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Guava fruits storage shelf life determination in different storage conditions using E-nose system

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ABSTRACT

The E-nose system based on metal oxide semiconductor sensors array is developed and extensively used for the determination of storage shelf life of guava fruit since harvest in two different storage treatments. The objective behind this experiment is to check whether the developed e-nose system is able to identify the ripening pattern of guava during different storage conditions. Two storage treatments were conducted; one is with paper wrapping and another is in plastic folded bag. PCA, MLP Feed forward neural network and fuzzy logic based pattern recognition techniques were used to distinguish the guava fruits with different storage treatment and storage time. The experimental results suggest that this e-nose system is capable to classify guava fruits storage shelf life since harvest and it would be a feasible system to be used in a real scenario.

Key words: *Electronic Nose, Guava fruit, Fruit classification, PCA, Fruit sorting, Feed forward neural networks*

Introduction

In recent years, there has been a considerable increase in demand for better quality fruit due to globalization of market. Consequently, it is important to evaluate fruit maturation stage and storage shelf-life. Many methods of monitoring maturation and shelf-life have already been proposed. The main disadvantages of these methods are that they are not practical for cultivars or storage stations, and most of them require the destruction of the samples used for analysis. This may be the reason that optimal harvest date and predictions of storage shelf-life are mainly based on practical experience (Verma *et al.*, 2000). Leaving these critical decisions to subjective interpretation implies that large quantities of fruit are always harvested too soon or too late and reach consumer markets in poor condition.

A strategy for evaluating the maturation and shelf-life consists of sensing the aromatic volatiles emitted from fruit by using electronic nose systems (Benady *et al.*, 1995).

Metabolic changes are mostly due to the following four items: post-harvest ripening, respiration, fermentation and phenolic oxidation (Young *et al.*, 1996). Aroma is an important food quality attribute. The aroma of a food product is detected when its volatiles enter the nasal passages at the back of the throat and is perceived by receptors of the olfactory system (Oshita *et al.*, 2000). Concerning the exploitation of the information contained in the heads pace of fruit, they have been studied in the recent past with the conventional analytical chemistry equipment, and the correlation between the state of over-ripening and the fruit aroma has also been found both in quantitative and in qualitative terms. Besides, some specific compounds have been identified to be responsible of the aroma of particular fruit.

In the last decade, the electronic nose offers a fast and nondestructive alternative to sense aroma, and, hence, may be advantageously used to predict the optimal harvest date and detect storage shelf-life of tropical fruits like guava adequately.

Some authors reported positive applications of electronic nose technology to the discrimination of fruit of different qualities, with oranges (Gomez *et al.* 2006), tomatoes (Berna *et al.,* 2004), apples (Berna *et al.,* 2004) and cherry (Nategh *et al.,* 2021), but as yet few literatures refer to control the fruit maturity in the shelf-life state.

The objective of this study was to evaluate the capacity of developed electronic nose in monitoring the change in VOC production of Guava fruit during different storage treatments and storage time, to prove the discrimination ability of developed electronic nose statistically using Principal Component Analysis (PCA) and to design and optimize the pattern recognition module using MLP feed forward neural network.

Materials and Methods

Origin and collection of experimental material

The Guava (*Psidium guajava*) fruit of Lucknow- 49 variety is selected for experimentation. The fruit samples were obtained from the orchard at altitude 504 m, latitude 19.76° north, longitude 74.48° east. Fruits were selected for uniformity of size, color and freedom from blemishes. The harvested fruits were washed under clean running water and immersed in a 1% sodium hypochlorite solution at 25°C for 5 minutes for disinfection.

For storage shelf life determination, 30 mature green guava fruits (about to ripe) were used and two storage treatments were conducted. For prediction study, 20 fruits of same variety were selected and harvested from orchard near 1km from the previous place of orchard and two storage treatments were conducted.

Storage condition

Two storage treatments were conducted in laboratory conditions. One batch of 15 guava fruits storage conducted in laboratory condition with paper wrapping and placed in cartoon box. The second batch of 15 fruits placed in plastic folded bag storage. The fruits were stored in a shelf of the laboratory for 8 days at temperature and relative humidity maintained at 26 ± 1 °C and 41 ± 5% respectively. The samples for prediction study also treated with above method.

Experimental design

The experimental design was completely randomized with each fruit treated as an experimental unit. Each Guava fruit samples removed from storage at days 0, 2, 4, 6 and 8 (day 2 is the second day since harvest, day 0 is the picked day) and evaluated using developed electronic nose system with two sets of observations for to each fruit sample. Each observation set consisted of 10 repetitions. For cross validation, the same treatments were applied for all guava fruits from the other orchard for 8 day storage

E-Nose system

The complete e-nose system designed, developed using eight Figaro Inc. made metal oxide semiconductor sensors in our laboratory and all details as well as procedure for experiment is reported in other work (Kanade *et al.,* 2014). E-nose was used at the temperature of 26± 2^{o}C and humidity of 41 ± 5% during all experiments. Figure 1 below shows the developed system photograph.

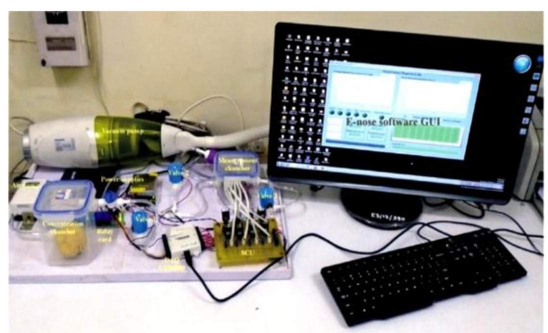

Fig. 1. Developed E-Nose system

The developed electronic nose system consisting of four functional components that operates serially on an odorant sample; a fruit sample handler called as concentration chamber, an array of eight different nonselective MOS gas sensors positioned into small measurement chamber, a signal conditioning unit, DAQ card connected to laptop which has software GUI for data acquisition and pre-processing programmed using LabVIEW software.

The developed electronic nose consists of array of eight metal oxide semiconductor sensors which are commercially available from Figaro Inc. Japan. The MOS sensors conductivity changes due to adsorption of odor molecules on surface of sensing material causes subsequent surface reactions. These types of sensors show a certain degree of affinity towards a specific odor but are sensitive towards a wide spectrum of gases with overlapping sensitivities. Table 1 specifies the gas sensors used in array and their primary target application gases.

Table 1. Sensors used in E-nose Array and their target gases

Sensor No.	Sensor Model	Target Gas Sensitivity
1,3	TGS2602	VOCs, ammonia, H_2S
2	TGS2600	hydrogen, ethanol, etc.
4	TGS2611	Methane
5	TGS2620	Alcohol, Solvent vapors
6	TGS822	Organic Solvent Vapors
7	TGS813	LPG, Methane
8	TGS832	Chlorofluorocarbon

The odor delivery system is most crucial part of the e-nose system. The purpose of this system is to transfer the headspace or VOC released by fruit which is to be analyzed to the gas sensors array. This has to be achieved with the maximum possible efficiency without changing the composition of the headspace. Figure 2 shows the schematic block diagram of e-nose system

The measurements process having three different phases: concentration, measurement and standby. The fruit sample was placed into an airtight plastic jar called as concentration chamber having volume of 1L and it was equilibrated for 0.5hr. Preliminary experiments indicate that the headspace reached a steady state after 0.5h of equilibration. Hence experiments were carried out after 0.5 h of equilibration. The headspace gas was pumped by

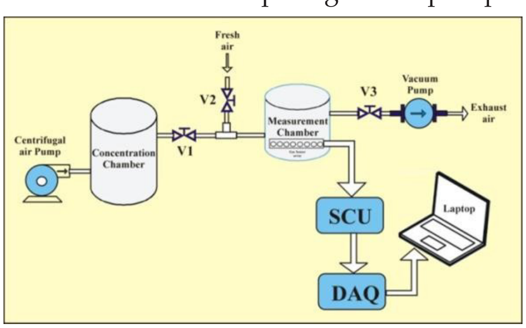

Fig. 2. Schematic of developed E-nose system

using centrifugal air pump with air flow-rate 60 ml/min through a rubber tube and non-return solenoid valves into air tight measurement chamber having 0.6 L capacity for 30s. Airflow always kept constant irrespective of measurement phase. When sensors exposed by the odorant gas during measurement phase, it produces a transient response as the headspace gas react with sensor's active material. Then measurement chamber was locked using solenoid valves and maintain steady for 60 second to allow sensors to reach its steady state condition.

The changes in sensors resistance due to headspace odor was recorded using computer programme. The fruit odor was measured by sensor array for 100 s with the data collection interval was 1 s. All the processes related to measurement are automatically controlled by software that we developed using LabVIEW. Samples of each guava fruit cultivar measured twice as per experimental design. The acquired sensor response during measurement was stored in the form of excel sheet for further analysis. After measurement phase, the measurement chamber was flushed out for 30 seconds using vacuum pump suction, so as to remove the odorant mixture from the surface and bulk of the sensor's active material. The main purpose behind flushing is to clean the measurement chamber, circuits and return sensors to their baseline. The air flow has been guided through electronic valves results in clean air enters the circuit, crosses the measurement chamber first and sucks the remaining volatiles out of the circuit using vacuum pump. The empty concentration chamber was also cleaned using this process. The acquired data is in the form of matrix array that contains 8 columns related to eight gas sensors present in the sensor array and no. of rows related to no. of data samples. The stored dataset was used for multivariate statistical as well as neural network analysis.

Data base generation

Data sets were gathered chronologically and stored in a file represented by Sij, where i indicate storage type and j indicates day number. The whole exercise of recording data sets was carried out for eight days, resulting in the database generation scheme is tabulated in Table 2.

The quality of database generated through experiment was tested using PCA analysis. The PCA analysis plot shows clear separation between different storage days in two different storage treatments.

Table 2. Database structure

Storage type	Day0	Day2	Day4	Day6	Day8
Paper wrapping	S10	S12	S14	S16	S18
Plastic folded bag	S20	S22	S24	S26	S28

After validation of dataset the MLP feed forward NN pattern recognition module was designed and optimized for identification of storage shelf life of Guava fruit since harvest.

PARC module design, optimization and training

In this experiment, the MLP back propagation ANN trained with the Levenberg-Marquardt training algorithm. The training used all the 8 sensors as inputs, 10 neurons in the single hidden layer and three neurons at output layer. The activation functions used are sigmoid and identity functions at the hidden and output layer, respectively. Figure 3 shows the optimized neural network architecture.

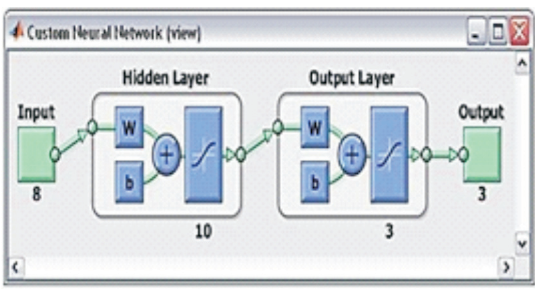

Fig. 3. MLP NN architecture

ANN Network trained with 2250 data samples corresponds to 5 storage classes in each storage treatment (450 data sample for each storage day in each treatment). 70% percent of the collected data sets were utilized during the training phase, 15% for validation and remaining 15 % for testing. In the training mode, the normalized features of the data sets were fed at the input of the MLP NN. The trained network was tested for validation batches of fruits and 1500 data samples were used (300 data samples correspond to each storage day in each storage treatment). The appropriate parameters is selected / decided for NN as shown in Table 3.

Table 4 shows the structure of input data set for training, testing and corresponding targets selected for five ripening classes.

The important training parameters were decided shown in Table 5. The Important performance parameter of trained MLP NN is tabulated in Table 6.

Table 3. Selected parameters for ANN of storage shelf life

Type of ANN	MLP feed forward back drop
Input data	2250X8
Target	2250X4
Training algorithm	Levenberg Marquart
Training function	Trainlm
Adaptive learning function	Learngdm
Performance function	MSE (mean square error)
No. of input neurons	8
No. of output neurons	3
No. of hidden layer	1
No. of neurons in 1st hidden layer	10
Activation function for hidden layers	Tansig (sigmoid)
Activation function for output layer	Identity

Table 4. Input dataset and corresponding target selected

Fruit class	Input Data	Testing Data		Target selected	
Day0	450x8	300X8	0	0	0
Day2	450x8	300x8	0	0	1
Day4	450x8	300X8	0	1	0
Day6	450x8	300X8	0	1	1
Day8	450x8	300X8	1	0	0
Total data	2250x8	1500X8		2250X3	

Lower value of MSE and gradient of trained network indicates appropriate training of the network hence expect better prediction results from it.

Table 5. Important training parameters

Training data division	Random (70% Train, 15% Validation, 15% Test)
Momentum (mu)	0.001
Learning rate (mu-dec)	0.1
No. of epochs	1500
Goal of MSE	0
Min gradient	1X10^{-7}

Table 6. Important performance parameters of trained NN

Momentum (mu)	0.001
No. of epoch required for training NN	35
MSE of the trained NN	6.2449×10^{-11}
Min. Gradient	7.6667×10^{-8}

Results and Discussion

Figure 4 and 5 shows a typical response of gas as sensors array during 8 days of storage in paper wrapped and plastic folded bag respectively.

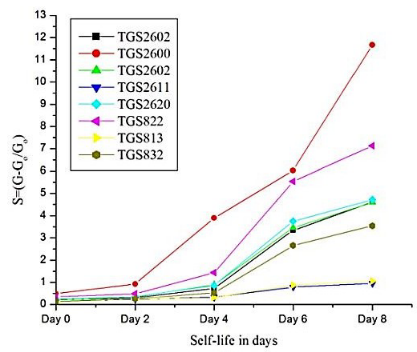

Fig. 4. Sensors response to storage time of guava fruit in paper wrapping storage

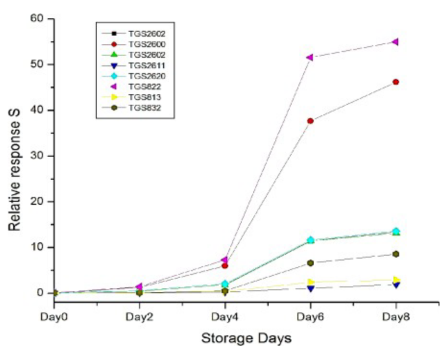

Fig. 5. Sensors response to storage time of guava fruit in plastic folded bag

The pre-processed data obtained are the fractional conductance change ratio between G and G0 (sensors conductance in presence of sample gas and fresh air respectively). Each curve represents the average signal variation of 45 guava fruits sampling respectively for one sensor of the array. The sensors conductance change was observed during various storage days since harvest and it is related to the maturity state that vapors from the fruit reached the measurement chamber. The result was similar to those obtained by (Gomez *et al.*, 2008) for monitoring storage life of tomatoes.

The relative response S= (G-Go/G0) values to volatiles of guava fruits kept in plastic folded bag was less than that in storage conducted in paper wrapping. In both storage treatments the sensors with minor response to fruit aroma have smaller erratic behavior during the experiment. It is inferred that in both storage treatments sensors arrays relative response was slow up to 4th day of storage and then slowly increases up to 6th day. From 6th day TGS822 and TGS 832 shows greater response to fruit volatile. The signals are steady state responses of sensor array (sensor was given 60 s to reach its steady state). In the experiment the sensors array detected the increase in VOC vapor generation as guava fruit ripened. Since guava fruit shows climacteric nature (Abreu *et al.*, 2012), respiration increased during ripening process.

Radar plot analysis

Figure 6 and 7 shows radar plots for dataset gathered in experiments using e-nose for two storage treatments respectively.

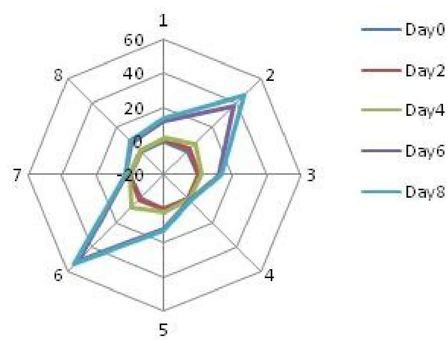

Fig. 6. Radar chart analysis for guava fruit stored with paper wrapping

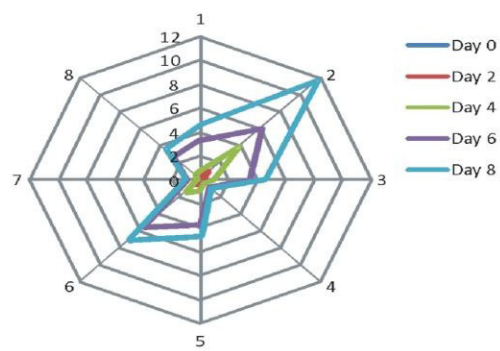

Fig. 7. Radar chart analysis for guava fruit storage in folded plastic bag

From radar plots it is clearly seen that respiration rate increased with number of storage days. The odor print nature is same, only magnitude on each axis increased as number of days since harvest. The paper wrapping indicates more VOC released during storage as compared storage in plastic folded bag. The obtained results indicate that guava fruits headspace in different storage conditions can be monitored by the E-nose, but very clear separation between initial storage days was not expected.

Classification using PCA

Fig. 8 shows PCA analysis plot for guava fruits stored using paper wrapping and represent the variation during day 0 to day 8 storage time. The processed data showed erratic shift of the clusters and no particular trend with storage time. The first principal component, PC1, explains 87.9% of the total variation, while 12.1% of the total variance is explained by PC2. The five clusters are clearly separated, thus the system has enough resolution to show the different storage shelf-life period of guava fruit.

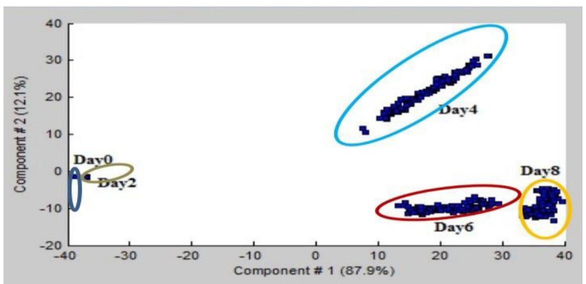

Fig. 8. PCA of Guava fruit stored in paper wrapping

Fig. 9 shows PCA analysis plot of data obtained from guava fruits stored in plastic folded bag. The two principal components $\{PC_{1,n}, PC_{2,n}\}$ was obtained and has the two greatest variances: 99.8% and 0.2% respectively. The scores of the five groups of fruits are plotted for principal component 2 (PC2) versus principal component 1 (PC1). The processed data shows a shift erratic of the groups at different storage time along the first principal component, and no particular trend with the guava fruit storage time along the axis-y. Thus the developed system has ability to trace the storage shelf-life period and type of storage treatment adequately.

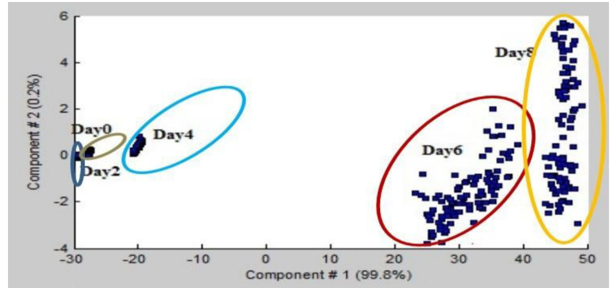

Fig. 9. PCA of Guava fruit stored in plastic folded bag

From both PCA plots it is observed that the discrimination is little in initial storage days; but after 2nd day in paper wrapping storage and from 4th day in plastic folded bag it increased significantly.

Prediction of storage shelf life using MLP NN

The dataset collected over eight days span of guava fruits using e-nose in two storage treatments were analyzed using MLP feed forward neural network with back propagation training algorithm. The average prediction results obtained with % accuracy are shown in below Table 7 for two storage treatments.

The average prediction results obtained by MLP NN for paper wrapped storage treatment are 87.33 % and plastic folded bag storage treatments are 85.33% respectively. The results suggest that developed e-nose system is capable to determine the storage shelf life of guava fruit with adequate accuracy.

References

Abreu, J. R. D., Santos, C. D. D., Abreu, C. M. P. D., Pinheiro, A. C. M. and Corrêa, A.D. 2012. Ripening pattern of guava cv. Pedro Sato. *Food Science and Technology*. 32: 344-350.

Benady, M. 1995. Fruit ripeness determination by electronic sensing of aromatic volatiles. *Trans. ASAE.* 38(1): 251–257.

Berna, A. Z., Lammertyn, J., Saevels, S., Di Natale, C. and Nicolai, B.M. 2004. Electronic nose systems to study

Table 7. Performance of trained pattern recognition modules

Fruits Class	Samples		Prediction performance		% performance	
	Train	Test	Paper Wrap	Plastic bag	Paper Wrap	Plasticbag
Day0	45	30	23/30	24/30	76.7	80
Day2	45	30	24/30	23/30	80	76.6
Day4	45	30	28/30	25/30	93.3	83.3
Day6	45	30	27/30	27/30	90	90
Day8	45	30	29/30	29/30	96.66	96.6
Average Performance			26.2/30	24.4/30	87.33	85.33

shelf life and cultivar effect on tomato aroma profile. *Sensors and Actuators B: Chemical.* 97(2-3): 324-333.

Gómez, A. H., Wang, J., Hu, G. and Pereira, A.G. 2006. Electronic nose technique potential monitoring mandarin maturity. Sensors and Actuators B: *Chemical.* 113(1): 347-353.

Gomez, A. H., Wang, J., Hu, G. and Pereira, A.G. 2008. Monitoring storage shelf life of tomato using electronic nose technique. *Journal of Food Engineering.* 85(4): 625-631.

Kanade, A. and Shaligram, A.D. 2014. Development of an E-nose using metal oxide semiconductor sensors for the classification of climacteric fruits. *International Journal of Scientific & Engineering Research*. 5(2): 467-472.

Differently, Nategh, N. A., Dalvand, M.J. and Anvar, A. 2021. Detection of toxic and non-toxic sweet cherries at different degrees of maturity using an electronic nose. *Journal of Food Measurement and Characterization.* 15: 1213-1224.

Oshita, S., Shima, K., Haruta, T., Seo, Y., Kawagoe, Y., Nakayama, S. and Takahara, H. 2000. Discrimination of odors emanating from 'La France'pear by semi-conducting polymer sensors. *Computers and Electronics in Agriculture.* 26(2): 209-216.

Qiao, J., Su, G., Liu, C., Zou, Y., Chang, Z., Yu, H. and Guo, R. 2022. Study on the application of electronic nose technology in the detection for the artificial ripening of crab apples. *Horticulturae.* 8(5): 386.

Verma, L.R. 2000. Postharvest Technology of Fruits and Vegetables: General concepts and principles.

Young, H., Gilbert, J. M., Murray, S. H. and Ball, R.D. 1996. Causal effects of aroma compounds on Royal Gala apple flavours. *Journal of the Science of Food and Agriculture*. 71(3): 329-336.