:

Odour handling and delivery system is the crucial part of the system. It is made of metallic (Aluminum) body having two parts. One part is sample holder, which contains sample, and another part is sensor holder, which holds the sensor array.

d. Water bath module:

Water bath module was used for preparing rice sample, which is the major component of the apparatus. It comprising: an inlet through which the water flow flows in; an outlet through which the water flows out. This unit helps to prepare rice sample with a specific water temperature of 100^{o}C. This module was made up with metallic (aluminum) body, heater attachment and temperature controller. Commercially available temperature sensor such as RTD Pt 100 was adopted to heat the water and the controller, which was transmitters, convert RTD resistance input to temperature display output and controls the constant temperature of water. The sample holder was placed on the top of the sample preparation unit for cooking. During cooking process, aroma was trapped inside the sample container.

e. Sniffing Unit:

Sensing unit is the second prime part of the apparatus, which consists of metallic (Aluminum) body, Sensor arrays, and Purging fan. The purging fan was positioned on the top of the sniffing unit. It comprising: an inlet through which the water flow flows in; an outlet through which the water flows out. The unit holds the cold water, which helps to cool down the temperature of cooked rice samples and eventually eliminate the moisture. Sensor array sense the aroma of cooked rice samples and data was transferred to PC through DAQ card. Purging fan mainly purge the sensors and bring them back in their base value.

f. Data acquisition module:

Data acquisition involves gathering signals from sensors and digitizing the signal for storage, analysis, and presentation on a PC. The outputs from the array of MOS sensors were fed to a PC-supported data acquisition card of the system. USB compatible card (USB 6008 National Instrument) was used which digitizes the analog data with a resolution of 12-bits at sample rate up to 250 K Samples /second. The captured data was stored in the PC for subsequent processing.

g. Operational principle:

The electronic nose for aromatic rice system consists of the following: 1) a sensor array; 2) a micropump and solenoid valves with programmable sequence control; 3) PC-based data acquisition; and 4) olfaction software. Specially designed sample holders that was made of aluminum were used for experimental runs. An aluminum sample holder was fixed to the instrument by simple lock fitting. The entire sniffing cycle consisted of an automated sequence of internal operations, viz., 1) headspace generation, 2) sampling, and 3) purging. Before headspace generation, 15 gm of rice grain with 60 ml distilled water were kept in a sample container that is made by aluminum and cooked for releasing more volatiles. After that cooked rice chamber was kept on the sniffing chamber for cooling to remove moisture. Headspace generation ensures the concentration of volatiles of aromatic rice before and during sampling; the sensor array was exposed to a constant flow of volatiles through pipelines inside the apparatus. During the purging operation, sensor heads were cleared with a blow of fresh air so that the sensors go back to their baseline values. The entire sniffing cycle consists of sequence of operations as described in Table 2. Figure 1 has shown schematic diagram of electronic nose system. Screen shot of various operation is shown Figure 2.

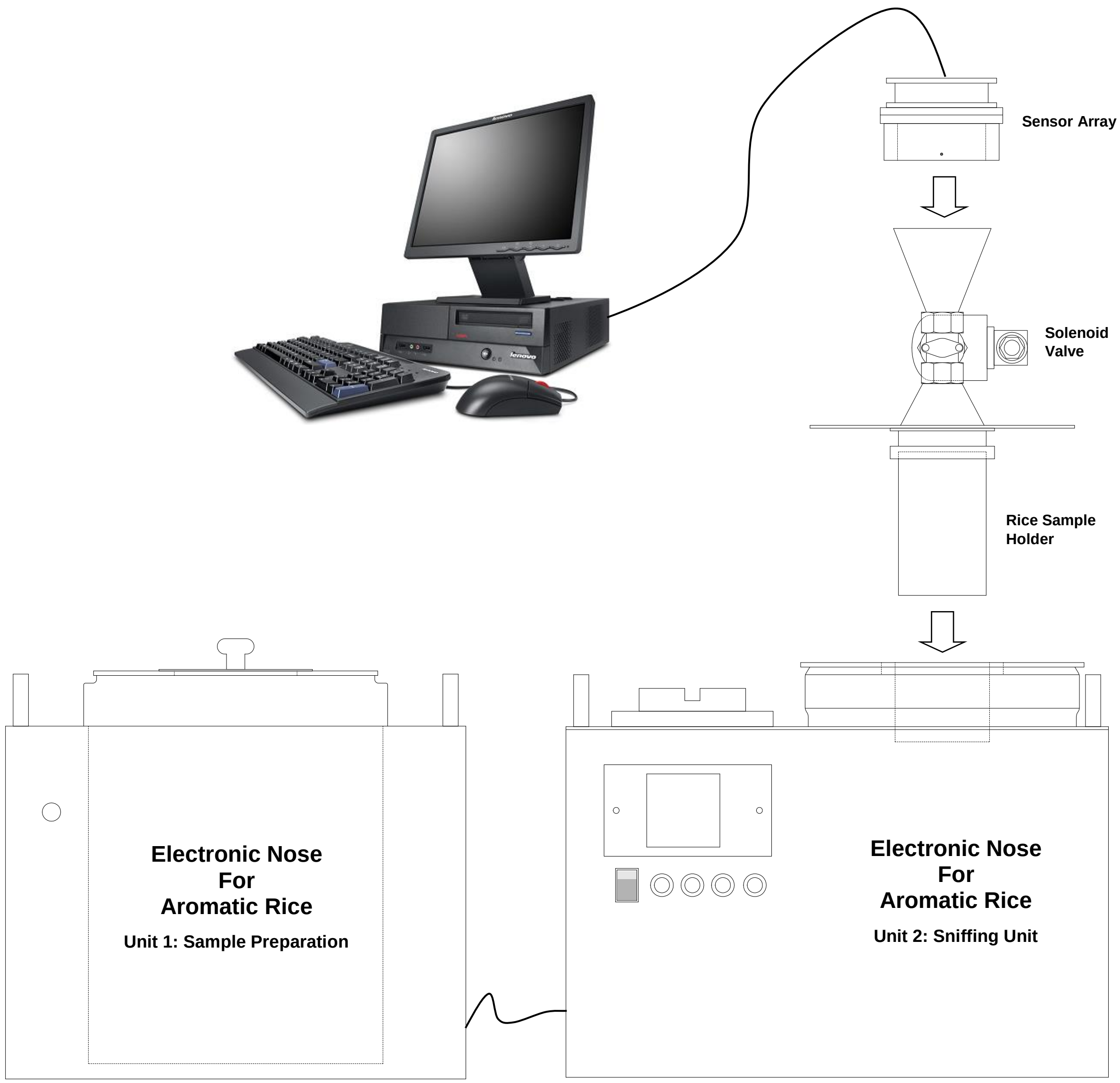

Figure 1. Schematic diagram of electronic nose

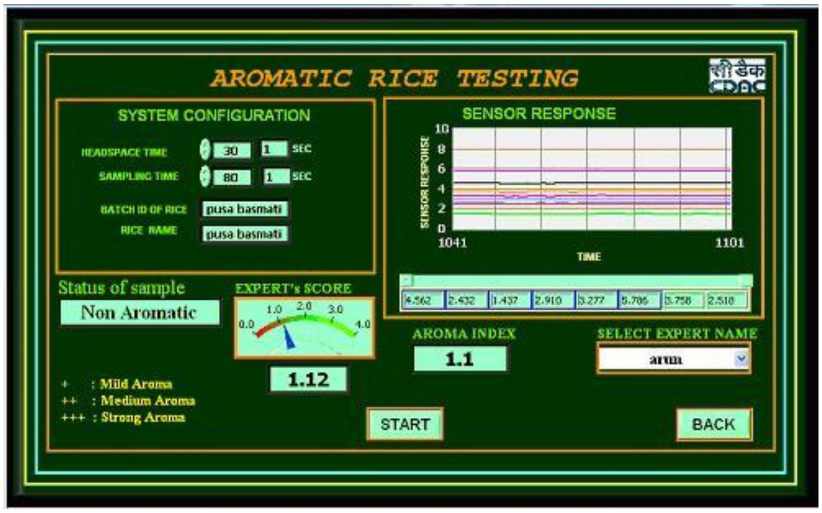

Figure 2. Various operations

Table 2. Sequence of operations in an experimental sniffing cycle

Operation	**Purpose**	**Duration**
Cooking	To cooked rice sample at 100^{o} C	20 min
Cooling	To coolled rice sample at room temperature	10 min
Headspace generation	To accumulate adequate volatile compounds before sampling	30 sec
Sampling	Sensor array is exposed to the aroma of aromatic rice.	80 sec
Purging	Cleaning the sensor surface with blow of fresh air so that the sensor output returns to the baseline value.	300 sec

III. RESULT AND DISSCUSSION

a. Principal Component Analysis

Principal Component Analysis (PCA) [14] was applied to the data obtained from the sensors. The results showed that the electronic nose was able to differentiate between samples and different clusters were observed for different varieties of aromatic rice. The obtained results of PCA reveal that selected sensors are correlated. The first and second component represented more than 90% of the total data variance. The PCA results showed that the sensors could effectively discriminate between different varieties of rice samples. The results of PCA shown in Figure 3.

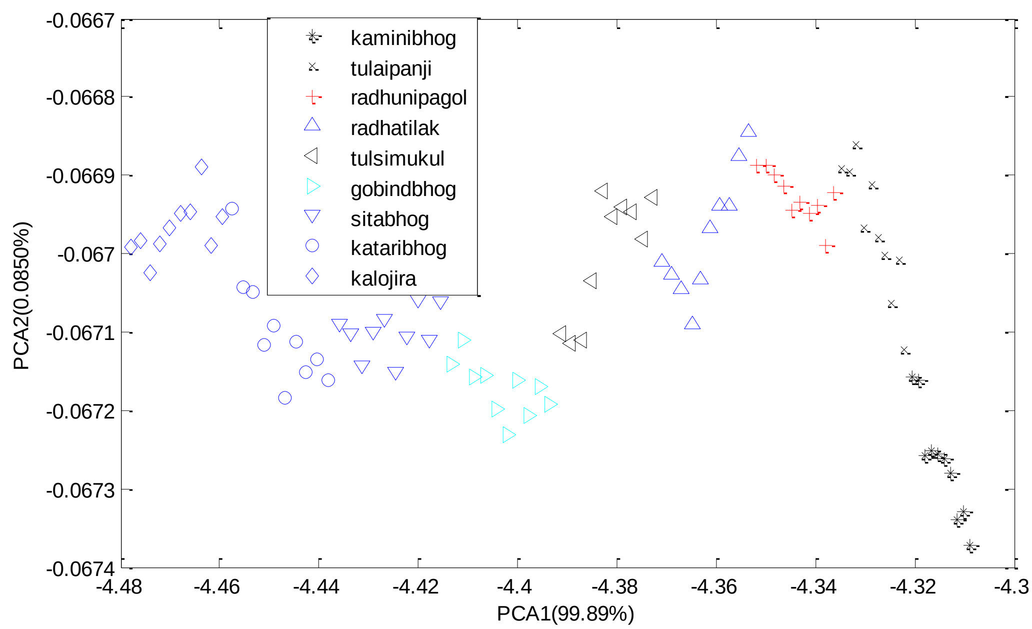

Figure 3. PCA plot of aromatic rice samples

b. Probabilistic neural network (PNN)

The PNN [15] architecture was designed with the following four layers: 1) input layer; 2) pattern layer; 3) summation layer; and 4) decision layer. The input layer consisted of eight nodes corresponding to eight sensors. For each training instance, there was one node in the pattern layer, and in our experiment, it was 90. In the summation layer, nine nodes corresponding to nine different samples of rice were kept. A classification rule on the basis of the class membership probabilities was employed at the decision layer. It was found that the classification accuracy of 89% for the different varieties of rice using PNN was obtained as shown in the Table 3.

c. Linear discriminant analysis

Linear Discriminant Analysis (LDA) [16] was used for dimensionality reduction and classification that projects high-dimensional data onto a low dimensional space where the data achieves maximum class separability. The derived features were linear combinations of the original features, where the coefficients were from the transformation matrix. In LDA, minimizing the within-class distance and maximizing the between-class distance simultaneously obtain optimal transformation, thus achieving maximum class discrimination. It was found that the classification accuracy is 78%.

d. Backpropagation Multilayer Perception (BPMLP)

A three-layer BP-MLP [17-18] model with one input layer, one hidden layer, and one output layer was considered. The input layer was fed with the output from the sensor array, and the output layer was configured to show the different varieties. For eight sensors in the multi sensor array, the artificial neural network was eight input nodes. As in the BPMLP architecture, the output layer of the network needs to be assigned with nine nodes. Convergence during the learning process was obtained with acceptable accuracy with only one hidden layer with six nodes. The results shown in Table 3. It was observed that the classification accuracy of different rice using BP-MLP data was 69%.

Table 3

Results

Name of algorithms	Training data	Testing data	Classification (%)
PNN	90	90	89
LDA	90	90	78
BP-MLP	90	90	69

e. Performance of the classifier

For performance evaluation of the classifiers, the cross-validation method [19] was used. In our experiment, a total of 162 samples of six different samples were considered for the tenfold cross-validation method. The number of variety was nine and each variety contains 20 data points. In every fold 90% data was considered for training and 10% data was considered for testing. Thus, every data point gets to be in the test set exactly once. The result of tenfold cross validation is tabulated in Table 4.

Table 4

Average efficacy of the classification performance.

No. of fold	No. of misclassification		
	LDA	PNN	BP-MLP
1	5	2	5
2	3	0	6
3	2	0	4
4	4	2	4
5	6	3	7
6	6	3	6
7	2	0	5
8	3	1	6
9	4	1	6
10	5	2	5
Total number of misclassification	40	14	54
Classification (%)	77.8	92.2	70

f. Response surface methodology

The result obtained by testing rice samples using sensor array and human panel testing of rice were used to build a response surface methodology model [20-22]. The sensor's response in the form of voltage was feed as input to the model and the human panel testing results acted as output of the model. In the model 8 sensor's output acted as input. The relationship of independent variable and response was calculated using following second order polynomial equation.

$$y(x) = a_0 + \sum_{i=0}^{N} a_i x_i + \sum_{i=0}^{N} a_{ii} x_{i\,i}^{\,2} + \sum\sum_{i<j} a_{ij} x_i x_j \qquad (1)$$

Where y is the predicted response; a_0 a constant; a_i the linear coefficient; a_{ii} the squared coefficient; and a_{ij} the product coefficient, N is the number of factors.

In this study, pure quadratic model was implemented to predict an aroma of aromatic rice. The equation of pure quadratic model is as follows:

$$y(x) = a_0 + \sum_{i=0}^{N} a_i x_i + \sum_{i=0}^{N} a_{ii} x_i^2 + \dots \tag{2}$$

Based on the Eq. (2) the following model was developed for prediction of aromatic rice sample using MATLAB® software.

$$Y = -0.1139 + 9.6258X_1 - 4.7662X_2 - 2.4203X_3 + 0.6527X_4 + 3.8916X_5 - 2.3406X_6 + 0.1838X_7 + 0.0001X_8 - 10.0284X_1^2 + 9.4907X_2^2 + 5.2558X_3^2 + 8.5818X_4^2 + 43.6770X_5^2 + 6.5736X_6^2 - 8.4542X_7^2 + 8.4298X_8^2 \tag{3}$$

Where $X_1, X_2, X_3, X_4, X_5, X_6, X_7, X_8$ are the TGS-825, TGS-816, TGS-823, TGS-832, TGS-830, TGS-2600, TGS-2620, and TGS-821 respectively. The P-values were used as tool to check the significance of each of the coefficients. The smaller the magnitude of P, more significant is the corresponding coefficient. The model adequacies were checked by R^2 and predicted error sum of squares (PRESS). A model with large R^2 and low PRESS value is considered to be a good model. The developed model had R^2 value of 0.9986 and PRESS value of 1346.31 and R^2 (pred) value of 0.9448. The R^2 value of the model represents how successfully the model fits the data. The high R^2 for the model shows that the developed models could explain the variations present in the independent variables. Whereas, R^2 (pred) which represents the ability of the derived model to predict the output for unknown samples was also found to be high for the model. Fisher's variance ratio F-value is calculated as ratio of mean square regression and mean square residual. It is measure of variance in the data about the mean. Table 3 represents the F-value and P-value for the model. The high F-value and very low P-value confirms the high significance of the model. The results obtained from human panel testing and sensory based instrument for different sample was divided for training (50%) and validation (50%) phases. To test the prediction capability of the fitted model developed using RSM an inverse range scaling was performed on all the experimental outputs (human panel testing) to return predicted response (sensor array output) for its subsequent comparison with experimental response (human panel testing).

Table 5

Response surface methodology model parameters.

R^2 (%)	R2 (pred) (%)	R2 (adj) (%)	F-value	P-value
99.86	94.48	99.78	135.3	<0.0001

Figure 4 shows a comparison between experimental values obtained as a result of human testing analysis and predicted response of sensor array using RSM. The prediction capability of the developed model was shown in figure by using two lines: one line represented an ideal model wherein experimental data is equal to predicted data, while the other line is obtained by plotting data fits obtained using developed RSM models and experimental responses of human panel.

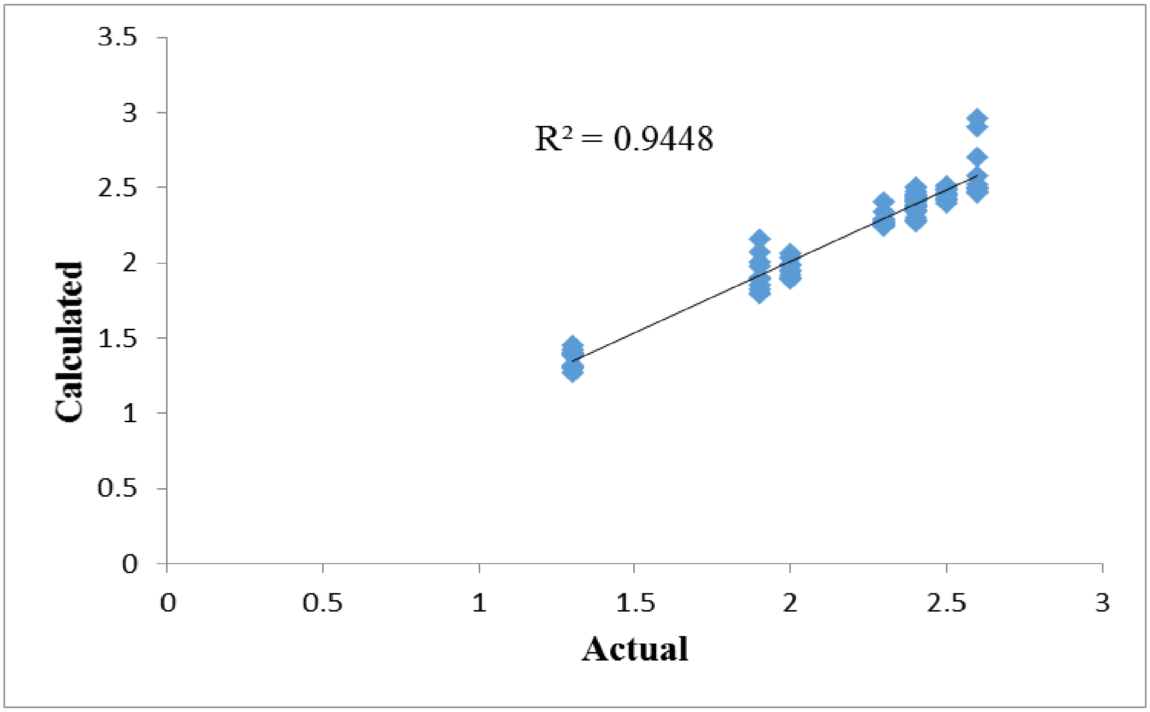

Figure 4. Human panel testing and predicted (output of electronic nose using RSM) of aromatic rice sample.

g. Discussion on the results

In total, 180 samples were considered for data analysis. Out of these 180 samples, 90 samples (10 of each variety) were used for training purpose of neural network algorithm and other 90 are considered for validation. PCA was performed to see the underlying cluster between the data points. The result of PCA in Fig. 3 was shown distinct nine classes for nine varieties of rice samples. For neural network training, the entire dataset was divided into nine categories depending upon the varieties. Three algorithms were considered for classification such as PNN, LDA, and BP-MLP, and among these, PNN was shown more than 80% rate of classification, which was most promising than the others. On the other hand, BP-MLP was shown 69% classification accuracy as because the BP-MLP model works on the iterative computation of weights and biases of various layers and therefore, a huge set of training data was a prerequisite for a reasonably accurate network, which was not available for this study. Furthermore, there is no standard rule on the number of hidden layers, the number of nodes in the hidden layers, and the network topology has been arrived at on the basis of trial and error.

IV. CONCLUSION

Aromatic rice is a very important export-worthy agricultural crop from the Indian subcontinent. In this paper, we describe a method of rapid classification of aroma of rice using multi-sensor based electronic nose. The experimental set-up is described and different clustering and classification methods have been explored with 180 samples of basmati and non-basmati rice. The accuracy of the classifiers using neural network and LDA ranges from 70% to 90%, which is quite satisfactory. All in all, a novel instrument for classification of aroma of rice is described here and the results presented prove the efficacy of the instrument. However, as diverse samples could not be collected due to practical difficulties, elaborate experimentation with large number of samples from different regions would be required prior to deployment of the instrument in the market.

ACKNOWLEDGEMENT

The authors are grateful to Col. A. K. Nath (Retd.), Executive Director, C-DAC, Kolkata, India for their valuable guidance during the course of experiment. The authors are also thankful to Mr. R. N. Kanjilal for fabrication of electronic nose. The author thanks the Department of Science and Technology (DST), Government of India for sponsorship.

REFERENCES

[1] P. Bhattacharjee, R. S. Singhal, and P. R. Kulkarni, “Basmati rice: a review,” *International Journal of Food Science and Technology*. Vol. 37, pp. 1 – 12, 2002.

[2] Y. Amarawathi, R. Singh, A. K. Singh, V. P.Singh, T. Mohapatra, T. R. Sharma, and N. K. Singh, “Mapping of quantitative trait loci for basmati quality traits in rice (Oryza sativa L.),” Mol Breeding. Vol. 21, pp. 49–65, 2008.

[3] Y. F. Tan, J. X. Li, S. B. Yu, Y. Z. Xing, G. C. Xu and Q. Zhang, “The three important traits for cooking and eating quality of rice grains are controlled by a single locus in an elite rice hybrid,” Theor Appl Genet, vol. 99, pp. 642–648, 1999.

[4] N. L. Hien, T. Yoshihashi, W. A. Sarhadi and Y. Hirata, “Sensory test for aroma and quantative analysis of 2-Acetyle-1-pyrroline in asian aromatic rice varieties,” Plant Prod. Sci. vol. 9, pp. 294 – 297, 2006.

[5] N. S. Ahn, N. C. Bollich, and D. S. Tanksley, “RFLP tagging of a gene for aroma in rice,” Theor Appl Genet. Vol. 84, pp. 825–828, 1992.

[6] C. J. Bergman, J. T. Delgado, R. Bryant, C. Grimm, K. R. Cadwallader and B. D. Webb, “Rapid Gas Chromatographic Technique for Quantifying 2-Acetyl-1-Pyrroline and Hexanal in Rice (Oryza sativa, L.),” Cereal Chem. Vol. 77, pp. 454–458, 2000.

[7] C. C. Grimm, C. Bergman, J. T. Delgado, and R. Bryant, ”Screening for 2-Acetyl-1-pyrroline in the Headspace of Rice Using SPME/GC-MS,” J. Agric. Food Chem. Vol. 49, pp. 245-249, 2001.

[8] J. Lozano, P. J. Santos, M. Aleixandre, I. Sayago, J. Gutierrez and C. M. Horrillo, “Identification of typical wine aromas by means of an electronic nose,” IEEE Sensors J, vol. 6, pp. 173-178, 2006.

[9] D. D. H. Boothe, and J. W. Arnold, “Electronic nose analysis of volatile compounds from poultry meat samples, fresh and after refrigerated storage,” J. Sci. Food Agric. Vol. 82, pp. 315-322, 2002.

[10] M. O’Connell, G. Valdora, G. Peltzer and M. R. Negri, ” A practical approach for fish freshness determinations using a portable electronic nose,” *Sens. Actuators B, Chem.* Vol. 80, pp. 149-154, 2001.

[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,” IEEE Tran. on Instrumentation. and Measurement. Vol. 57, pp. 1313-1321, 2008.

[12] N. Bhattacharyya, S. Seth, B. Tudu, P. Tamuly, A. Jana, D. Ghosh, R. Bandyopadhyay, and M. Bhuyan, “Monitoring of black tea fermentation process using electronic nose,” Journal of Food Engineering. Vol. 80, pp. 1146-1156, 2007.

[13] B. Tudu, B. Kow, N. Bhattacharyya and R. Bandyopadhyay, “Normalization techniques for gas sensor array as applied to classification of black tea,” International Journal on Smart Sensing and Intelligent Systems, Vol. 2, pp. 176 – 189, 2009.

[14] W. J. Gardner, “Detection of vapours and odours from a multisensor array using pattern recognition. Part 1: principal components and cluster analyses,” Sensors and Actuators B, vol. 4, pp. 108–116, 1991.

[15] R.E. Shaffer, R A. McGill, S.L. Rose-Pehrsson,. “Probabilistic neural networks for chemical sensor array pattern recognition: comparison studies, improvements, and automated outlier detection”, NRL Formal Report, 6110- 97-9879, 1998.

[16] S. Pang, S. Ozawa, N. Kasabov, “Incremental linear discriminant analysis for classification of data streams”, IEEE Trans. Syst., Man,Cybern. B, Cybern., 35 905–914, 2005.

[17] S. Haykin, Neural Networks: A Comprehensive Foundation, 2nd ed. Hong Kong: Pearson Educ. Asia. 2001.

[18] B. Tudu, B. Kow, N. Bhattacharyya, R. Bandyopadhyay, “Normalization techniques for gas sensor array as applied to classification of black tea”, International Journal on Smart Sensing and Intelligent Systems, 2, 176 – 189, 2009.

[19] S. Singh, “A single nearest neighbour fuzzy approach for pattern recognition”, Int. J. Pattern Recogn. Artif. Intell., 13, 49–54, 1999.

[20] N. Aslan and Y. Cebeci,"Application of Box–Behnken design and response surface methodology for modeling of some Turkish coals,"Vol.86, January 2007, pp. 90-97, doi:10.1016/j.fuel.2006.06.010.

[21] N. Aslan, “Application of response surface methodology and central composite rotatable design for modeling the infuence of some operating variables of a Multi-Gravity Separator for coal cleaning,” Vol.86, March-April 2007, pp. 769-776, doi:10.1016/j.fuel.2006.10.020.

[22] A. I. Khuri, “Response Surface Methodology And Related Topics, ”World Scientific Publishing Company, January 2006, pp. 472.