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DEVELOPMENT OF ELECTRONIC NOSE FOR CLASSIFICATION OF AROMATIC HERBS USING ARTIFICIAL INTELLIGENT TECHNIQUES

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Abstract

In normal practice, herbs identification is done mainly by botanists. However, it is difficult for a botanist to recognize herbs based on aroma measurement for species under the same family because they may have almost the same aromas. Moreover, several factors might influence the accuracy of the human olfactory system as a sensory panel such as physical and mental conditions. Meanwhile, non-human factors might involve various experimental exercises that are time-consuming, less efficient and costly. Therefore, a small portable electronic nose that is easy to operate is proposed in this research. The herb leaves were blended as a mechanism in sample preparation was found as a preeminent procedure to overcome the drawback of the existing system. The emphasis on the ability of proposed electronic nose enhance with herbs recognition algorithm in this project was to distinctive odour pattern of the herbs leaves from three families group. Two classification methods, Artificial Neural Network (ANN) and Adaptive Neuro-Fuzzy Inference System (ANFIS) were used in order to investigate the performance of classification accuracy for this E-nose system. From the results, the developed E-Nose with both Artificial Intelligence (AI) techniques had performed well in distinguishing twelves herbs species. However, E-nose with ANFIS gives 94.8% percentage of accuracy higher than E-nose with ANN as 91.7% of accuracy. As a conclusion, the proposed E-nose system with AI technique application can classify the aromatic herbs species successfully.

Keywords: Adaptive neuro-fuzzy inference system, Artificial neural network, Electronic nose.

1. Introduction

Herbs is referred to as the leafy green part of a plant that does not develop persistent woody tissue [1]. Herb species have unique leaf characteristics such as the shape, colour, texture and the nature of odours. Most herbs have their own characteristic odour due to the presence of phytochemicals in the form of volatile compounds. Common herbal constituents such as terpenes, steroids, phenolic compounds, amino acids, lipids and alkaloids offer beneficial properties [2].

Numerous researchers have used chemical gas and liquid to differentiate herbs odour using a complex experiment with a huge budget. According to Wilson and Baldwin et al. [3, 4], the ability to classify distinctive odour patterns for aromatic plants species, especially for herbs, can significantly impact application fields that use herbs such as food industry, medicine, culinary, healthcare product and pharmaceutical. Therefore, the aim of this study is to explore, analyse and identify the differences between herbs leaves based on their odours.

E-Nose instruments were developed since 1982 for a diverse of application. Electronic nose devices are used with increasing frequency due to the advantages in the acquisition of real-time information on the chemical, physical nature and quality of plants [5-9]. Many recent works have used the E-nose technology in the medical field, for example in detecting the lung cancer and EGFR Mutation [5], detecting colorectal cancer [9], and distinguish between gastroenterological disease states [10]. These devices are also used in other fields such as to study roasting temperature degree to find the best quality of cocoa beans [6], to detect adulterations in Saffron [8], to monitor emitted odours and to analyse chemical in municipal solid waste [7], to monitor air quality [11], and to predict the freshness of Pseudosciaena crocea [12].

In this paper, E-nose was developed as a portable small size device with a user-friendly interface. This paper will present the experimental setup, data collection, and the development of the E-nose system. The objective of the E-nose system was to see the ability of the developed E-nose to distinctive aromatic herbs leaves odour from family Lauraceae, Myrtaceae, and Zingiberaceae. Five Metal Oxide Semiconductor (MOS) gas sensors were used in this system; TGS 2610, TGS 2611, TGS 2620, TGS 823, TGS 832. The algorithm design referred to the pattern recognition system technique, which consists of experiment setup, data collection, signal processing, feature selection, classification, and cross-validation. In the classification phase, two AI methods, namely, ANN and ANFIS, were applied in this system to determine the classification accuracy. Robustness of the proposed E-nose system coupled with ANN or ANFIS will be discussed in the results and discussion section.

2. Materials and Methods

2.1. Development of the electronic nose system

The volatile odour of the sample was captured by an array of the gas sensors. The processing unit collected the data and transferred to the detection algorithm. Then, the detection algorithm compared the signals with a collection of patterns in the database and hence, classified each herb.

The sample preparation involved using a blender to crumple the leaves. This system was effective for acquiring signals and advantageous as a rapid sample preparation step compared to existing systems that involve chemical and complicated laboratory procedures, which are time-consuming and costly. The general process of the electronic nose is as shown in Fig. 1.

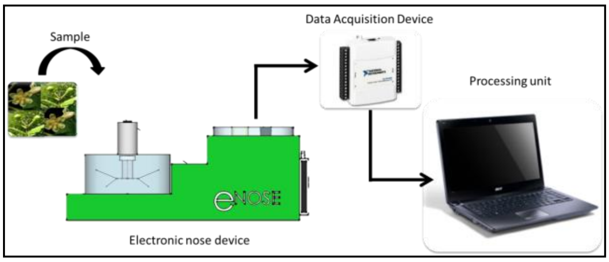


Fig. 1. General process of the E-nose system.

2.2. E-Nose sensor detection array

The gas sensors for the electronic nose device were selected based on type and sensitivity to target detection. The sensitivity of a gas sensor towards an odour depends on the chemical compounds in the herb sample. Thus, the phytochemical compositions of the selected herbs were reviewed and the resulting correlations were considered when selecting the best gas sensor array for the system. Thus, the MOS gas sensor was chosen for the development of the electronic nose device due to its low cost, flexibility, and simplicity of use, as well as the ability to detect a large number of gases.

2.2.1. Aromatic herbs

The objective of this study was to develop an electronic nose to recognize herb species under the same family that may have almost identical odours. Therefore, three families of aromatic herbs were chosen to identify their odour patterns. Then, four species were selected under each family. The herbs, as listed in Table 1, were chosen with the consultation of botanists from the Institute of Bioscience, Universiti Putra Malaysia (IBS UPM). The samples were collected from the Agricultural Conservatory Park, Universiti Putra Malaysia.

Table 1. Species and family of aromatic herbs.

Family name	Herb species name
Lauracea	LCI: Cinnamomum Iners
	LCP: Cinnamomum Porrectum
	LCV: Cinnamomum Verum
	LLE: Litsea Elliptica
Myrtaceae	MMA: Melaleuca Alternifolia
	MRT: Rhodomyrtus Tomentosa
	MSA: Syzygium Aromaticum
	MSP: Syzygium Polyanthum
Zingiberaceae	ZEC: Elettariopsis Curtisii
	ZET: Etlingera Terengganuensis
	ZSK: Scaphoclamys Kunstleri
	ZZZ: Zingiber Zerumbet

2.2.2. Phytochemical composition of sample and gas sensor sensitivity detection

The selection of gas sensors was based on the chemical specificity in the target herbs. Based on study by Mohamad Yusof et al. [13], the major phytochemical compositions of the herbs in the sample study were reviewed from the literature and listed as in Table 2.

Alcohol can be found in each family of sampled herbs. Halocarbon may give off a unique composition to differentiate the Lauraceae family from the Myrtaceae and Zingiberaceae. Meanwhile, phenolic acid was detected in the Myrtaceae family, while methane and benzenoids were identified in the Zingiberaceae family.

Table 2. Common chemical compound in herb samples.

Family name	Common chemical compounds
Lauraceae	Butane, Alcohol, Xylene, Halocarbons
Myrtaceae	Propane, Alcohol, Butane, Phenolic acid
Zingiberaceae	Methane, Alcohol, Propane, Benzenoids

2.2.3. MOS gas sensor

In this study, a MOS gas sensor was selected due to its fast response, affordable cost, low power consumption, and a large number of target gas detection. However, metal oxide semiconductor gas sensors are not commercially available specifically for herb odour detection. Therefore, multiple MOS sensors from Figaro were selected, as listed in Table 3, to detect the broad range of chemical compounds according to the phytochemical compositions of the herbs in the sample study.

2.3. Experimental setup

The complete configuration of the developed electronic nose device is as shown in Fig. 2 for data collection. The device consists of a blender with a sample container, a sensor slot that holds the gas sensor array, a data acquisition system, NI USB-6009, from National Instrument, and the graphical user interface.

At the beginning of the data collection procedure, the sensor in the electronic nose was preheated to stabilise the signal. The voltage was kept between 0 V and 1 V as a common baseline for the gas sensor. Next, 15 grams of fresh leaves was placed in the sample container and blended for 15 seconds.

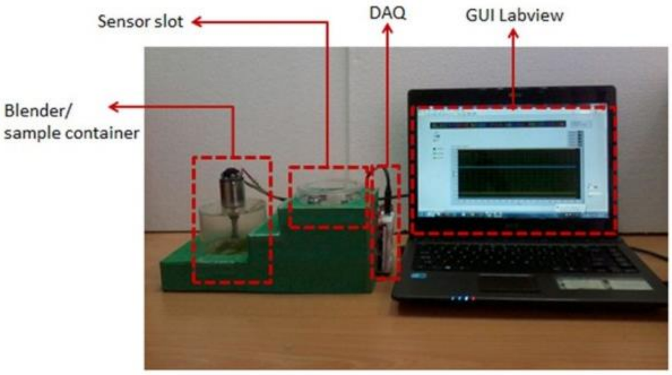


Fig. 2. Complete configuration of the proposed electronic nose for data collection.

Signal measurement commenced when the ‘START’ button on GUI was pressed. The baseline voltage was captured during the first 60 seconds. Then, the sample container was placed on the sensing slot and the response time was set at 120 seconds. Next, the container was removed from the sensing slot and recovery time was recorded for another 120 seconds. Subsequently, the entire process of capturing signal responses, with complete response signals, was conducted within 300 seconds.

Table 3. MOS gas sensor for E-nose.

Sensor type	Type of gas detection
TGS 2610	Butane, propane, liquefied petroleum gas
TGS 2611	Methane, natural gas
TGS 2620	Alcohol, toluene, xylene, volatile organic compound
TGS 823	Organic solvent vapors
TGS 832	Halocarbon, chlorofluorocarbon

2.4. Data pre-processing

The moving average technique was applied in this study for smoothing the signal and data reduction. Raw data from five signal responses from the gas sensor were extracted at the beginning. Each signal was smoothed and transformed using the moving average formula in Eq. 1.

$$\hat{x} = \frac{1}{n}\sum_{i=1}^{n} x_i = \left(\frac{1}{n}\right)x_1 + \left(\frac{1}{n}\right)x_2 + \cdots + \left(\frac{1}{n}\right)x_n \tag{1}$$

where; n = number of sample data.

Eventually, this technique could cause the loss of data. However, the percentage of loss data was calculated using Eq. 2 to observe the performance of the E-nose and to maintain the analytical pattern of the data.

$$\%Loss\ data = \frac{v_{\max(input)} - v_{\max(output)}}{v_{\max(input)}} \times 100 \tag{2}$$

where; $v_{max\ (input)}$ is the maximum voltage from the original data,

$v_{max\ (output)}$ is the maximum voltage after processed data.

2.5. Statistical test of data

One-way Analysis Of Variance (ANOVA) is a statistical test to determine whether the means on a metric variable for three or more populations are all equal. In this study, ANOVA was applied to statistically prove whether the sampled data can be grouped based on family and species, or not. The null hypothesis in ANOVA stated that all means of the groups are the same, while the alternative hypothesis stated that at least one mean is different. The ANOVA output was used to determine the significance value as a conclusion whether to reject the null hypothesis or at least one mean is different from the others.

2.6. Structure of feature analysis

Feature analysis in this study was intended to determine the best combination of sensors for the classification process. Two to five features were analysed using two techniques. The first technique was to plot the graph. For the analysis of two and three features, the two-dimensional plot and the three-dimensional plot were applied. Observations from the plotted graphs were used to determine the best features of the sensors that succeeded in classifying the herb species.

The second technique was to calculate the Euclidean distance of sensors with four and five features. From the calculations, the higher value of distance will indicate a better separation of group, or species compared to the lower value of distance. The Euclidean distance used in this analysis is as shown in Eq. 3. In addition, the Euclidean distance was also calculated for sensors with two and three features for validation purposes.

$$d^2(p,q) = (p_1 - q_1)^2 + (p_2 - q_2)^2 + \ldots (p_n - q_n)^2 \quad (3)$$

where d is Euclidean distance, and p and q are data matrix of the sensor signal for observations.

2.7. Classification method

The classification of the herbs in this study involved the Artificial Neural Network (ANN) and the Adaptive Neuro-Fuzzy Inference System (ANFIS). The performances of both techniques were evaluated from the percentage of accuracy of the system when classifying the herb species.

2.7.1. Artificial neural network design

The ANN model was designed from two to five inputs to determine the best herb classifications. The scaled conjugate gradient back-propagation algorithm was applied for training. Sigmoid activation function was used in the neural network model of this study. The architecture of the neural network consisted of the input from sensor_1 to sensor_n and twenty hidden layers, and twelve species of herbs as the output. Each node from the input layer was connected to a node from the hidden layer, and every node from the hidden layer was connected to a node in the output layer. The weight, w was associated with every connection. The input layer represented the raw information being fed into the network. Every single input to the network was duplicated and sent down to the nodes in the hidden layer. Thus, the hidden layer accepted data from the input layer. It used the input values that were modified from the weight, w_{ij}, value. Then, a new value was sent to the output layer and modified again by weight, w_{jk}, from the connection between the hidden and output layers. Finally, the output layer would process the information received from the hidden layer and produce the output. The two-layer feed-forward back propagation structure is as shown in Fig. 3.

2.7.2. Structure of the adaptive neuro-fuzzy inference system

The second classification technique used in this study was the Adaptive Neuro-Fuzzy Inference System (ANFIS). Subtractive clustering was selected for the fuzzy inference system to build the structure. The hybrid optimization method was applied for a better performance in data training. The first layer consisted of sensor_1-to-sensor_n input layer of the ANFIS structure. The second layer contained premises or antecedent parameters dedicated to the fuzzy sub-space. Consequent parameters from the fifth layer were used to optimise the network. During the forward pass of the hybrid-learning algorithm, node outputs would go to the fifth layer and the consequent parameters were identified using the least-square method. In the backward pass, error signals would propagate backwards and the premise parameters were updated using the gradient descent method. The structure of ANFIS in this study is shown in Fig. 4.

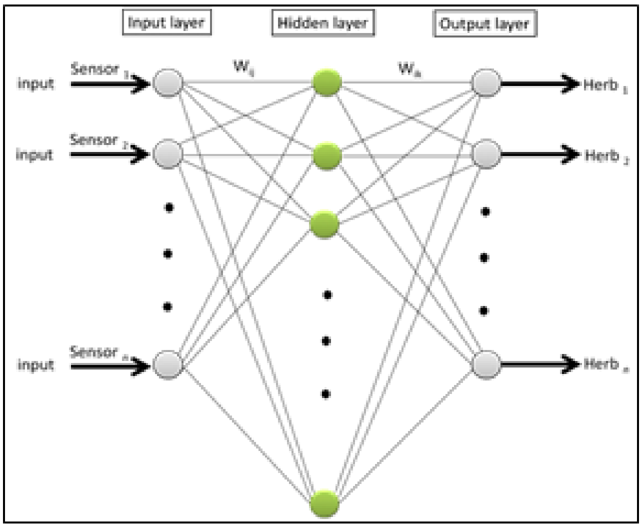


Fig. 3. Structure of neural network.

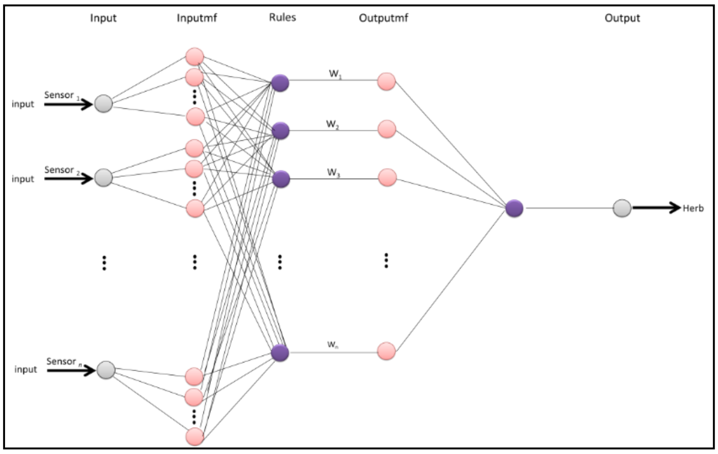


Fig. 4. Structure of ANFIS.

3. Results and Discussion

3.1. Data pre-processing

Data of the herbs' odours were successfully captured using the gas sensor array in the experiment. Each sample produced 300 raw data. However, the raw data had contained a large amount of noises in the form of repeated values. To improve the quality of the data, the raw data were pre-processed to ease the mining process. The signal captured by the gas sensor was smoothed and data reduction was done to reduce a large amount of sampling data by applying the moving average technique. Based on Eq. (2), the percentage data loss is 0.547%, which is negligible, and thus, the new set of data was reliable to be used in further analyses.

3.2. E-nose response curve

The baseline voltage was captured during the first 60 seconds. The response time occurred within 120 seconds when the gas sensor was exposed to the herb sample. The recovery time was set within another 120 seconds to eliminate the herb odour from the detection sensors. A complete cycle for the gas sensor to capture the odour signal was within 300 seconds, as shown in Fig. 5.

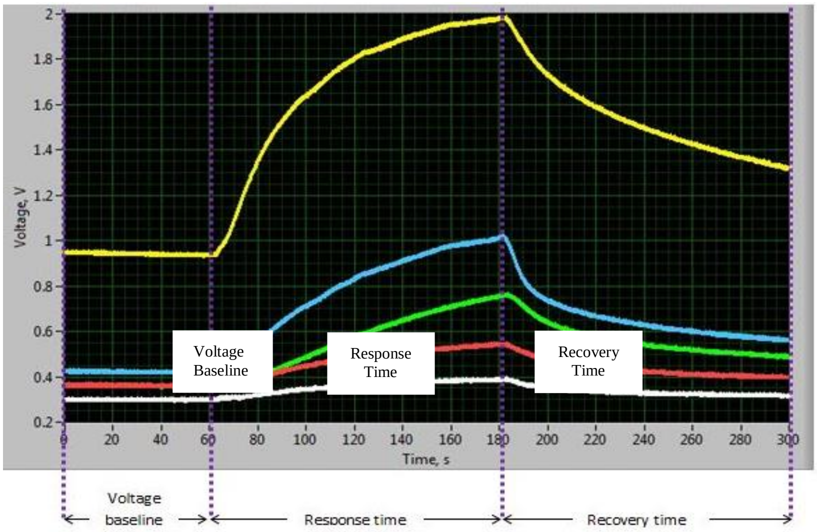


Fig. 5. Complete curve response of E-nose.

3.3. Analysis of one-way ANOVA

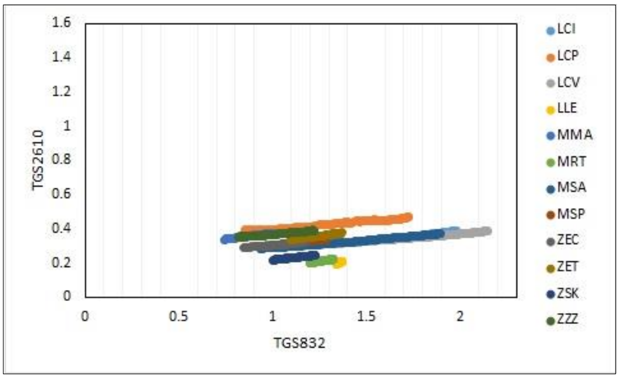
The priori alpha level for one-way ANOVA was set as 0.05 (α = 0.05). The significance level must be greater than the priori alpha level for the null hypothesis to be rejected. From the output of the one-way ANOVA, each gas sensor has a significance value that was lesser than the priori alpha level. Therefore, the null hypothesis was rejected and the conclusion was that the collected data were statistically significant, with different means between the groups of herb species.

3.4. Feature analysis

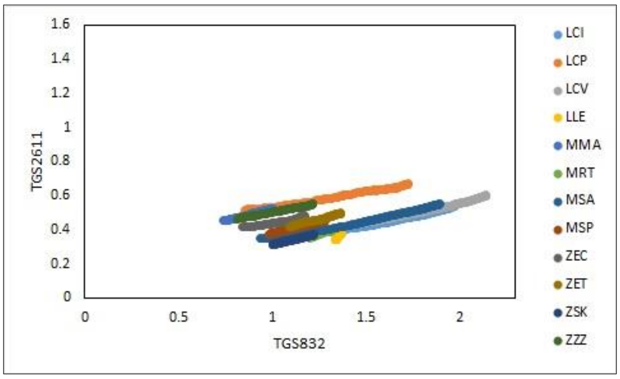
The features analysis was conducted mainly to determine the best combination of gas sensors for application in the classification process. The analysis of gas sensors with two and three features was conducted using the plotting technique. The Euclidean distance was calculated to obtain objective results from the observation of the plotted graphs. Meanwhile, analysis of gas sensors with four and five features was validated by calculating the Euclidean distance. The higher value of distance will indicate better separation in the data to classify the herb species.

The two-dimensional plot was used to analyse the best two combinations of sensors that can represent the best classification of herb species, as shown in Fig. 6.

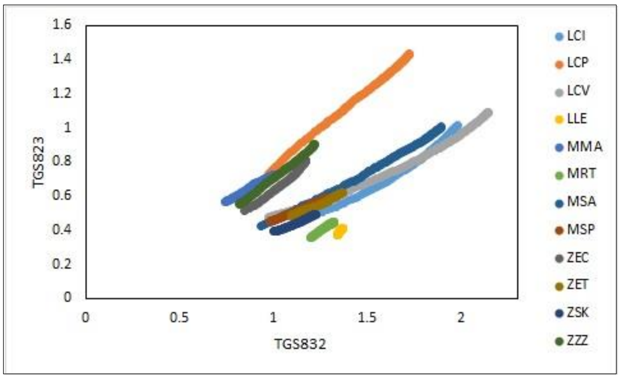
However, the data from the graphs were overlapped and were difficult to interpret. Thus, to validate the analysis, the Euclidean Distance (ED) was calculated for quantitative and objective results, as shown in Table 4.



(a)TGS2610 vs. TGS832.



(b) TGS2611 vs. TGS832.



(c) TGS823 vs. TGS832.

Fig. 6. Two feature analysis.

Table 4. MOS gas sensor for E-nose.

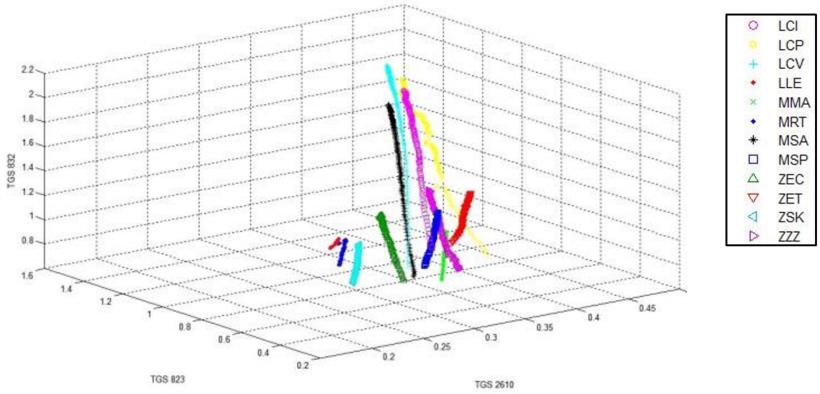
	Two Features									
Sensor	S1	S1	S1	S1	S2	S2	S2	S3	S3	S4
	S2	S3	S4	S5	S3	S4	S5	S4	S5	S5
ED	0.479	0.629	1.318	3.536	0.304	0.891	3.079	0.779	2.960	2.390
	Three features									
Sensor	S1	S1	S1	S1	S1	S1	S2	S2	S2	S3
	S2	S2	S2	S3	S3	S4	S3	S3	S4	S4
	S3	S4	S5	S4	S5	S5	S4	S5	S5	S5
ED	1.722	2.075	3.883	2.168	3.933	4.290	1.938	3.527	3.921	3.829
	Four features									
Sensor	S1	S1	S1	S1	S2					
	S2	S2	S2	S3	S3					
	S3	S3	S4	S4	S4					
	S4	S5	S5	S5	S5					
ED	1.091	3.143	3.349	3.240	3.092					
	Five features									
Sensor	1									
	2									
	3									
	4									
	5									
ED	51.895									

where; S1 represents gas sensor TGS2610, S2 represents gas sensor TGS2611,
S3 represents gas sensor TGS2620, S4 represents gas sensor TGS823,
S5 represents gas sensor TGS832.

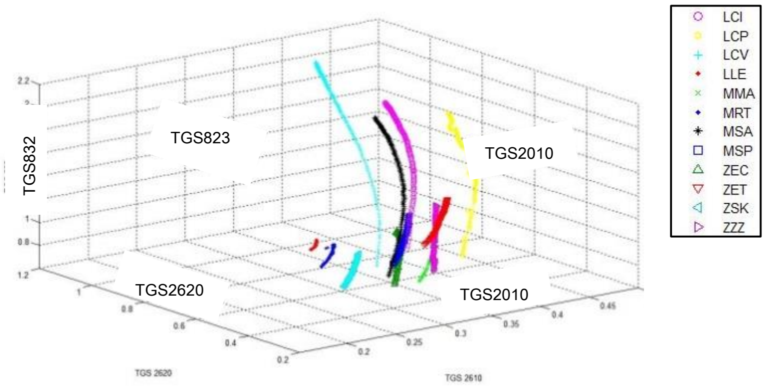
Three combinations of two sensors offered better visualisation for the classification of herb species, namely, TGS2610 vs. TGS832 (Figure 6(a)), TGS2611 vs. TGS832 (Figure 6(b)), and TGS823 vs. TGS832 (Figure 6(c)). Meanwhile, the Euclidean distance results for the two-feature analysis are presented in Table 4.

From the three-dimensional plot, most of the sensor combinations were capable of identifying the herb species with less overlapping compared to the two-dimensional plot for the two-feature analysis. The best visualisation of herb species in the three-dimensional plot can be seen in Fig. 7. The validation for the three-feature analysis by the Euclidean distance shows that TGS2610, TGS823, and TGS832 were the best combination of sensors.

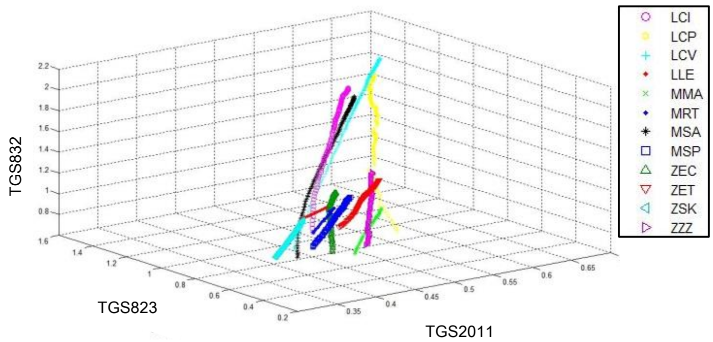
To implement the four-feature and five-feature analysis, the Euclidean distance was calculated. The results are listed in Table 4. TGS2610, TGS2611, TGS823, and TGS832 offered the highest Euclidean distances that implied the best combination of sensors in the four-feature analysis and hence, was selected as the input for the classification process. On the other hand, the Euclidean distance for the five-feature analysis was 51.895, which was the highest distance among the other features. The combination of five gas sensors could have been the best input for the classification process. However, the hypothesis could only be proven in the classification process.



(a) TGS832 vs. TGS823 vs. TGS2610.



(b) TGS832 vs. TGS2620 vs. TGS2610.



(c) TGS832 vs. TGS823 vs. TGS2011.

Fig. 7. Three features analysis.

3.5. Classification

The feature analysis provided the information for the best combination of sensors as the input in the classification process. The classification in this study was implemented using ANN and ANFIS.

3.5.1. Artificial neural network

The classification results using ANN are shown in Table 5. Two to five classification inputs were analysed and the percentage of accuracy is obtained to indicate the performance of the system.

Table 5. Classification results using ANN.

Input	Network	MSE	Accuracy
TGS 2610 **TGS 832**	[2 20 12]	1.948E-2	83.4%
TGS 2610 **TGS 823** **TGS 832**	[3 20 12]	9.769E-3	85.8%
TGS 2610 **TGS 2611** **TGS 823** **TGS 832**	[4 20 12]	8.868E-3	90.2%
TGS 2610 **TGS 2611** **TGS 2620** **TGS 823** **TGS 832**	[5 20 12]	7.554E-3	91.7%

The lowest percentage of 83.4% accuracy was obtained from the two-input structure of ANN. Meanwhile, the five-input structure shows the highest percentage of 91.7% accuracy to classify the herb samples. Next, the ANN network was evaluated by testing the data for five inputs to determine the performance of the system. From the results in Table 6, ANN has yielded 84.2% of accuracy for the classification process.

Table 6. ANN network test.

Dataset	MSE	Accuracy
Training	7.554E-3	91.7%
Testing	2.742E-2	84.2%

3.5.2. Adaptive neuro-fuzzy inference

The highest percentage of classification was obtained by the five-input ANFIS structure at 94.8% of accuracy. The lowest percentage was obtained from the two-input structure at 85.4% of accuracy. The results are shown in Table 7 for the classification using ANFIS. The ANFIS structure was also evaluated using the testing data. The result shows that the percentage of accuracy is slightly lower, as listed in Table 8.

Table 7. Classification results using ANFIS.

Input	RMSE	Accuracy
TGS 2610 **TGS 832**	8.6912E-4	85.4%
TGS 2610 **TGS 823** **TGS 832**	4.301E-4	92.7%
TGS 2610 **TGS 2611** **TGS 823** **TGS 832**	2.713E-4	94.7%
TGS 2610 **TGS 2611** **TGS 2620** **TGS 823** **TGS 832**	2.472E-4	94.8%

Table 8. Comparison of error and accuracy for training set and testing set.

Dataset	RMSE	Accuracy
Training	2.472E-4	94.8%
Testing	3.965E-4	92.7%

4. Conclusions

The artificial olfaction system, which was inspired by the human biological system was improvised using artificial structures for better applications. The approach in this study was to fill in the gaps in agriculture, especially in the herb field. The electronic nose device was successfully developed, consisting of four main components, namely, a blender, an array of metal oxide gas sensors, a data acquisition device, and a graphical user interface. The different odours from the herb species were investigated by capturing the signal responses for twelve samples from three families. To enhance and extract the mined data, the moving average technique was used to pre-process the collected data. One-way ANOVA was applied in the statistical test. Two-to-five feature analysis was conducted and the Euclidean distance was calculated to validate the results from the analysis. Finally, the classification of the twelve herbs was successfully conducted using ANN and ANFIS. The ANFIS technique had performed better, with a slightly higher percentage of accuracy (94.8%) compared to the ANN technique (91.7%). Overall, the results demonstrated that the proposed electronic nose system had succeeded in achieving the objective and can be seen as a considerable improvement in the artificial olfactory system.

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Nomenclatures

d	Euclidean distance
n	Total number of data
p, q	Data matrix of the sensor signal
v_{max}	Maximum voltage
x	Sample data

Greek Symbols

α	Priori alpha level

Abbreviations

AI	Artificial Intelligent
ANFIS	Adaptive Neuro-Fuzzy Inference System
ANN	Artificial Neural Network
ANOVA	Analysis of Variance
EGFR	Epidermal Growth Factor Receptor
E-Nose	Electronic Nose
IBS	Institute of Bioscience
MOS	Metal Oxide Semiconductor
UPM	Universiti Putra Malaysia

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