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Development of a cost effective customised electronic nose useful for discrimination of tea quality

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Abstract

This paper presents the development of a cost-effective electronic nose (E-Nose) system using five commercially available metal oxide semiconductor (MOS) sensors- TGS2600, TGS2602, TGS2610, TGS2611 and TGS2620. The developed E-Nose system was used to evaluate the quality of different black tea samples. Here, fifteen different tea samples were taken from different tea gardens for testing using the E-Nose and the Overall Liquor Rating (OLR) is obtained from the tea-taster. Further, the data collected and recorded from the E-Nose were analyzed using three machine learning techniques viz. Principal Component Analysis (PCA), Radar plot and K-Nearest Neighbors (KNN). PCA shows the variance discrimination rate of 98.77% and 96.15% for dry and infused tea samples respectively. Radar plots show the sensor TGS2620 as the most significant, whereas TGS2611 is the least significant and the sensors TGS2600, TGS2602 and TGS2610 show almost equal significance. The classification accuracy obtain from the KNN classifier is 97% and 94% for dry and infused samples respectively. The developed system is found to be a cost-effective system as compared to many other E-Nose systems available, which makes it affordable for the marginal tea farmer.

Keywords: E-Nose, MOS, PCA, Radar plot, Tea taster, VOCs, OLR

1. Introduction

Tea is the highest consumed beverage all over the world. Due to its health-promoting benefits, the drinking habits of tea are always appreciated. The popularity of tea is always increasing due to its unique taste and aroma. Tea has a huge international market and for India, it is one of the major sources of income from foreign countries/markets. As reported by the "Tea Board of India", India has the second-largest tea production of the global total production. Assam contributes 51% of India's total tea production which is 1/6th of the world's production. Along with different tea types - Black tea, Oolong tea, green tea etc., Black tea is the most popular with a 74% production rate over all other tea [1,2].

The black tea production process involves several sequential stages as shown in Figure 1. The quality of the produced tea is dependent on these manufacturing processes and techniques. Firstly, fresh, and young tea leaves are plucked and sent for the withering process for moisture reduction. Withered tea leaves are fed into a roller for size reduction. The rolled leaves are then passed through a rotor vane, where small particles are allowed for the fermentation process and large pieces are again loaded for rolling. These rolled tea particles are classified as "first dhool", "second dhool", "third dhool" etc. according to their number of rolling. Classified tea particles are then exposed to air for oxidation, where the chemical compound of tea reacts and produce different characteristic constituents [3]. Thereafter, fermented tea leaves are dried, where several characteristic changes such as moisture reduction, moderate colour changes and some flavour component formation occur [4]. The finished tea is then classified and assigned a grade. After grading, finished teas are sent for packaging where different grades of tea are packed and sent for selling.

Among all the manufacturing process, fermentation and drying is the key process for the final tea quality. The most important quality attributes of tea are colour, aroma and strength are dependent on the most important constituent catechins, also known as the oxidizable matter of tea, that is oxidized during the fermentation. Other important constituents are enzymes, caffeine, pectin etc. Caffeine is mostly responsible for the briskness of made tea and pectin helps in retaining the quality of the tea [4,5]. From the literature review, fermentation is found to be the most crucial point for the final tea quality and is directly related to fermentation time. Therefore, finding optimum fermentation time is of great importance. In many tea industries, the floor supervisors used to monitor the optimum fermentation time manually based on their sense of smell from grassy to specific fragrance and colour changes. However, these manual methods are not reliable and highly subjective [3,6]. Also, for quality evaluation of tea common method used is tea taster, where an expert human panel is used to assign a grade for respective tea quality. The market value of tea is directly dependent on the tea taster's score and the final market value of tea is decided depending on this score [7]. Another method used for tea quality evaluation is the chemical analysis method, where several analytical instruments such as gas chromatograph (GC), high performance liquid chromatograph (HPLC) [8], colorimetric test [9] etc. are used. However, these analytical instruments are very costly, and the analysis is only possible in the laboratory. The inherent disadvantage of these laboratory analyses is that the sample tea characteristics change due to several reactions during the time taken from factory to laboratory.

Therefore, an automatic and portable cost-effective operable device with minimum human intervention is needed. Many research groups are working in the field of electronic nose to make an effective, efficient, and cost-effective next quality evaluation device. Currently, researchers have been working on the development of electronic nose (E-Nose) to use in various fields such as food and beverage industries, pharmaceutical industries and health care, chemical industries, security systems, tea quality evaluation etc. [6]. Recent studies combine the effect of E-Nose and Electronic Tongue (E-Tongue) for tea quality evaluation [10,11]. However, most of these studies were done in laboratory conditions, therefore taking on such technology in the practical field has various challenges.

The objective of this paper is to develop a customized and cost-effective E-Nose system for black tea quality evaluation. The developed electronic nose system uses the minimum number of sensors and minimizes human intervention. This paper suggests the development of a budget-friendly E-Nose system, that will also be affordable for small and home tea farmers.

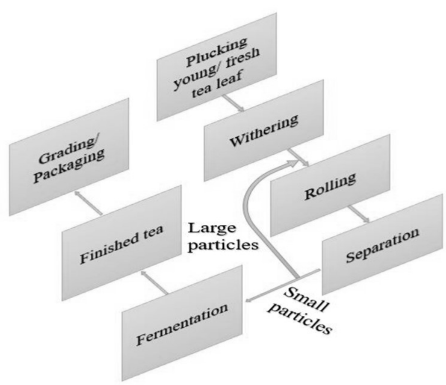

Figure 1 Flowchart of black tea production process.

Since tea is the most popular liquor among people all around the globe due to its taste, smell and aroma, and also tea has a direct effect on human health, therefore quality evaluation of tea is very important and is a wide research topic. As reported in the literature, chemical components like amino acids and catechins may help to prevent diseases like cardiovascular diseases, chronic gastritis etc. [12]. The classical methods of tea quality evaluation have their inherent limitations like- time consuming, maximum human intervention, expensive, and not suitable for production site monitoring. Therefore, the evolution to assess tea quality from classical methods to the development of handheld, portable and online monitoring E-Nose technology can be useful to resolve the limitation of classical evaluation methods. For the development of an E-Nose, the selection of an appropriate sensor is the most important part. For the electronic sensory evaluation, the selection of efficient sensors that are sensitive to tea volatile organic compounds (VOCs) is the most crucial point. Banerjee et al. [8] had made an experiment on sensitivity analysis of seven metal oxide semiconductor (MOS) sensors for an E-Nose. They optimized the sensor array from seven to five sensors based on the changes in sensor resistance which is measured as $\Delta R_s/R_s$ (ΔR_s-resistance change in MOS sensor and R_s-base resistance of the sensor). Further, the obtained data were analyzed using three neural network topologies viz. backpropagation multilayer perceptron (BP-MLP), radial basis function (RBF) and probabilistic neural network (PNN), the accuracy obtained was 84.21%, 83.11% and 79.43% respectively. The optimized sensor sets were TGS-823, TGS-832, TGS-2600, TGS-2610, and TGS-

2611 [8]. Currently, E-Nose has been explored in various research fields from food and beverage to health care systems, chemistry to biohazards detection etc. Tang et al. [13] showed a potential application of E-Nose to detect pyrethroid pesticide contamination present in tea leaves. They used a PEN3 E-Nose system that contains 10 MOS sensors. Using loading analysis, out of the 10 sensors -W5S, W1S, W1W, and W2W showed substantial contribution to the concentration gradient of the pesticides- cyhalothrin, bifenthrin and fenpropathrin present in tea leaves. Further, these four sensors were selected to detect different concentration gradients of the considered pesticides. They further developed a principal component analysis (PCA) and BP neural network model to differentiate and quantify them having a differentiation success rate 98.75%, 97.08%, 97.08% and 96%, 92%, 88% respectively for the considered group of pesticides [13]. Saha et el. performed a tea quality classification using an array of five sensors in the electronic nose system. For the classification process support vector machine (SVM), vector-valued regularized kernel function approximation (VVRKFA) and nonparallel plane proximal classifier (NPPC)) were used. VVRKFA classifier was found as the best among other classifications with accuracy (98.33%) [7]. As the quality of tea is dependent on various process parameter like fermentation time, drying temperature, moisture content, humidity etc. and the final tea product value depend on the tea taster score/overall liquor rating (OLR) evaluated by a human expert taster. However, these crucial parameters are monitored or measured manually or sometimes by the prediction of experienced workers. Therefore, to correlate the final tea quality with the process parameters, an onsite parameter monitoring system is required, such a system is reported in [14] to monitor temperature and relative humidity during the fermentation and drying process. Saikia et al. studied the correlation between the process parameters collected by a sensor network-based on-site process parameter monitoring system and the OLR rating of tea taster using multivariate linear regression (MLR) and artificial neural network (ANN) based technique. The correlation study result for input process parameter and output OLR rating shows 58.22% and 63.90 for MLR and BPMLP(ANN) respectively [15]. As numerous commercial brands of tea are available in the market, it is required to evaluate their quality. Lui and their group developed an electronic nose system to identify and assessment of Longjing green tea using machine learning algorithms [16]. They have developed the multi sensor array E-Nose comprised of sensors sensitive to Longjing green tea aroma listed as TGS813, TGS822, TGS2600, TGS2602, TGS2620, MQ-6, MQ135 and MQ138. Further, for quality detection. The researcher used three machine learning algorithms - SVM, Multi-Layer Perceptron (MLP) and Random Forest (RF). RF shows the best suitable result with accuracy 99.42%.

2. Materials and methods

2.1 Sensor selection

The most important part of the development of an E-Nose is to select the sensors sensitive to target VOCs. Any sensor sensitive to gas or VOCs has the potential to be a part of an Electronic-Nose system. As reported in the literature, MOS sensors, sensitive to the various volatile organic compounds are widely used sensors in the electronic nose due to their several features like reliability, stability, high sensitivity, long life etc. [3,4]. The principle is based on the adsorption of a gas molecule at the surface of metal oxides. Adsorption of sample odour on the oxide surface followed by oxidation or reduction results change in the electrical resistance of the oxide material. The commonly used metal oxides are SnO_2, ZnO, and WO_3 [17]. For the developed E-Nose five MOS sensor related to black tea odour has been selected from cited literature [8,20,21]. The array of the sensor for the E-Nose system contains five commercially available sensors are- TGS2600, TGS2602, TGS2610, TGS2611 and TGS2620 which are sensitive to the black tea aroma like B-ionine. Linalool, Linalool Oxide, Geraniol, Terpeniol etc. The sensor used for the E-Nose system and sensitive gases is shown in Table 1.

Table 1 Sensors used for developing the E-Nose.

Sensor	Main compound
TGS-2600	Ammonia/ Amine/ Odour
TGS-2602	Carbon monoxide (CO), hydrogen(H_2)
TGS-2610	NO, NO_2
TGS-2611	Hydrogen, Ethanol, Ammonia, Toluene
TGS-2620	Alcohol, Organic Vapor

2.2 Design of experimental set-up

An E-Nose setup has been developed using five commercially available MOS sensors from Figaro, Japan. The MOS sensors sensitive to black tea VOCs as given in Table-1 are assembled on a printed circuit board (PCB) and inserted into an 11cm×11cm×5cm plexiglass chamber. The block diagram and the developed E-Nose set-up are shown in Figure 2, Figure 3 respectively. The developed E-Nose works as follows- Firstly, ambient air was pumped into the sample space with the help of the micro-air pump. When valve-I is open, pumped air enters (at 2 m/s flow rate) the sample space through the pipeline connecting the micro-pump to the sample chamber. As valve-II is opened and valve-III is closed, sample VOCs are allowed to pass to the sensor chamber and the sensor heads are exposed to a constant flow of sample VOC. The sensor data are then sent to the personal computer (PC) for data analysis. An inclined glass plate is placed inside the sensor chamber so that sample VOCs are closely passed through the sensor head instead of spreading into the whole chamber. The purging operation has been done to clean the sensor head with a blow of fresh air for about 10 minutes to return the sensor to its base value so that sensors are free from previous sample VOCs. The suction blower/fan is used to suck up the sample VOC from inside the sensor chamber.

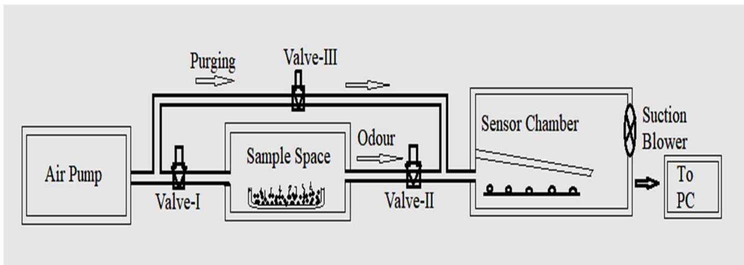

Figure 2 Block diagram of the odour capturing system.

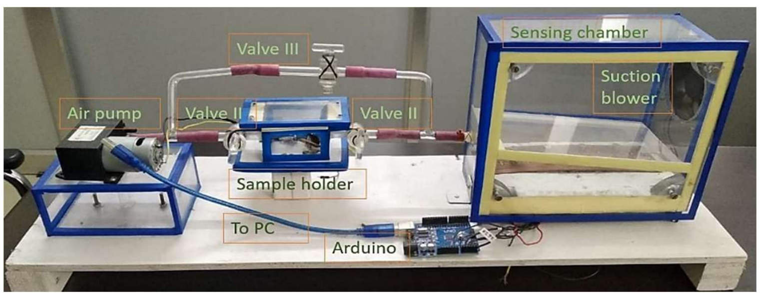

Figure 3 The developed E-Nose system.

2.3 Experimental sample collection and preparation

The tea samples were collected from different tea gardens and the local vendor of Guwahati, Assam. The sample collection was differentiated according to the OLR rating provided by the human expert tea taster as mentioned in Table 2. Fifteen black tea samples named S1, S2, S3, S4, S5, S6, S7, S8, S9, S10, S11, S12, S13, S14, S15 and S16 were used for the experiment. The samples were used in two different ways:
1) Dry tea samples (2 g) were directly used from the moisture barrier bag as collected from a vendor and tea garden.
2) Infused tea samples were prepared using the brewing method. Firstly, 2 g of dry tea leaves were infused in 100 mL of hot water heated at the boiling temperature of the water. The mixture was stirred for about 2 to 3 min and then the tea liquor was passed through a semi-permeable filter paper to separate the tea leaves residue. 1mL of filtered tea was used for the experiment [18].

Table 2 The OLR rating provided by tea taster.

Sample	OLR
S14	4.3
S13	4.1
S15	3.3
S6	2.7
S11	2.4

3. Results

3.1 Data collection and analysis

In the developed E-Nose system the sensors responsible for the detection of black tea VOCs are listed above. The experiment was carried out in a controlled environment at a constant temperature of 26°C and 85% RH. The raw data for each sample is collected as voltage value from each sensor has ranged from 0 V to 4.5 V recorded for 270 sec at an interval of 0.5 sec. The more sensitive the sensor to the target sample, the more the sensor output voltage variation. We experimented to observe the discrimination of fifteen types of samples S1, S2, S3, S4, S5, S6, S7, S8, S9, S10, S11, S12, S13, S14 and S15 by each sensor.

3.2 Principal component analysis

For the data visualization, the PCA algorithm was used. PCA is a statistical procedure that transforms multidimensional datasets into a reduced dimensional representation. The multidimensional data set obtained from the E-Nose system has been subjected to PCA. The PCA plot obtained for fifteen representative dry samples is shown in Figure 5. For the dry tea sample, more than 98.77% of significant information is carried out by the PCA1 and PCA2 axis as shown in Figure 5(A). Again, the PCA plot for infused tea sample is shown in Figure 5(B), where more than 96.15 % of the significant information is carried out by PCA1 and PCA2. From the PCA plots, it can be observed that samples belonging to a particular group clustered well mannered.

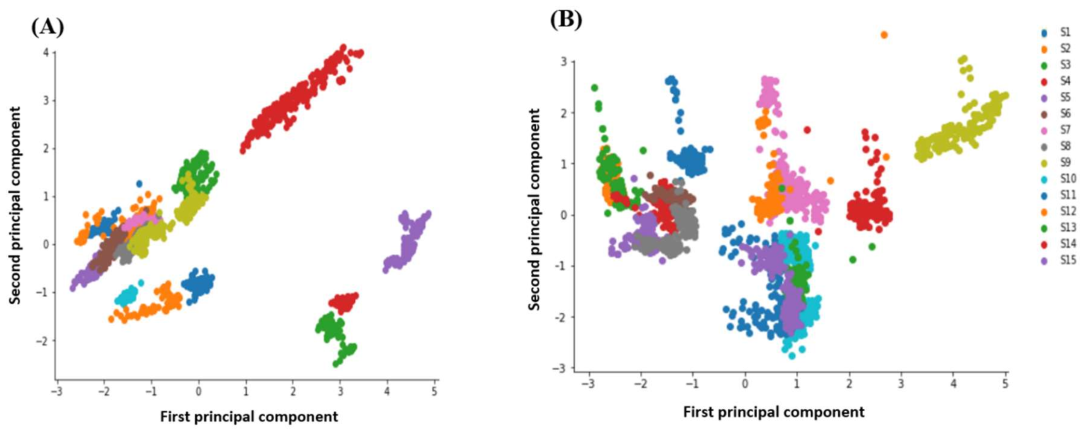

Figure 5 PCA plot for- (A) Dry sample and (B) Infused sample.

3.3 Radar plot

The data collected are represented by the radar plot for the competitive analysis among the sensors used. The radar plot is a visual tool to represent multivariable data in a two-dimensional (2D) plane. The radar plots corresponding to Figure 6 show the sample VOCs spread amongst the sensors. Figure 6(A) represents the radar plot for the dry tea sample and Figure 6(B) represents the same for the infused tea sample. From the observation, it is evident that the contribution of the sensor TGS2620 is highest while the sensors TGS2600, TGS2602 and TGS2610 show almost equal contribution. The sensor TGS2611 shows the least contribution compared to others for both the cases of dry sample and infused liquor.

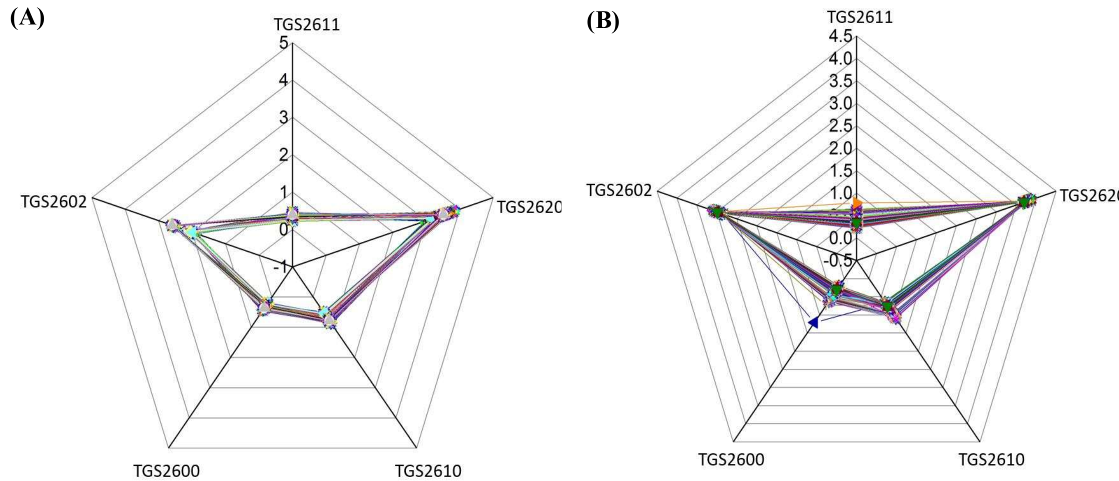

Figure 6 Radar plot for- (A) Dry sample and (B) Infused sample.

3.4 K-nearest neighbors (KNN) classification

The K-Nearest Neighbors (KNN) is the simplest algorithm that relies on the choice of similarity of the most common K sample for the classification. The gas sensors were taken as features and the sensor voltage response of each sample is taken as the observation [22,23]. The entire dataset is split into 80% training dataset and 20% for testing the model. The 10-fold cross validation is performed on the training model to optimize the best K value and the model observed the best performance at K=4. The yielded classification accuracy for dry tea samples is 97% and 96.4% for infused tea. The percentage precision obtained is 96.4% and 93.5% for the dry and infused sample as shown in Table 3.

Table 3 Performance rate of KNN classification.

Sample	Accuracy (%)	Precision (%)
Dry sample	97	96.4
Infused sample	94	93.5

4. Discussion

A cost-effective customized E-Nose has been developed for tea quality discrimination and tested in the laboratory. The experiment has been performed with six different tea samples in two different conditions: dry sample and infused sample. The sensor output was collected and recorded for analysis. The developed E-Nose were applied to assess the aroma profile of the dry tea leaf and the tea infusion. Firstly, five features have been extracted from the five-sensor and were processed by PCA. The most significant principal components axis PCA1 and PCA2 were plotted for dry leaf and infused tea samples. The PCA analysis clearly shows the clustering of different samples corresponding to a particular group.

Further, Radar plot analysis for the dry and infused tea samples shows the correlation among the sensors. For both cases, it is seen that the plot has an intense sharpness along the sensor TGS2620 representing the most significant one among the other. Again, the sensor TGS2600, TGS2602 and TGS2610 can be seen to draw almost the same significance. However, sensor TGS2611 has the least response compared to other sensors corresponding to the E-Nose sensor array.

The KNN classification for the dry and infused tea samples shows a good classification rate. The classification accuracy as a measure of correct prediction to the total observation is obtained as 97% for dry sample and 94% for infused sample.

The developed E-Nose is a low-cost system compared to commercially available systems with an average price of INR. 19,108 which is affordable for marginal tea farmers. The overall cost of the developed system is shown in Table 4. Table 5 illustrates a comparative analysis with a few other related practices.

Table 4 The development cost of the E-Nose.

Component	Price (INR)
TGS2600	2750
TGS2602	3000
TGS2610	3275
TGS2611	3038
TGS2620	3645
Vacuum pump	1000
Suction fan	300
Arduino board	500
Airtight valve	600
Manufacturing expenses	1000
Total	19,108 Rupees

Table 5 Comparison of the developed E-Nose system with other researchers work.

Used sensor	Tea type	Results	Remarks	References
TGS816, TGS-823, TGS-831, TGS-832, TGS-832, TGS-2600, TGS-2610, and TGS-2611	Black tea	BP-MLP (84.21%) RBF 83.11% PNN 79.43	Based on sensitivity analysis number of sensors are optimized to five	[8]
TGS-832, TGS-823, TGS-2600, TGS-2610 and TGS-2611	Black tea	VVRKFA 98.33%	Quality classification and prediction of tea quality score	[7]
TGS813, TGS822, TGS2600, TGS2602, TGS2620, MQ-6, MQ135, MQ138	Longjing green tea	RF 99.42%	Identification and quality assessment of certified and non-certified tea brand	[16]
TGS2600, TGS2602, TGS2610, TGS2611, TGS2620	Black tea	PCA 98.77% KNN 97% (Dry sample) PCA 96.15% KNN 94% (Infused sample)	Customized and cost-effective Discrimination of black tea	Present study

5. Conclusion

In this paper, we proposed a budget friendly customized E-Nose for the discrimination of different black tea qualities based on their prices. The efficacy of the developed E-Nose system has been verified experimentally. We have developed the E-Nose system using a minimum number of MOS sensors according to their ability to sense the black tea quality determining VOC. The sensor selection is based on the literature review. For the discrimination analysis, the tea samples are used in two different ways- dry tea leaf and infused tea liquor. After that, E-Nose data is collected and recorded to observe the discrimination rate of different tea samples using PCA. The PCA analysis shows good accuracy of about 98.77% for dry tea samples and 96.15% for the infused tea sample. The significance of each sensor in the discrimination has been analyzed using the radar plot. The observation shows that the contribution from the sensor TGS2620 is the highest and almost equal contribution has been seen for the sensors TGS2600, TGS2602 and TGS2610 following slightly less contribution from sensor TGS2611. The different tea samples classification obtained by the KNN classifier shows good accuracy of 97% and 94% for dry and infused tea respectively.

The developed E-Nose system is an easy to use and cost effective one which is also affordable for the marginal farmer. The future aspect of this work includes the testing of a large number of tea samples and the classification of these samples based on their quality and prices using machine learning. E-Nose combined with E-Tongue and computer vision could be a better opportunity to study all the aspects of quality dependent parameters and to make it more efficient.

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