

DEVELOPMENT OF NEURAL NETWORK-BASED ELECTRONIC NOSE FOR HERBS RECOGNITION

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Abstract- The ability to classify distinctive odor pattern for aromatic plants species provides significant impact in food industry especially for herbs. Each herbs species has a unique physicochemical and a distinctive odors. This project emphasizes on the techniques of artificial intelligence (AI) to distinguish distinctive odor pattern for herbs. Neural Network method has been exploited for the classification and optimization of various odor patterns. Based on AI techniques, Neural Network-based electronic nose system for herbs recognition has been developed. The system consist multi-sensor gas array which detects gas through an increase in electrical conductivity when reducing gases are absorbed on the sensor's surface. The output from individual sensors are collectively assembled and integrated to produce a distinct digital response pattern. A selected sensor array shows its relationship with the aroma of the herbs through the GC-MS test. By using five samples of herbs, the E-nose system has been tested with five different types of sensor. From the results, E-nose system with five sensors has the

highest capability in classifying herbs sample. Accuracy in classifying the correct herbs increases with the number of sensors used. This investigation demonstrates that the neural network-based electronic nose technique promises a successful technique in the ability to classify distinctive odor pattern for aromatic herbs species.

Index terms*:* electronic nose; artificial neural network; array of sensor; classification; recognition

I. INTRODUCTION

Many of the existing plant species on earth are still unknown, which might be at the margins of extinction. Each plant species has unique leaves which differ from each other in characteristics such as the shape, color, texture and the nature of odors. Therefore, it is important to correctly and quickly recognize the plant species in order to understand and managing them. However, it is difficult for a layman to recognize the plant species and currently, Botanist is the expert. The role of a botanist is very important in recognizing and characterizing plant leaf. They have to go to the field for the identification process. Due to the limited number of resources and experts, it is very important to automatically recognize the different kinds of leaves for plant classification based on their very unique characteristics.

Each plant leaf is characterized according to their physical and chemical criteria. Currently, many researchers have investigated the methods of plant species recognition based on physical or texture of leaves [1-7]. Herb is one of the plant species that each has unique odor. Odor from herb is one of the important parameter in identifying the unique criteria for different type of herbs species. This project will focus on the process of identifying herbs from their unique odors extraction by getting the unique electrical signal for each herb. Currently, the research involving herbs species recognition based on the odors is still rare. Previously, botanist uses their skill to identify the herbs species based on the odors of the herbs.

Recently a lot of researchers use chemical gas and liquid to differentiate herbs odor with very complex experiment and need huge budget for appropriate odor equipment [8- 13]. This current practice is very labour-intensive and inefficient. In this project, we proposed the E-nose system which has less complexity to do the experiment. The herbs leaves are crumpled before being tested with E-nose sensor so that the odor will be completely released from the herbs. The signal output from the sensor arrays will send to the developed pattern-recognition algorithm to

recognize and classify the herbs according to their respective group. We intend to prove the hypothesis that artificial olfactory sensing system such as electronic nose (E-nose) can be used to discriminate herbs odor by means of various gas sensors.

An electronic nose system has two steps signal processing and pattern recognition. The e- nose consists of an array of commercial gas sensor. Every sensor has its own concentration, when gas is present it will produce an output signal. The output of sensors is then classified by using neural network method to find the unique pattern of herbs species. The implementation of artificial intelligence (AI) technique for aromatic plants classification is relatively a new research area especially for herbs industry. Therefore the new portable e-nose based on neural network technique for herbs recognition is expected to give confidence and promote industrial herbs internationally. The herbs recognition system must be easily usable by community, which comprises scientists, botanists, forest rangers and engineers from a wide variety of disciplines.

The paper is organized as follows: In section 2 and section 3, the electronic nose (E-nose) technology and the principle of E-nose system are explained briefly. Section 4 discusses in detail the design concept and development of the E-nose system. Section 5 discusses experimental setup and the measurement process. The next section, the data analysis and the results from classification are discussed. The conclusion of this paper is summarized in the last section.

II. ELECTRONIC NOSE (E-NOSE) TECHNOLOGY

Electronic sensing technology is developing field of study that has greatly advanced over the decade. Previously, human nose had been used in many industries to measure the quality of food, drinks, perfumes, cosmetic as well as chemical products. A human nose acts as an analytical tool in the case. However, this sensory panel is subjective and inaccurate. Many factors such as physical, mental health, fatigue and other body conditions might influence the accuracy of human sensory system [14-15]. In order to solve human nose limitations, first attempt on aroma measurements were done in 1920s [16] and found that the addition of volatile substances to water will increase spray-electricity. This spray electricity could be used to detect presence of small amounts of aromatic compounds. Aroma measurement is further developed when two groups published studies and experiments on olfaction devices which are modulation of conductivity and

contact potential which intended to differentiate between aroma bouquets and monitor aromas respectively [17].

After several years of revolution, E-nose is first introduced in year 1982 [18]. It is said to be an intelligent chemical array sensor system for aroma classification. Initial research of E-nose focused primarily on sensor aspect of the problem exploring the use of metal oxide devices and conducting polymers. By that time, the development of computers and electronic sensors made it conceptually possible to obtain an electronic device capable of imitating the mammalian olfactory system.

Revolution continues where E-nose was introduced in 1988 and more and more sensors are developed. E-nose is re-defined as an instrument which comprises an array of electronic chemical sensors with partial specificity and appropriate pattern recognition system, capable of recognizing simple or complex odors [19]. After years of research and development, E-nose has now transformed to a system which provides a cost-effective solution to the human sensing limitations and capable in performing real time identification portable form.

III. PRINCIPLE OF ELECTRONIC NOSE SYSTEM

The mammalian olfactory system is the sensory system used for olfaction, or the sense of smell. The sensitivity and range of the olfactory system is remarkable, enabling organisms to detect and discriminate between thousands of flow molecular mass, mostly organic compounds which is commonly known as odors. Odorant molecules emanating from different sources must be sufficiently volatile to arrive at the olfactory receptors in the nose that causing patterns of brain activity which is essentially the sense of smell [20].

Despite the importance of olfactory systems of odor and flavor, more analytical approach has been developed in response to overcome dispute in comparing different person experience of smell and quantifying of odor. Research into alternative olfactorial sensing methods within an electronic nose as quantitative measurement intended to fill up this desire. The comparison between mammalian olfaction system and E-nose system is shown as in Figure 1.

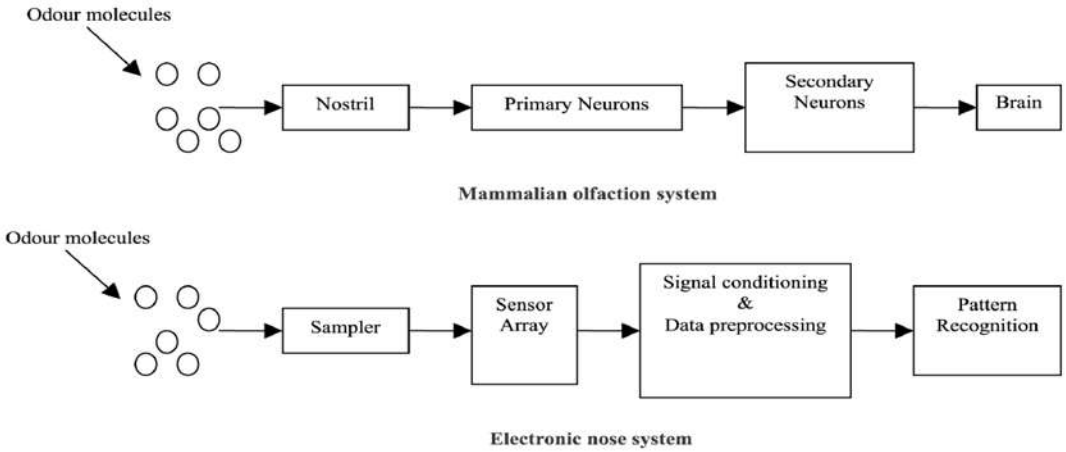


Figure 1. Comparison between mammalian olfaction and E-nose system [14]

Over the last decades, chemical senses captured the attention of scientists who started to investigate the different stages of olfactory pathways [21]. This growing knowledge took over in replication of mammalian olfactory system to develop E-nose system. As a consequence, some of the functions for both systems were resemblance. For instance, sensor array consists of similarities with primary neurons in the human olfaction system and the other similarities are discussed in Table 1.

Table 1: Function of each component in mammalian olfaction system and E-nose system

Mammalian olfaction system	**E-nose system**	**Functions**
Nostril	Sampler	Serves as gas detection chamber
Primary neuron	Sensor array	Sense odor and collect data
Secondary neuron	Signal conditioning & data preprocessing	Analyze and process data
Brain	Pattern recognition	Classify and identify the odor

Block diagram in Figure 2 further illustrates the sensing concept of E-nose. An E-nose is composed of functional blocks such as odor handling and delivery system (input system), sensor array and signal conditioning in detector module, data acquisition system, signal processing, and software with pattern-recognition algorithm and reference-library databases in classification module.

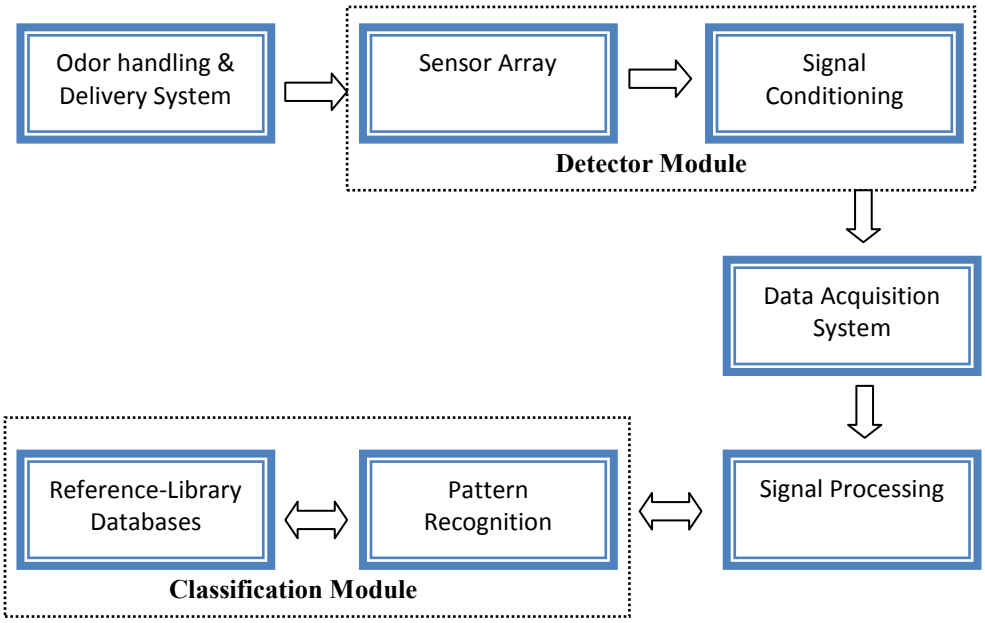


Figure 2. Block diagram of E-nose

E-nose operates when volatile organic compounds samples are placed on the odor and handling mechanism simulating a signal carrying the characteristic of the odor. The sampling technique such as headspace, diffusion methods, bubblers or pre-concentrators are being used to draw the odor molecules into the E-nose [14-15]. Odor sample particles that attracted to the sensor array will go through chemical reactions. Incrementally-different sensors are chosen to make up the cross-reactive sensor array, purposely to act in response to a vast range of chemical classes. The diverse mixtures of possible analyses are then discriminated. At the signal conditioning stage, a distinct digital response pattern is produced, using the assembled and integrated output collected from each individual sensor.

In an E-nose, the pattern recognition and data processing techniques played a very important role in the classification module. At this point, recognition of the unique aroma identity (electronic fingerprint) of collective sensor responses will accomplish the identification and classification of an analyzed mixture. The unique aroma identity pattern represents the characteristic of a simple or complex mixture that can be determined without separating the mixture into its individual components before or throughout the analysis. Preceding the analysis of unknown, digital aroma identity reference library for known samples must be constructed. Training is necessary for the pattern classifier with a database of known samples prior to E-nose commercialization in order to

predict the response for an unknown sample. To complete the system, computer central processing unit (CPU) as interface, recognition library and recognition software as brain and graphic user interface to process input data from the sensor array for succeeding data analysis must be provided. Included in the library are the pattern recognition algorithms that search the differences between all analyses type patterns which are used to configure the ANN through learning process (neural net training. This ongoing process will only stop when a level of discrimination selected earlier is met. Unknown samples then can be compared with the validated and assembled results in the reference library. Identification of unknown can be done by comparing the similarity of the pattern present in the library databases with the aroma attributes distribution or components that the analyses pattern has.

The system is completed by providing an interface using computer central processing unit (CPU), recognition library and recognition software that serve as brain and graphic user interface to process input data from the sensor array for subsequent data analysis.

IV. METHODOLOGY

The proposed electronic nose (E-nose) system is divided into 3 sections. The first is the hardware development. In the hardware development, the detector circuit which consists of the sensors arrays and ADC (signal conditioning) are designed and tested. The second part focuses on the software development to design the pattern-recognition algorithm based on artificial neural network (ANN) using MATLAB software. The ANN is used to classify the types of herbs into their respective groups. The last part is to interface the software and hardware using data acquisition system with the DAQ device. The block diagram of designed E-nose is shown in Figure 3.

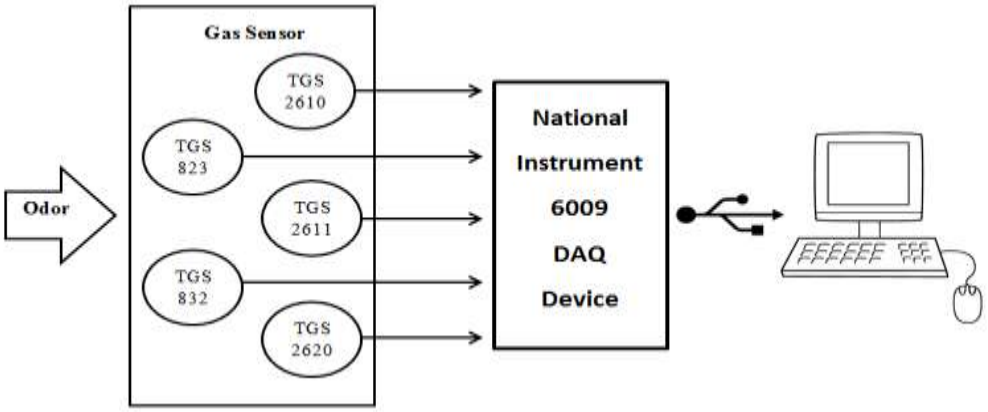


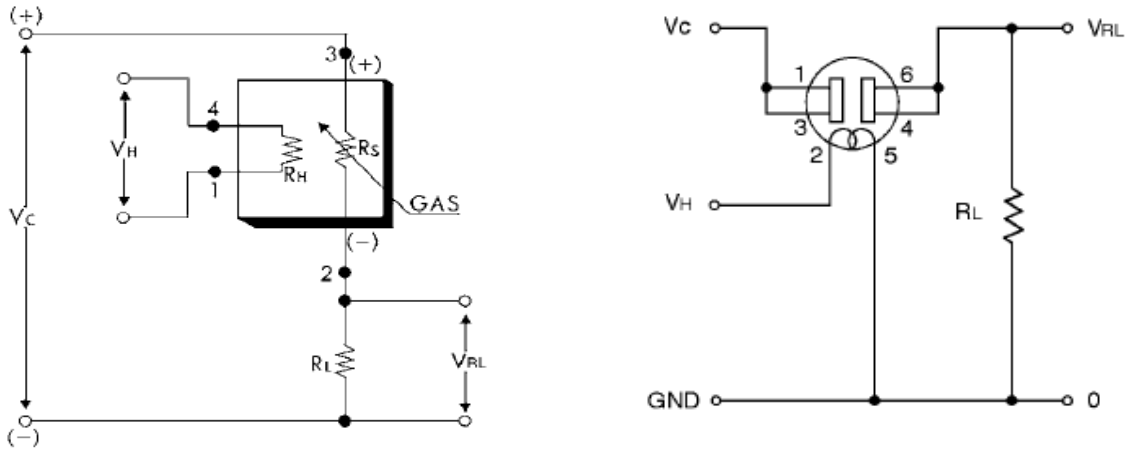
Figure 3. Block diagram of designed E-nose

a. Part 1:Hardware Development

This project started with circuit design of sensors and the simulation is done using Proteus. The designed sensor circuit is being tested on breadboard before it is printed on PCB board.

Metal oxide based gas sensor from Figaro is chosen for this project due to its high sensitivity and simple measuring circuit. There are two types of measuring circuit being used in this project and are shown in Figure 4. Both basic measuring circuits require two different types of voltage sources, one for the circuit voltage (V_C) which is required to power up measuring circuit while the heater voltage (V_H) is used to heat up heater circuit. The sensor is expected to be sensitive to a particular gas present in the air at an elevated temperature. Sensor conductivity increases and measuring circuits convert changes in conductivity to a voltage signal in presence of detectable gas.

After the designed sensor circuit has been tested on breadboard, complete circuits are drawn using ISIS (circuit design software) as in Figure 5. Circuit drawn is then imported to ARES (layout design software) for layout drawing. Afterwards, the drawn layout is fabricated and all components are being soldered to the PCB board as shown in Figure 6. The developed prototype is installed in gas chamber for data collection. Gas sensors will detect odor of the herbs and output voltage from the sensor will be sent to DAQ system. This data are then sent to the computer for classification.



(a) (b)

Figure 4. Basic detector circuits: (a) for TGS 2610, 2611 and 2620 and (b) for TGS 823 and 832

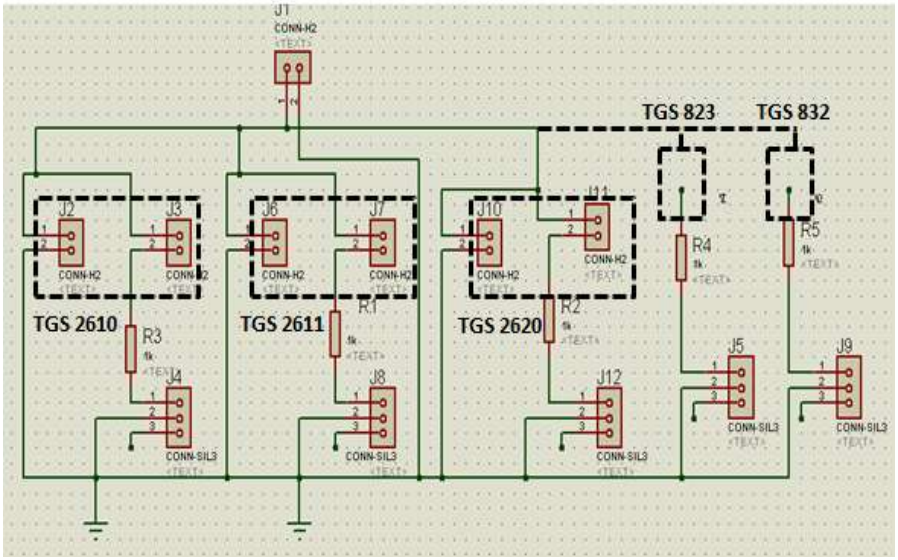


Figure 5. Schematic diagram in Proteus

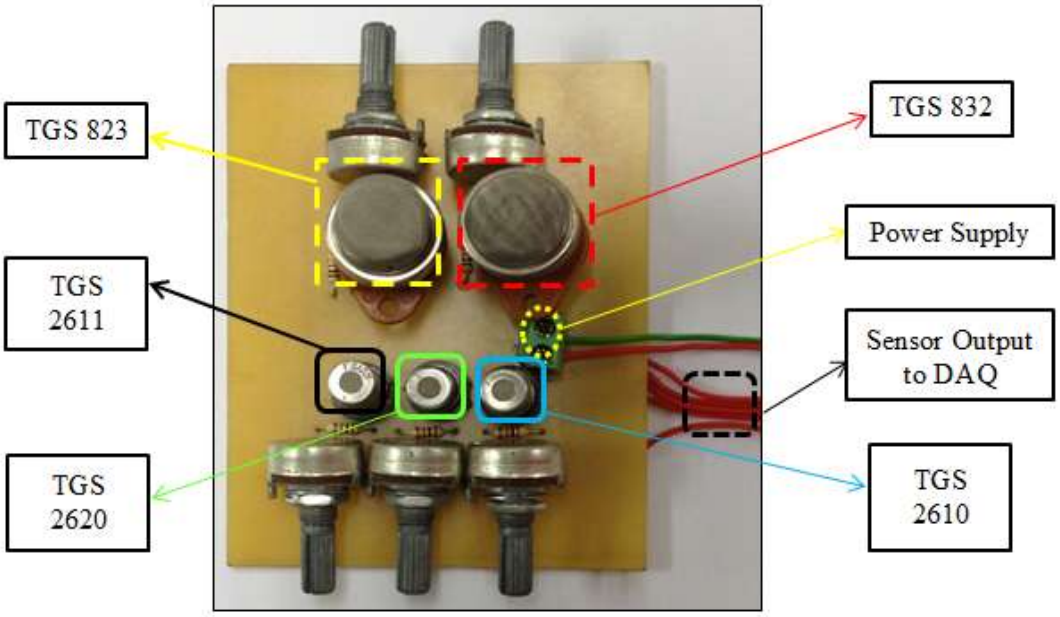


Figure 6. Prototype of detector circuit

b. Part 2: Software Development

In this part, the work is focused on designing the pattern-recognition algorithm based on artificial neural network (ANN) for classification module using MATLAB software.

ANN model is designed to have the [5 2 5] configuration (refer Figure 7) where it has 5 input layer nodes, 2 hidden layer nodes and 5 output layer nodes. Feed-forward back propagation is used as a learning algorithm in this neural network model.

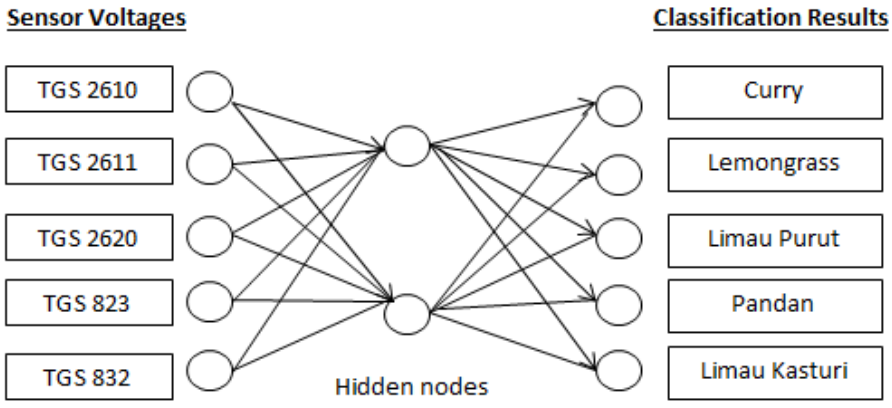


Figure 7. ANN configuration for classification module

A neural network consists of a set of interconnected processing algorithms functioning in parallel. The first layer is called as input layer; the second is hidden layer while the last one will be the output layer. Signals are passed from layer to layer and the values are determined by the transfer function and the weights between two different neurons. Each neuron weight is randomly assigned and is adjusted by the process of learning.

There are two different ways in which training can be implemented: incremental mode and batch mode. In incremental mode, the gradient is computed and the weights are updated after each input is applied to the network. In batch mode, all the inputs in the training set are applied to the network before the weights are updated. This model is using the batch mode training with the *train* command. Tan-Sigmoid neural transfer function (refer Figure 8) is used for three neural layers of the model. Since the output is between the range of [-1 to 1], it is recommended to use the tan-sigmoid for the output layer for proper training.

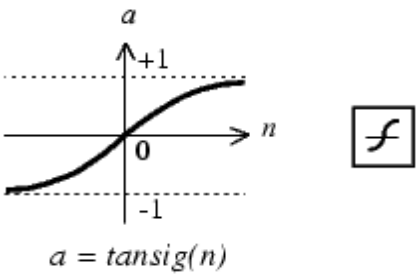


Figure 8: Tan-sigmoid transfer function

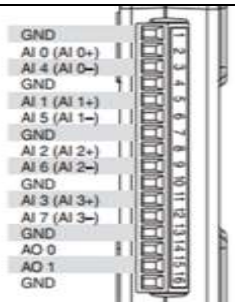
Various instrument-training methods are employed through pattern-recognition algorithms that look for similarities and differences between identification elements of known aroma patterns found in an analyte-specific reference library. The training process requires a discrete amount of known sample data to train the system and is very efficient in comparing unknown samples to known references. The result of ANN data analysis usually is in the form of a percentage match of identification elements in the sample with those of aroma patterns from known sources in the reference library.

c. Part 3: Interfacing between Hardware and Software

Last part is to interface the hardware and software using the DAQ device. This stage is to communicate the software and hardware before measurement and experimental process. The

DAQ NI USB-6009 being used to supports the eight single-ended analogue input (AI) channels, two analogue output (AO) channels, 12 digital input/output (DIO) channels, and a 32-bit counter with a full-speed USB interface. USB cable is connected to establish communication between DAQ and the computer. The DAQ input ports are connected to sensor arrays by using the configuration as in Table 2.

Table 2: List of configuration of components with respect to the port in DAQ 6009

DAQ Ports	Configuration	Sensors	Port Involved
	Analog Input	TGS 823	ai0
		TGS 832	ai1
		TGS 2620	ai2
		TGS 2611	ai3
		TGS 2610	ai4

The Measurement and Automation Explorer is used to check whether DAQ is connected successfully to the computer. If it is connected successfully, the “NI USB-6009 Dev 1” will be shown on left hand side of main panel in Figure 9 under the option of Devices and Interfaces. Now, the hardware is ready to use and can be tested by clicking the “test panel”.

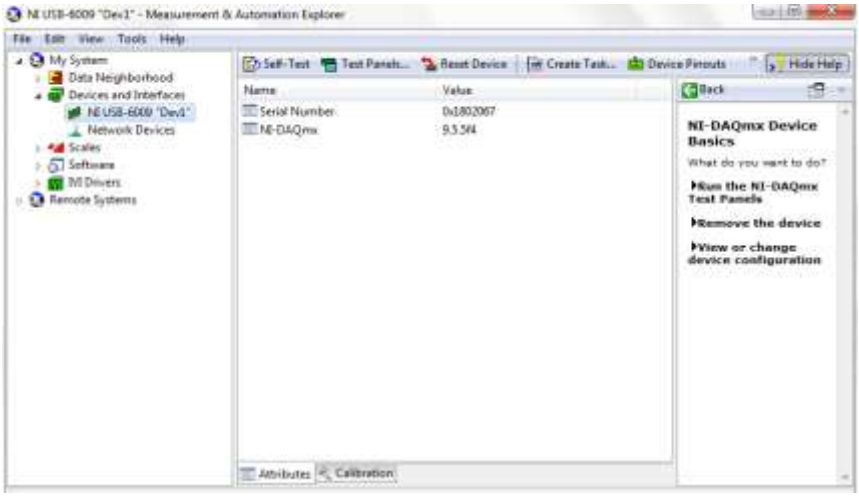
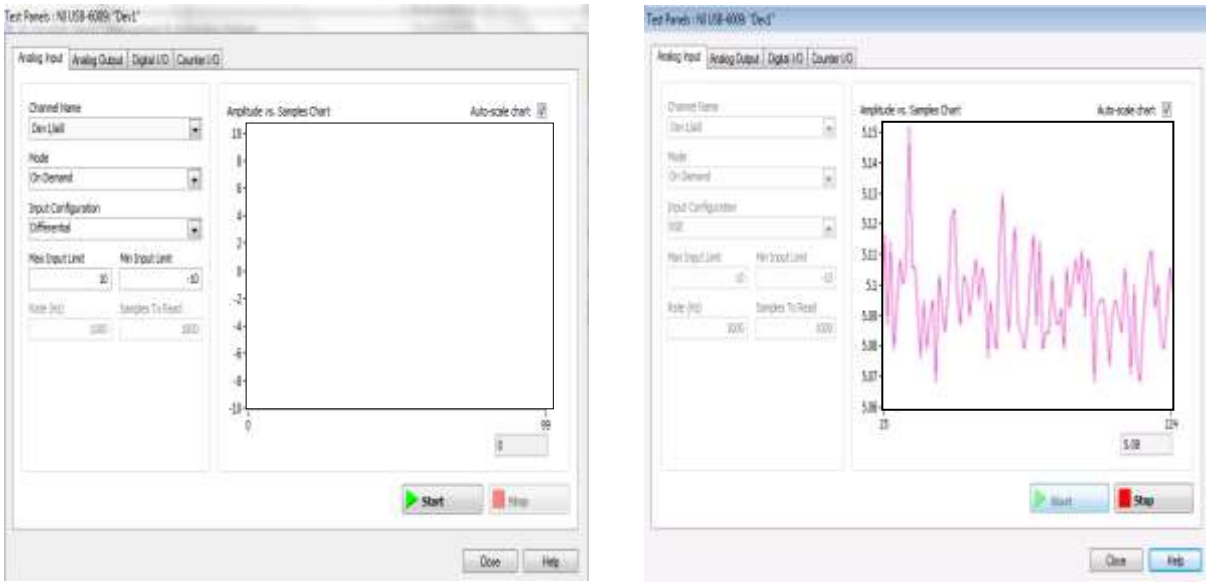


Figure 9. Main panel of the Measurement and Automation Explorer

Once the test panel is opened, it can be observed that there are 4 selectable options to be tested including the analog input, analog output, digital I/O and counter I/O. For this project, only

analog inputs are being used. In order to test the functionability of the port, positive +5 voltage is connected to a port of ai0 and negative is to the ground. +5 V is appeared in waveform chart as in Figure 10. Same procedure is repeated for the other input ports.



(a) Without input (b) With +5V as input

Figure 10. Test panel of NI 6009 with +5V as input

Next, the Matlab software is opened and Simulink is chosen. The analogue inputs is selected from "Data Acquisition Toolbox" and choose the synchronous mode which initiates acquisition at each time step and will not continue until the data are obtained. Single ended input mode is chosen rather than the differential mode as it can support up to 5 analogue inputs while the differential can support 4 channels inputs at a time. The DAQ device is now ready to collect data from the sensor arrays.

V. EXPERIMENTAL AND MEASUREMENT

The developed E-nose system in this project contains an array of commercial gas sensor that detects gas through an increase in electrical conductivity when reducing gases are absorbed on the sensor's surface. It uses five Figaro metal oxide sensors to evaluate five different types of herbs namely Curry *(Murraya Koenigii),* Lemongrass *(Cymbopogen Citrates),* Kaffir Lime/Limau Purut *(Citrus Hystrix),* Pandan Leaves *(Pandanus Amaryllifolius)* and Golden

Lime/Limau Kasturi *(Citrus Microcarpa)*. The leaves are crumpled before being tested with the E-nose sensor so that the odor will be completely released from the herbs for better recognition. The sensor arrays sense the odor and generate data which will be sent to the developed algorithm for further process.

Sample of herbs are measured by using procedures as below:

1) Sample is weighted as 10 grams and is ready to be put into the gas chamber as shown in Figure 11.
2) E-nose system is being preheated for 1 minute before samples are put into the gas chamber. Preheating time of the sensors is set to be 1 minute so that all the sensor voltages are stabilized and stop fluctuating.
3) Samples are crumpled before putting it into measurement chamber. Crumpled leaves emit significant odor for better recognition. The chamber lid is opened and herbs sample are put into the chamber. The net will hold the herbs to avoid direct contact with sensors.
4) Output voltages from each sensor are recorded with 8 time intervals of 10 seconds. Around 3 sets of data are recorded for the same herbs sample and each set of data contains 10 trials. Cooling time for each sensor is around 5 minutes before next set of data is being taken.
5) Steps 1-4 are repeated for four other types of herbs. Environment inside the gas chamber is ensured to have humidity between 55-65% RH and temperature of 27-30°C by conducting the experiment in the same laboratory.

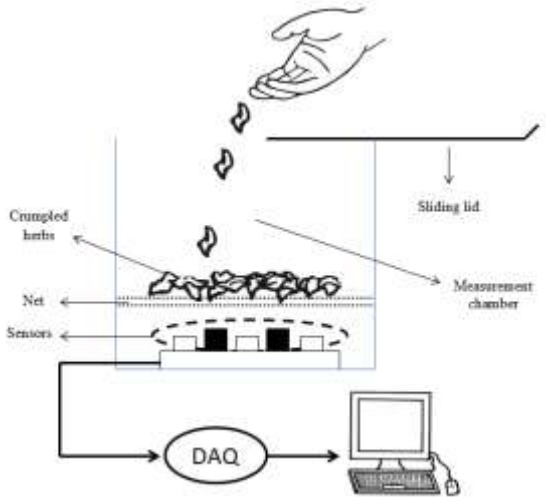


Figure 11. Experimental setup for proposed E-nose

VI. CORRELATION BETWEEN ELECTRONIC NOSE SIGNALS AND CHEMICAL COMPOUND OF HERBS

The Figaro metal oxide sensors are chosen to form sensor arrays of proposed e-nose. The principle of operation of the gas sensor is that when the SnO_2 is heated, oxygen from the air is adsorbed on the crystal surface. Electron is transferred from the SnO_2 to the adsorbed oxygen, leaving the positive charges at the conduction band near surface. Due to this removal of the electron, an insulating region is produced and increases the contact resistance between powder grains .

Surface density of negatively charged oxygen decreases in the presence of a deoxidizing gas, so barrier height in the grain boundary is reduced. The reduced barrier height decreases sensor resistance, thus, an output signal will be formed. Sensor type being used and type of gas detection is shown in Table 3. According to the table, it can be concluded that each sensor being selected is sensitive to ethanol chemical compound which is originated from alcohol family.

Table 3: Sensor type and type of gas that sensor can detect

Sensor Type	Type of gas detection
TGS 2610	Liquefied Petroleum (LP), **Ethanol,** Hydrogen
TGS 2611	Methane, **Ethanol,** Iso-butane
TGS 2620	Carbon Monoxide, **Ethanol,** Hydrogen
TGS 823	Acetone, **Ethanol,** Benzene
TGS 832	Chlorofluorocarbon (CFC), **Ethanol,** Ethane

Next, GC-MS test is performed to evaluate relationship between the Figaro sensors with target herbs. Gas chromatography–mass spectrometry (GC-MS) is a method that combines the features of gas-liquid and mass spectrometry to identify different substances within a test sample. Herbs leaves are extracted into oil form before the test is carried out.

From analysis of GC-MS in Table 4, it shows all the herbs contain compounds with suffix-ol which is used in organic chemistry to represent alcoholic compounds. In common, the word alcohol refers specifically to ethanol which shows some positive relations with gas detected by the sensor arrays. Thus, sensors should be sensitive to target herbs with different sensitivity posed by each sensor.

Table 4: GC-MS analysis on herbs

Herbs	Chemical Compound
Curry *(Murraya Koenigii)*	Pinene <alpha->, **Terpinen-4-ol,** Caryophyllene (E-), Sabinene, Selinene <alpha->
Lemongrass *(Cymbopogen Citrates)*	Myrcene, Neral, Geranial, **Intermedeol<neo->,** Valencene
Kaffir Lime/Limau Purut *(Citrus Hystrix)*	Sabinene, **Linalool,** Citronellal, **Citronellol,** Citronellyl propanoate
Pandan Leaves *(Pandanus Amaryllifolius)*	Sabinene, Tetradecanal, **Menthol<iso->, Isophytol,** Phytol acetate <E->
Golden Lime/Limau Kasturi *(Citrus Microcarpa)*	Pinene <beta-> , Germacrene D, **Hedycaryol,** Eudesmol <gamma->

VII. RESULTS AND DISCUSSIONS

a. Data Analysis

In this section, the average values obtained from each sensor are plotted. The graph is plotted based on the features which represent the output signals from the five sensors. The analyses based on one to five features are done in order to prove that the ability of the E-nose system to classify the herbs increases as the number of sensors increases.

For the analysis in this section, the sensors are represented by sensor 1 to 5 for simplification as in Table 5.

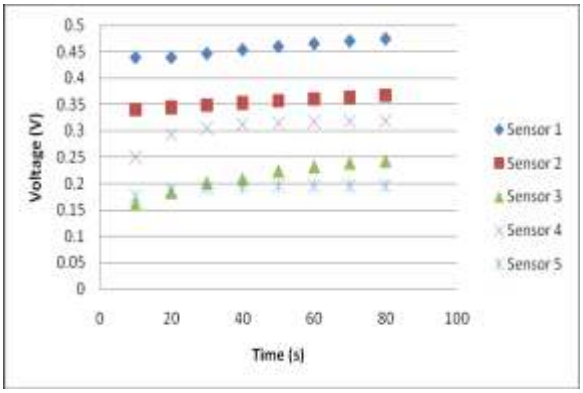
Table 5: Representation of TGS series sensors

Sensors	Synonyms
TGS 2611	Sensor 1
TGS 2610	Sensor 2
TGS 2620	Sensor 3
TGS 823	Sensor 4
TGS 832	Sensor 5

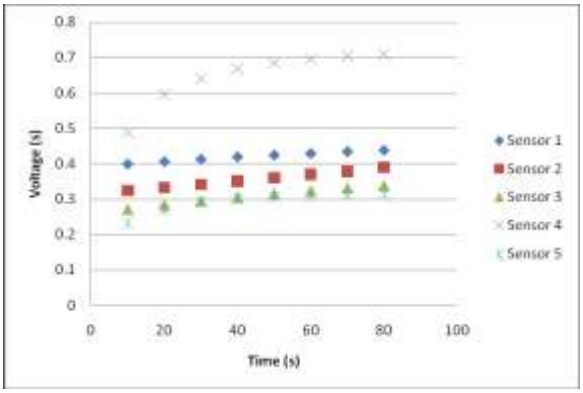
a.1 One-Feature Analysis

From Figure 12, it is concluded that all sensors are unable to show clear classification for each sample group. It is because sensor voltages detected by sensors are overlapping and are very

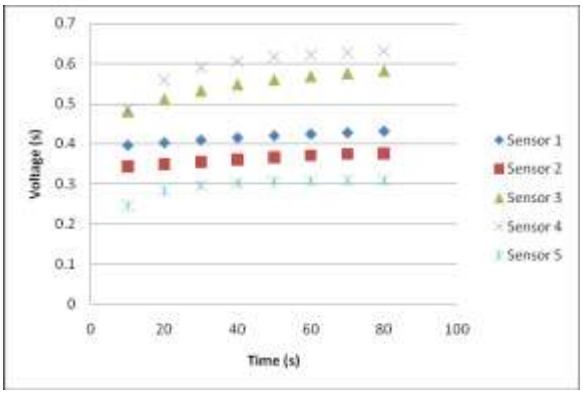
close to each other which are hard for classification. In order to have a better view on overlapping data, two-feature analysis is conducted which the data obtained are then plotted against the sensor voltage for each sample.



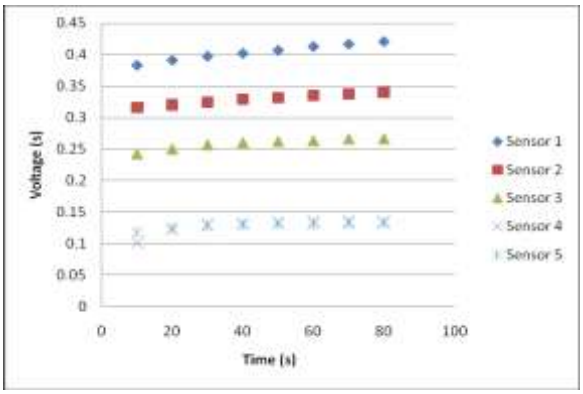
(a) Curry *(Murraya Koenigii)*



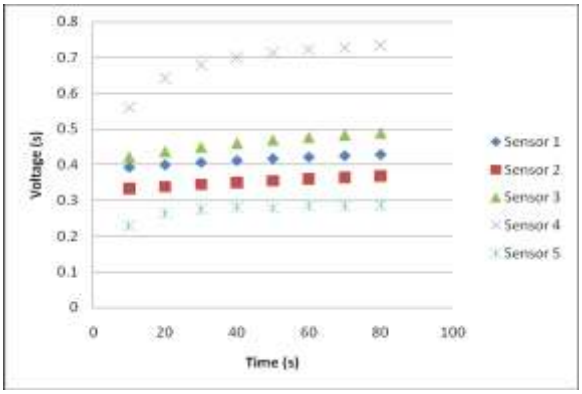
(b) Lemongrass *(Cymbopogen Citrates)*



(b) Kaffir Lime/Limau Purut *(Citrus Hystrix)*



(d) Pandan Leaves*(Pandanus Amaryllifolius)*



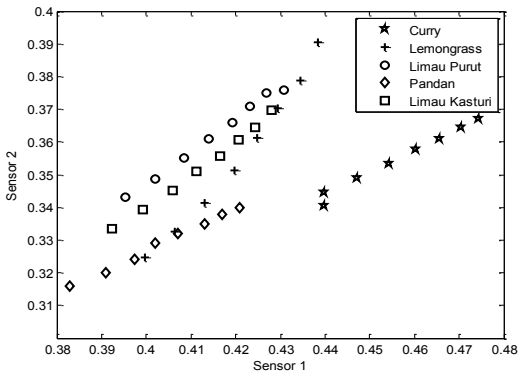
(e) Golden Lime/Limau Kasturi*(Citrus Microcarpa)*

Figure 12. One-feature analysis

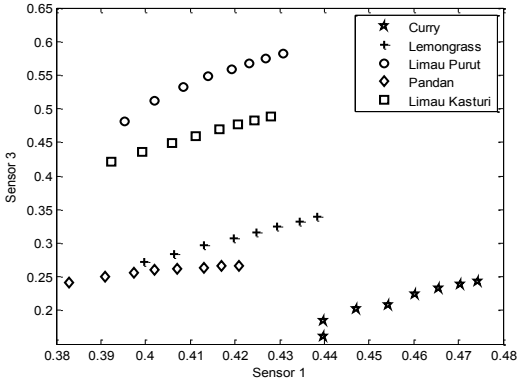
a.2 Two-Feature Analysis

Most of the graphs are able to classify Pandan Leaves *(Pandanus Amaryllifolius)* successfully from others except Figure 13(a), 13(b) and 13(e) which the data are overlapping and is close to the adjacent group. All two-feature graphs are able to classify Curry Leaves *(Murraya Koenigii)*. According to all two-feature graphs, Lemongrass *(Cymbopogen Citrates)* group has higher probabilities in false identification because some points of other groups are too close.

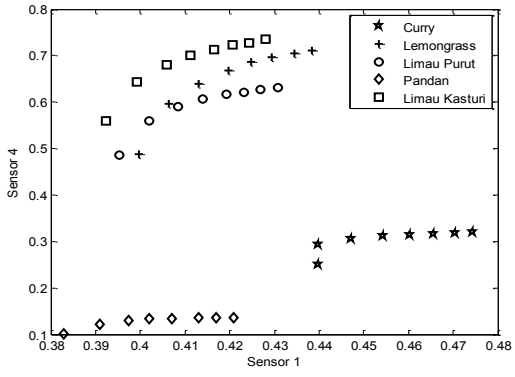
It can be seen that graph for *sensor 3 vs sensor 4* and *sensor 3 vs sensor 5* (refer Figure 13(h) and 13(i)) display a better classification of herbs because all the herbs are being separated nicely and are not close to each other. However, most of the two-feature plots are not successful in classifying the herbs.



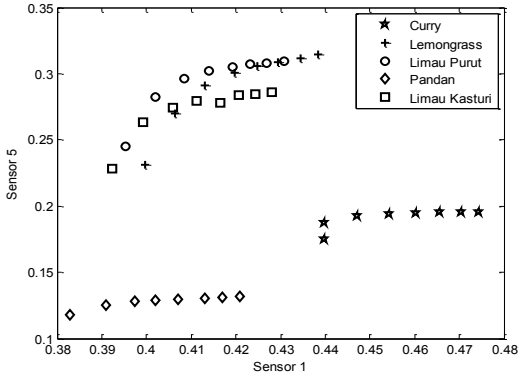
(a) Sensor 1 vs Sensor 2



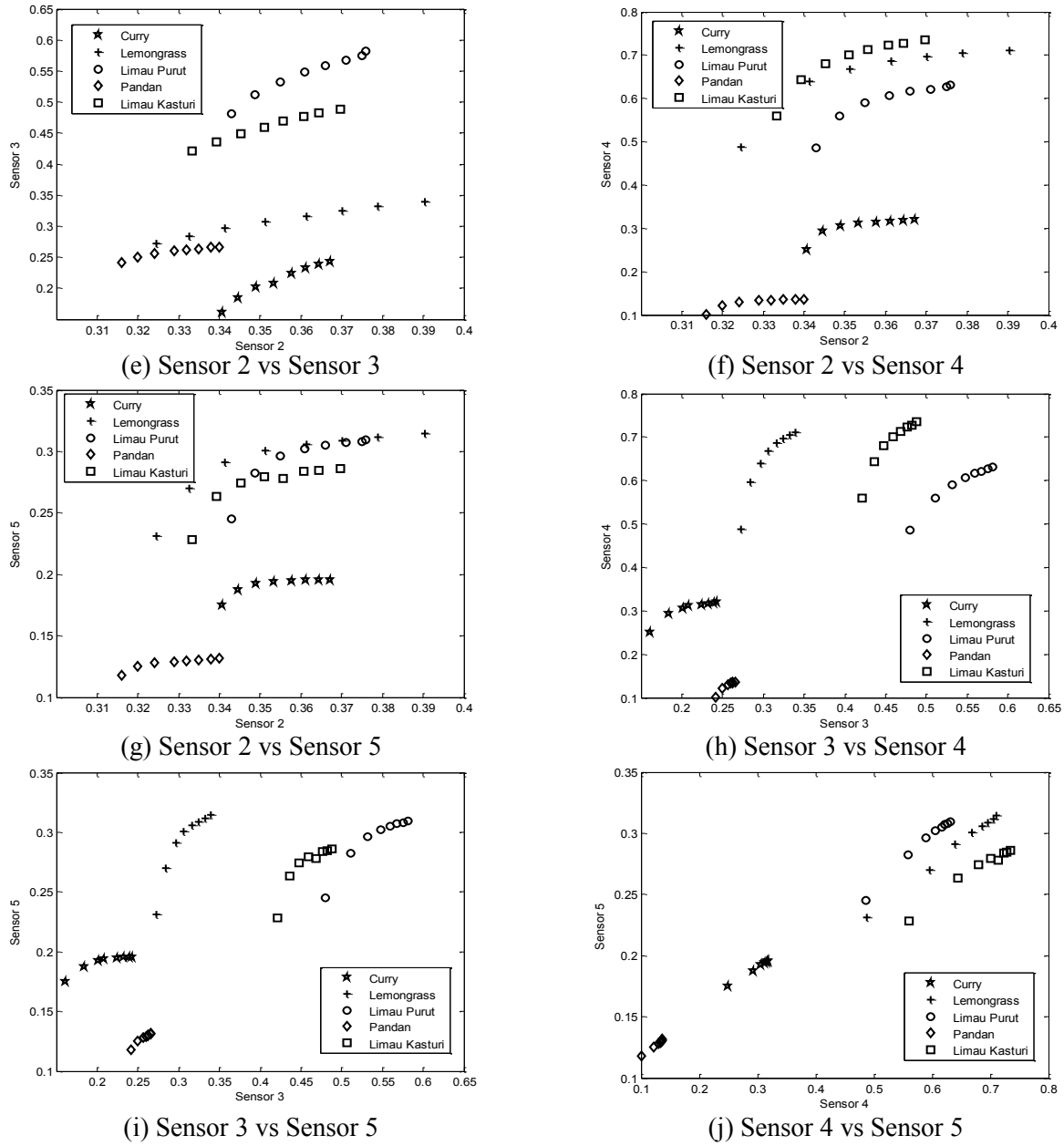
(b) Sensor 1 vs Sensor 3



(c) Sensor 1 vs Sensor 4



(d) Sensor 1 vs Sensor 5



(e) Sensor 2 vs Sensor 3

(f) Sensor 2 vs Sensor 4

(g) Sensor 2 vs Sensor 5

(h) Sensor 3 vs Sensor 4

(i) Sensor 3 vs Sensor 5

(j) Sensor 4 vs Sensor 5

Figure 13. Two-features analysis

a.3 Three-Feature Analysis

There is confusion in classifying the herbs since voltages in Figure 14 are overlapped and close to adjacent herbs. All the herbs in Figure 15 are separated clearly; however, some points of the herbs are not clustered into their own group. Figure 16 gives the best classified graph for the herbs which are clustered and separated from the adjacent herbs. For data analysis in various features, it can be concluded that the ability of sensors to classify herbs increases as the number

of sensors is increased. Next, the data are analysed further by using neural network to evaluate the relationship between the number of sensors and classification accuracy. Graph plotting can only support up to 3 axes, therefore five features analysis is carried out using ANN.

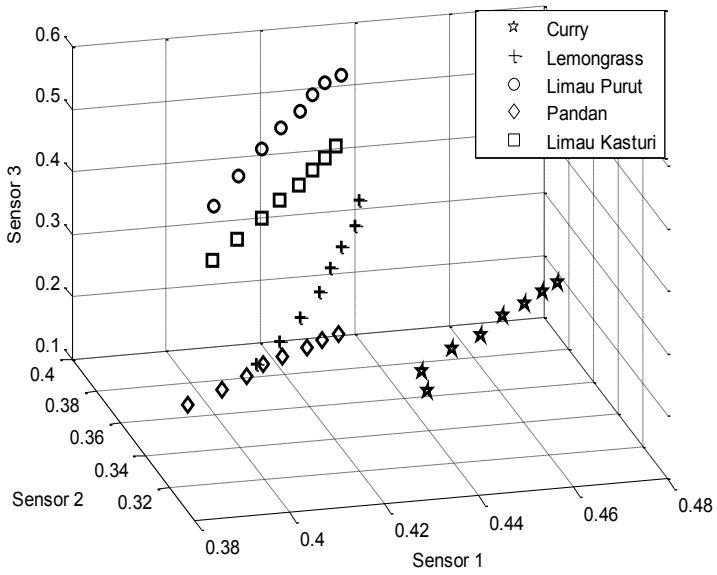


Figure 14. Graph of sensor TGS 2611 (Sensor 1), TGS 2610 (Sensor 2) and TGS 2620(Sensor 3) for five types of herbs samples

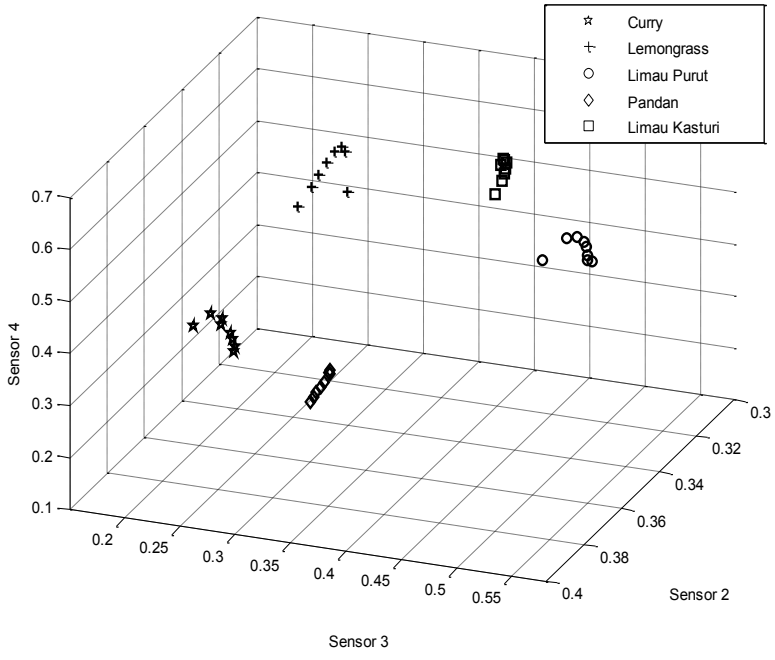


Figure 15. Graph of sensor TGS 2610 (Sensor 2), TGS 2620 (Sensor 3) and TGS 823(Sensor 4) for five types of herbs samples

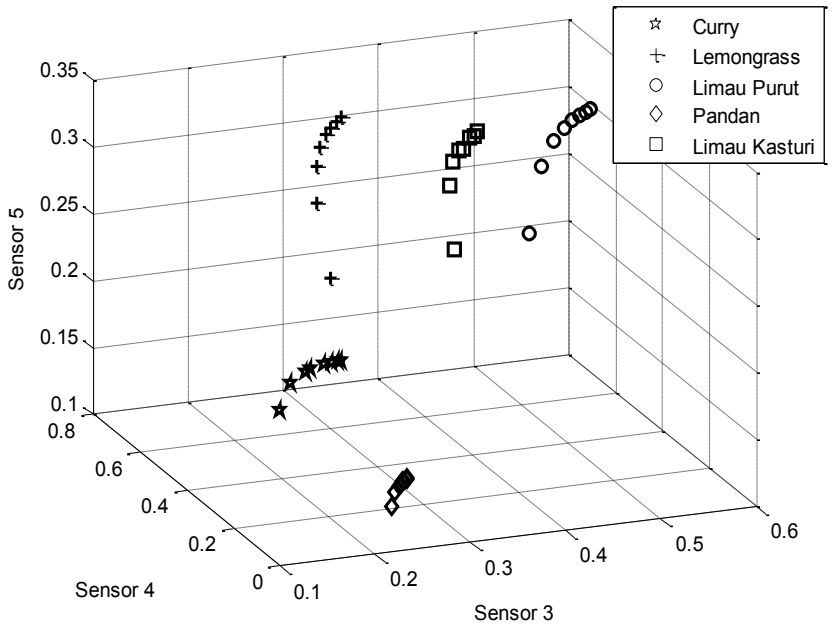


Figure 16. Graph of sensor TGS 2620 (Sensor 3), TGS 823(Sensor 4) and TGS 832(Sensor 5) for five types of herbs samples

b. Herbs Classification

Herbs classification is done by using the artificial neural network which includes training and testing process. Data measured in the previous step are divided into three sets which include training set and two testing set. The training set is used for modeling the recognition system while the tests set are served to evaluate the system performance. Basically, the performance of the system is measured by computing the percentage of correctly recognized patterns on all the input patterns presented to the system. Data analyzed in Table 5 are used as training data for ANN model. Parameters of ANN model are set before training the model. If the model is being trained successfully, testing set will be input into the model and herbs classification will be conducted.

Table 5: Training Data for ANN model

Time/s	TGS 2611	TGS 2610	TGS 2620	TGS 823	TGS 832	Target for ANN Model	Herbals Group
10	0.4398	0.3406	0.16138	0.2498	0.1749	-1	Curry
20	0.4398	0.3445	0.18372	0.293	0.1875	-1	
30	0.4472	0.349	0.2017	0.3056	0.1923	-1	
40	0.4544	0.3533	0.2082	0.3117	0.194	-1	

50	0.4602	0.3577	0.224	0.3148	0.1947	-1	
60	0.4657	0.3611	0.232	0.3168	0.1953	-1	
70	0.4704	0.3644	0.2388	0.3182	0.1954	-1	
80	0.4744	0.3672	0.24306	0.3192	0.1955	-1	
10	0.3996	0.3246	0.27256	0.4874	0.2314	-0.5	Lemongrass
20	0.4064	0.3326	0.28442	0.5957	0.2702	-0.5	
30	0.4131	0.3414	0.2964	0.6403	0.2908	-0.5	
40	0.4197	0.3513	0.30654	0.6684	0.3004	-0.5	
50	0.4248	0.3613	0.31638	0.6857	0.3059	-0.5	
60	0.4294	0.3702	0.3243	0.6964	0.309	-0.5	
70	0.4345	0.3789	0.33218	0.7052	0.3117	-0.5	
80	0.4384	0.3905	0.33938	0.7105	0.3143	-0.5	
10	0.3954	0.343	0.48046	0.486	0.2453	0	Kaffir Lime/ Limau Purut
20	0.4019	0.3488	0.51152	0.5589	0.2825	0	
30	0.4084	0.355	0.53226	0.5892	0.296	0	
40	0.4141	0.361	0.54786	0.6056	0.3018	0	
50	0.4194	0.366	0.55904	0.6166	0.3053	0	
60	0.4233	0.371	0.568	0.6219	0.3072	0	
70	0.427	0.375	0.57524	0.6274	0.3083	0	
80	0.4308	0.376	0.58132	0.6314	0.3091	0	
10	0.3829	0.316	0.242	0.101	0.118	0.5	Pandan
20	0.391	0.32	0.25	0.122	0.125	0.5	
30	0.3974	0.3241	0.2566	0.13	0.128	0.5	
40	0.402	0.329	0.26	0.133	0.1287	0.5	
50	0.407	0.332	0.262	0.1347	0.1297	0.5	
60	0.413	0.335	0.2628	0.1359	0.1306	0.5	
70	0.417	0.338	0.2658	0.136	0.1314	0.5	
80	0.421	0.34	0.2662	0.136	0.1319	0.5	
10	0.3924	0.3334	0.42108	0.56	0.2286	1	Golden Lime/Limau Kasturi
20	0.3993	0.3394	0.4362	0.6436	0.2636	1	
30	0.4059	0.3453	0.44826	0.68	0.2745	1	
40	0.4113	0.351	0.4596	0.701	0.2796	1	
50	0.4166	0.3556	0.469	0.714	0.2783	1	
60	0.4206	0.3606	0.47662	0.7234	0.2841	1	
70	0.4244	0.3645	0.48272	0.7283	0.2846	1	
80	0.428	0.3696	0.48844	0.7351	0.2858	1	

From Table 6, designed E-nose yields an average accuracy of 66 % by using two sensors while the accuracy increases to 85% when 3 sensors are used. 90 % accuracy is achieved when 5 sensors are being used. Similar trend goes to the comparison between training set and test set 2 as

in Table 7. It shows an accuracy of 66 % and 85 % respectively when using 2 and 3 sensors. When using 5 sensors, the system hits an accuracy of 87.5 %.

Summarizing these two tables, five features analysis shows the highest accuracy as compared to the others. Conclusion can be made that five sensors have the highest capability in classifying herbs sample. Accuracy in classifying the correct herbs increases with number of the sensors used. Results in Table 6 and 7 indicate a success of using ANN in classifying the herbs.

Table 6: Comparison between the training set and test set 1

Sensors	**Five-Features**	**Three-Features**	**Two-Features**		
	All	**2, 3 and 4**	**2 and 3**	**2 and 4**	**3 and 4**
Curry	8/8	7/8	6/8	7/8	7/8
Lemongrass	8/8	6/8	3/8	7/8	4/8
Kaffir Lime/ Limau Purut	6/8	7/8	4/8	3/8	6/8
Pandan	6/8	7/8	5/8	4/8	8/8
Golden Lime/ Limau Kasturi	8/8	7/8	7/8	4/8	4/8
Total	**36/40**	**34/40**	**25/40**	**25/40**	**29/40**
Accuracy	**90 %**	**85%**	**62.5%**	**62.5%**	**72.5%**

Table 7: Comparison between the training set and test set 2

Sensors	**Five-Features**	**Three-Features**	**Two-Features**		
	All	**2, 3 and 4**	**2 and 3**	**2 and 4**	**3 and 4**
Curry	7/8	7/8	6/8	7/8	7/8
Lemongrass	8/8	6/8	3/8	7/8	4/8
Kaffir Lime/ Limau Purut	6/8	7/8	4/8	3/8	6/8
Pandan	6/8	7/8	5/8	4/8	8/8
Golden Lime/ Limau Kasturi	8/8	7/8	7/8	4/8	4/8
Total	35/40	34/40	25/40	25/40	29/40
Accuracy	87.5 %	85%	62.5%	62.5%	72.5%

V. CONCLUSIONS

In this project, our objective is to develop the E-nose system with enhanced classification module based on ANN techniques for herbs recognition. The proposed E-nose has been designed to have

a simple system, thus the botanist can handle the system easily without having to do the complex experiment as compared to the current E-nose system.

The proposed E-nose system is built using five Figaro metal oxide sensors purposely to evaluate five different types of herbs which includes Curry *(Murraya Koenigii),* Lemongrass *(Cymbopogen Citrates),* Kaffir Lime/Limau Purut *(Citrus Hystrix),* Pandan Leaves*(Pandanus Amaryllifolius)* and Golden Lime/Limau Kasturi *(Citrus Microcarpa)*. Selected sensors array shows its relationship with the odor of the herbs through the GC-MS test and proves the reason why there are voltage changes when the herbs are present.

In this study, the data signal from the sensors array are plot according to one-feature analysis, two-feature analysis and three-feature analysis. The purpose of these analyses is to observe the capability of the E-nose to achieve the highest accuracy using various number of sensors to classify the types of herbs based on the odor. Also, we can check whether all the sensors are suitable to be used in this E-nose system. In this project, we use the types of herbs from different family. So, the aroma from the herbs are quite different. So, in our case it is easy to classify only using this feature. From the graphs, we can observe that the herbs are already classified according to the group. For confirmation, the data signal obtained from sensors array are sent to classification using ANN techniques. The ANN can successfully classify the herbs. Results also show that the developed E-nose system with five sensors has the highest capability in classifying herbs sample. As a conclusion, the performance of E-nose in classifying the correct herbs increases with the number of sensors used.

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