Odour Distinction Using Sensor Arrays

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Abstract: Electronic-nose devices have received considerable attention in the field of sensor technology during the past 30 years, largely due to the discovery of numerous applications derived from research in diverse fields of applied sciences. Recent applications of electronic nose technologies have come through advances in sensor design, material improvements, software innovations and progress in embedded systems integration. In this study, we have developed a prototype of a portable electronic nose (E-Nose) comprising a sensor arrays of many commercially available sensors, a data acquisition interface and a microprocessor. A based on different detection principles and mechanisms, is closely correlated with the expansion of new applications. Electronic noses have provided a plethora of benefits to a variety of commercial industries, including the agricultural, biomedical, cosmetics, environmental, food, manufacturing, military, pharmaceutical, regulatory, and various scientific research fields. Experimental results indicate that the proposed system prototype is able to identify the fragrance of many fruits, namely lemon, banana, litchi and etc.

Keywords: portable electronic nose system; sensor array; E-Nose; fruity odor detection

I. Introduction

The sensor technology of artificial olfaction had its beginnings with the invention of the first gas multi-sensor array in 1982. Advances in aroma-sensor technology, electronics, biochemistry and artificial intelligence made it possible to develop devices capable of measuring and characterizing volatile aromas released from a multitude of sources for numerous applications. These devices, known as electronic noses, were engineered to mimic the mammalian olfactory system within an instrument designed to obtain repeatable measurements, allowing identifications and classifications of aroma mixtures while eliminating operator fatigue. Unlike other analytical instruments, these devices allow the identification of mixtures of organic samples as a whole (identifiable to a source that released the mixture) without having to identify individual chemical species within the sample mixture. Hundreds of different prototypes of artificial-nose devices have been developed to discriminate complex vapor mixtures containing many different types of volatile organic compound (VOCs). These prototypes collectively represent various electronic aroma

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detection (EAD) technologies that utilize different sensor types including metal-oxide semiconductive polymers conductive electroactive polymers, optical, surface acoustic wave and electrochemical gas sensors.

An electronic nose system typically consists of a multisensory array, an information-processing unit such as an artificial neural network (ANN), software with digital pattern-recognition algorithms, and reference-library databases the cross-reactive sensor array is composed of incrementally-different sensors chosen to respond to a wide range of chemical classes and discriminate diverse mixtures of possible analytes. The output from individual sensors are collectively assembled and integrated to produce a distinct digital response pattern. Identification and classification of an analyte mixture is accomplished through recognition of this unique aroma signature (electronic fingerprint) of collective sensor responses. The identity of a simple or complex mixture represented by a unique aroma signature pattern may be determined without having to separate the mixture into its individual components prior to or during analysis. A reference library of digital aroma signature patterns for known samples is constructed prior to analysis of unknowns. The ANN is configured through a learning process (neural net training) using pattern recognition algorithms that look for differences between the patterns of all analyte types included in the reference library. This process continues until a previously selected level of discrimination is met. The results are validated and assembled into the reference library to which unknown samples can be compared. Identification of unknowns is based on the distribution of aroma attributes or elements that the analyte pattern has in common with patterns present in databases of the reference library.

Applications are continuously being developed in many new areas of applied research such as for volatile emissions assessments, homeland security, environmental protection, biomedical diagnoses, personnel safety, and in product development research. This paper summarizes some theoretical aspects of electronic-nose technologies by describing and comparing some of the basic types of e-nose technologies that have been developed Applications are continuously being developed in many new areas of applied research such as for volatile emissions assessments, homeland security, environmental protection, biomedical diagnoses, personnel safety, and in product development research. This paper summarizes some theoretical aspects of electronic-nose technologies by describing and comparing some of the basic types of e-nose technologies that have been developed, shown in figure.1

Fig. 1: Smell testing through natural sense.

II. The Proposed E-Nose System

Figure 2 shows a block diagram of the proposed E-Nose system, comprising a sensor array, an interface a Microcontroller MSP430F5438 board embedded with a pattern recognition algorithm, as well as a verification program. Sensor responses pass through a data acquisition card (DAQ) to a laptop with a self-developed Matlab program for the purpose of verifying the function of the portable E-Nose system.

One approach to developing a chemical sensing system is to mimic mammalian olfaction. Over 1,000 different receptor genes have been identified in the olfactory system of mammals. Learning from the mammalian system, an array of different sensors is used for odor identification, with each sensor designated to respond to a number of different chemicals. In such an array, no individual sensor responds solely to a specific odor. Rather, the collective response of the entire array produces a unique pattern for the odor of interest. Ideally, to respond to the largest cross-section of analytes, the elements of the sensor array have to possess as much chemical diversity as possible. Within the range of this diversity, the sensor array produces a distinct pattern, taken as an odor signature (odor fingerprint), that can be utilized for odor classification and identification.

This operational principle has the advantage of being able to identify and classify a complex mixture of odors, such as those of fruits, over a one-to-one sensing mode (each sensor responds to a specific odor). In practical applications, odors of interest are usually complex mixtures, rather than pure gases. The fragrance of a fruit, for example, is a complex combination of dozens of individual scents. This complexity makes it almost impossible to find sensors corresponding to every individual component of gas mixture. For instance, banana aroma comprises several ester groups, and litchi contains higher amounts of monoterpene hydrocarbons in its scent. The odor thresholds of the human nose to these gaseous constituents generally fall in the range of ppb. However, a number of researchers have shown that an electronic nose could classify fruit very nearly as well as a panel of tasters. In this manner, an E-Nose could be useful for the classification of the odor of fruits.

Three sets of identical sensors were incorporated (TGS822, TGS825, and TGS826) in the sensor array for the following reasons shown in table 1:

1. To increase the effectiveness of the sensor: For example, if TGS822 responds to a specific odor, two responses could be recorded, due to the presence of two of the same kind of sensors.
2. To investigate the behavior of identical sensors: Sensors of the same kind may not necessarily behave in exactly the same way. This behavior was investigated during the experiment.
3. In the future, algorithms will be incorporated to average the signals among identical sensors to tune out background noise and interference from temperature or humidity.

Sensor number	Sensor Type	Target gas (according to datasheet)
1	TGS2620	Alcohol, Solvent vapors
2	TGS826	Ammonia
2	TGS822	Alcohol, Solvent vapors
2	TGS825	Hydrogen sulfide
1	TGS2602	General air contaminants

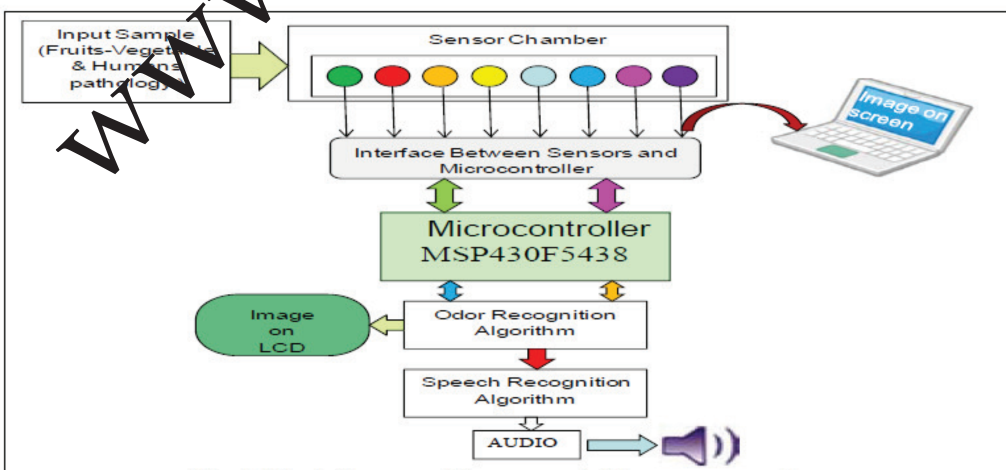

Fig. 2: Block diagram of the proposed chip on a nose system.

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III. Interface Between Sensors and Microcontroller

Because the array consists of eight sensors, the interface PCB includes eight interface processing circuits (IPC), an eight to one multiplexer (MUX), and an 8-bit analog-to digital converter (ADC). The eight interface processing circuits are connected to the eight sensors, which actively adapt the circuit to a preset baseline voltage. The multiplexer reduces the need for multiple ADCs by scanning the eight channels and choosing one channel at a time. The ADC converts sensor data into a digital form for data processing. Figure 3 shows a block diagram of the interface PCB. Figure 4 shows the basic architecture of the interface processing circuit (IPC), which operates in one of the two following modes Fig. 2: Block diagram of the proposed chip on a nose system.

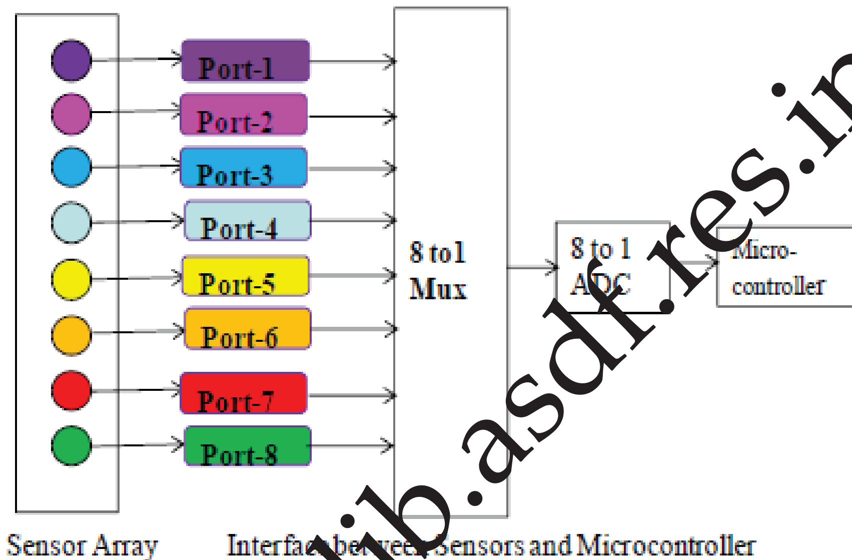

Fig. 3: Block diagram of the interface PCB;

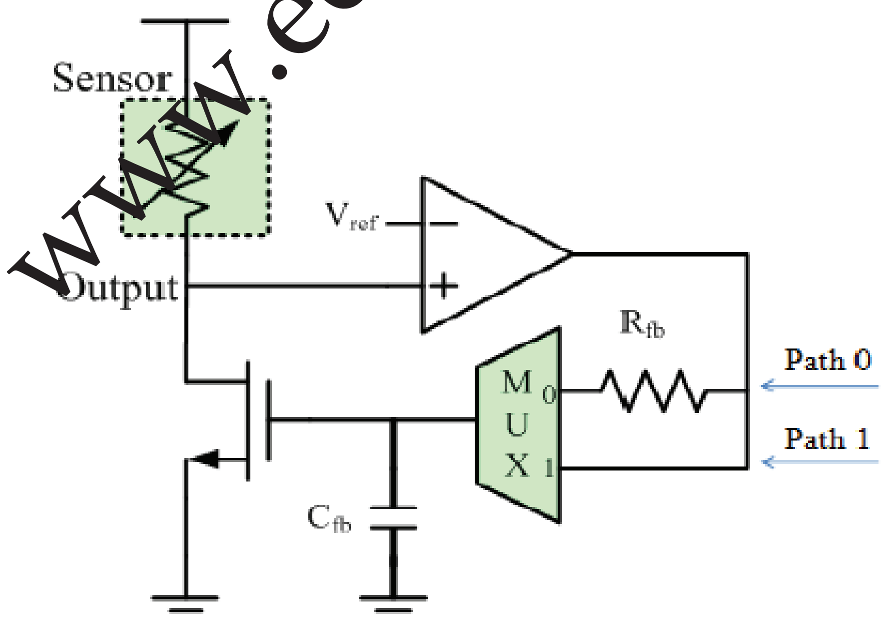

Fig.4: Basic architecture of the IPC.

(1) Adaptation mode: in this mode, the circuit adjusts its operating point to a preset baseline voltage. The multiplexer chooses path "1" in Figure 4, to equalize the output voltage with the reference voltage Vref, which is set as the baseline value prior to sensing odors. In this mode, the NMOS transistor operates as a variable current source. At the end of the adaptation mode, the circuit enters the sensing mode, the gate voltage of the transistor becomes stable, and the transistor operates as a constant current source. After completing the adaptation mode, the E-Nose system is ready to accept input gas.

(2) Sensing mode: in this mode, the circuit is ready for sensing. The multiplexer chooses path "0" in Figure 4, to form a negative feedback loop, which establishes the gate voltage of the NMOS. Due to a large time constant RfbCfb, the gate voltage of the NMOS can be maintained a long enough time, comparing with the sensor response time. As a result, the IPC responds to the sensor while tuning out background signals; which is similar to the process performed by biological noses. In this mode, variations in the sensor resistance are translated to a change in output voltage, which is fed into an ADC through an eight to one MUX, whereupon, the ADC output is send to the 8051 microprocessor.

III. Electronic-Nose Applications

Electronic-nose systems have been designed specifically to be used for numerous applications in many different industrial production processes. A wide variety of industries based on specific product types and categories, such as the automobile, food, packaging, cosmetic, drug, analytical chemistry and biomedical industries utilize e-noses for a broad and diverse range of applications including quality control of raw and manufactured products, process design, freshness and maturity (ripeness) monitoring, shelf-life investigations, authenticity assessments of premium products, classification of scents and perfumes, microbial pathogen detection and environmental assessment studies. Some individual examples of electronic nose applications in each of these individual industries and product areas are discussed in more detail in the following sections.

1. Food Freshness, Quality, Ripeness and Shelf-Life
2. Milk and Dairy Products
3. Meat Products
4. Medical Pathology
5. Plant Identifications
6. Chemistry and Chemical Detection

IV. Experimental Results and Discussion

Running parallel to the 8051 microprocessor, sensor data enters a laptop computer through a National Instrument data acquisition card (interface card: NI DAQ 6009), with a Matlab program developed for this study, to characterize sensor and odor data and verify possible classification algorithms. Three data processing interfaces were developed to operate the E-Nose system. These include a data acquisition interface, a training interface, and a classification interface. Figure 5 shows a screenshot of the operating window of the program.

The data acquisition interface records changes in sensor resistance, and plots the change ratio of sensor resistance $\Delta R/R$ (ΔR = Rsense – Rb) in real-time. The recorded data builds pattern recognition models for performing classification in the other two interfaces. The training interface uses data stored by the data acquisition interface, to build a classification model, which is used to recognize odors in the classification interface. A radar plot of the odor is shown by the interface for the user to observe.

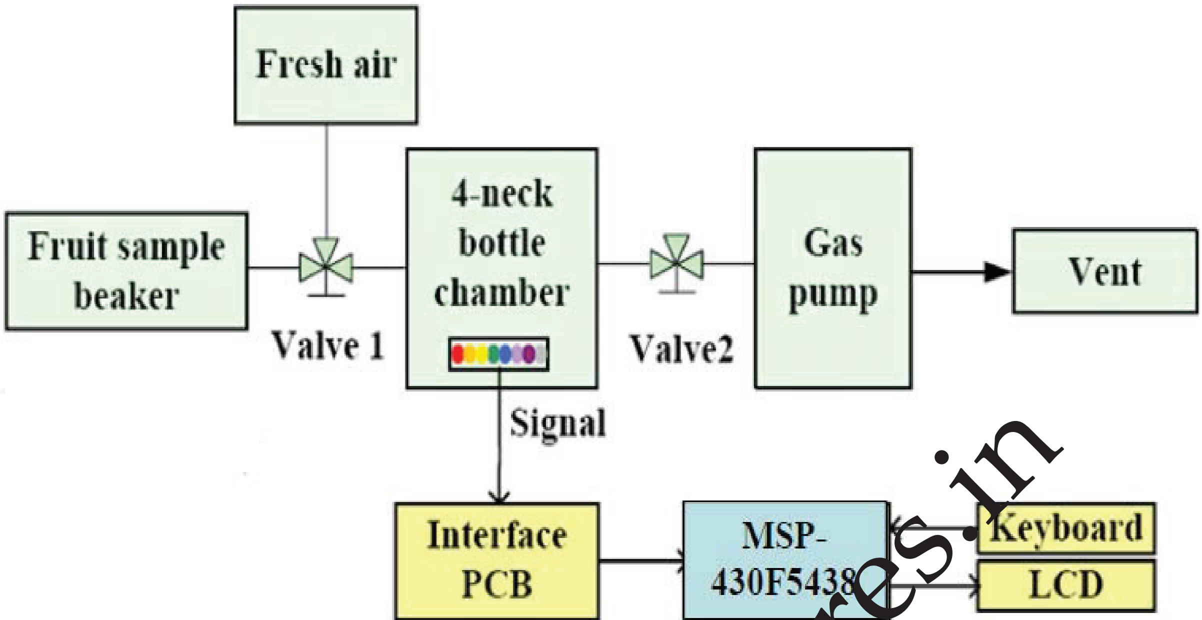

Fig. 5: The gas testing setup for the proposed E-Nose system.

Users can read and classify odors through the classification interface, which implements six different algorithms, including nearest neighbor (NN), K-nearest neighbor (KNN), and principle component analysis with nearest neighbor (PNN), principle component analysis with K-nearest neighbor (PKNN). Performing six different algorithms simultaneously enables the user to investigate and compare the efficiency and accuracy among each of the algorithms. The classification results, the "smell print", and PCA plots are also shown on the interface.

A. Experiment with the Odors of Three Fruits (Banana, Lemon, and Litchi).

Three fruits (banana, lemon and litchi) were used to test the proposed E-Nose system. The data regarding the fruit odors was collected over a five-day span. On the first day, five different samples of each fruit were collected. The average response of the five samples was used as the odor signature for that fruit. Figure 6 shows the resulting patterns for testing the odor of the fruit samples. The magnitude of each axis indicates the resistance change ratio ($\Delta R/R$) in each sensor when reaching equilibrium. A unique odor fingerprint of each of the three odors is shown in the figure. This is an indication of the potential to use non-specific sensor arrays to construct an odor database.

Between the second day and the fifth day, two series of experiments were conducted. In the morning, the fruit samples were purchased for that day (current day), and five different samples of each fruit were collected. In the afternoon, the fruit samples purchased on the first day were used, and five different samples of each fruit were collected. For the duration of the experiment, the temperature was 24– 28 ºC, the humidity was 59–78%, and the fruit samples weighed 8–15 grams. Table 2 is a summary of classification results for the 4 algorithms used in the verification software.

The result is shown as a fraction, whose denominator is the total number of samples, and the numerator is the number of samples correctly classified by the algorithm. For lemon and litchi, the totals number of the current day samples was 19 and 18, respectively, due to data collection problem causing the sensors to not respond. Otherwise, the total number of samples would have been 20. In real applications, it may not be known which day the fruit is purchased, thus current day data and first day data were summed to provide the values in Table 3.

Name of Fruit		NN	PNN	KNN (K=3)	PKNN (K=3)
Litchi	Current day	17/18	16/18	18/19	16/19
	First day	20/20	19/20	20/20	18/20
Banana	Current day	18/20	19/20	18/20	18/20
	First day	17/19	16/20	18/19	18/19
Lemon	Current day	15/20	15/20	15/20	15/20
	First day	20/20	18/20	20/20	18/20

Table 2: Summarized fruity odor classification result for the four algorithms.

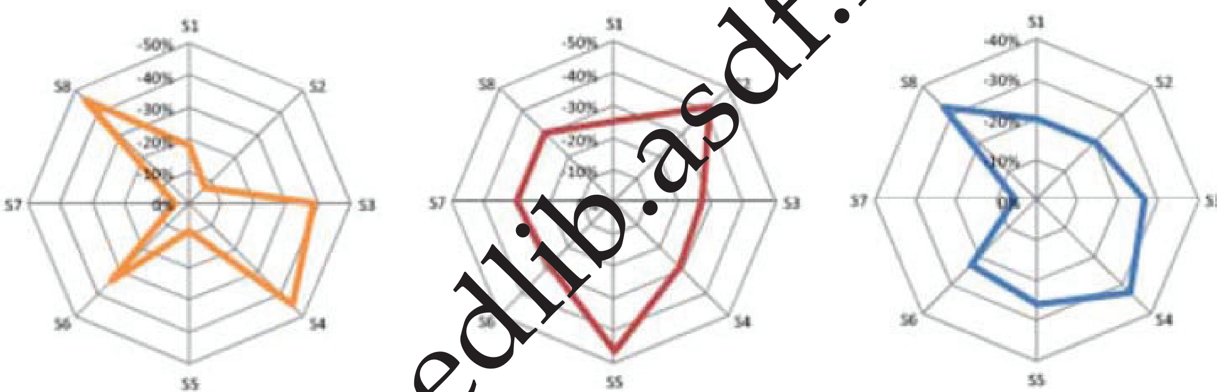

Fig. (a) **Litchi**

Fig. (b) **Lemon**

Fig. (c) **Banana**

Figure 6: Fruit pattern of (a) Litch, (b) lemon, and (c) Banana.

Name of Fruit	NN	PNN	KNN (K=3)	PKNN (K=3)
Litchi	37/39	33/39	37/39	35/39
Banana	39/41	39/41	39/41	38/41
Lemon	38/40	36/40	38/40	36/40
Total	114/120	108/120	114/120	109/120
Accuracy	95%	90%	95%	90.84%

Table 3: Total Classification Result for The Three Fruity Odors.

Figure 7 shows a three-dimensional projection of the PCA results of all data points regarding the odor of the fruit. From our experimental results, several inferences can be made:

(1) The figure shows good recognition boundaries for the three fruit odors, and a high classification accuracy percentage was therefore expected.
(2) A number of data points from the three classes were mixed; therefore, a certain degree of misclassification was expected.
(3) Both the proposed portable E-Nose system (implemented with KNN) and the laptop verification software achieved an accuracy of 96.6% when identifying these three fruit odors.
(4) The odor patterns of different fruits were distinguishable, enabling the possibility of recognizing the odor of fruit.
(5) Although commercial gas sensors have specific target odors, they still respond to other gases (that are not stated in the datasheet as target odors), because of the sensing mechanism used. This is one of the main reasons for the interference problems of these sensors causing false alarms.
(6) Even if specific commercial gas sensors are not designed for sensing the odor of fruits, with the help of proper recognition algorithms, effective fruit recognition systems could still be developed

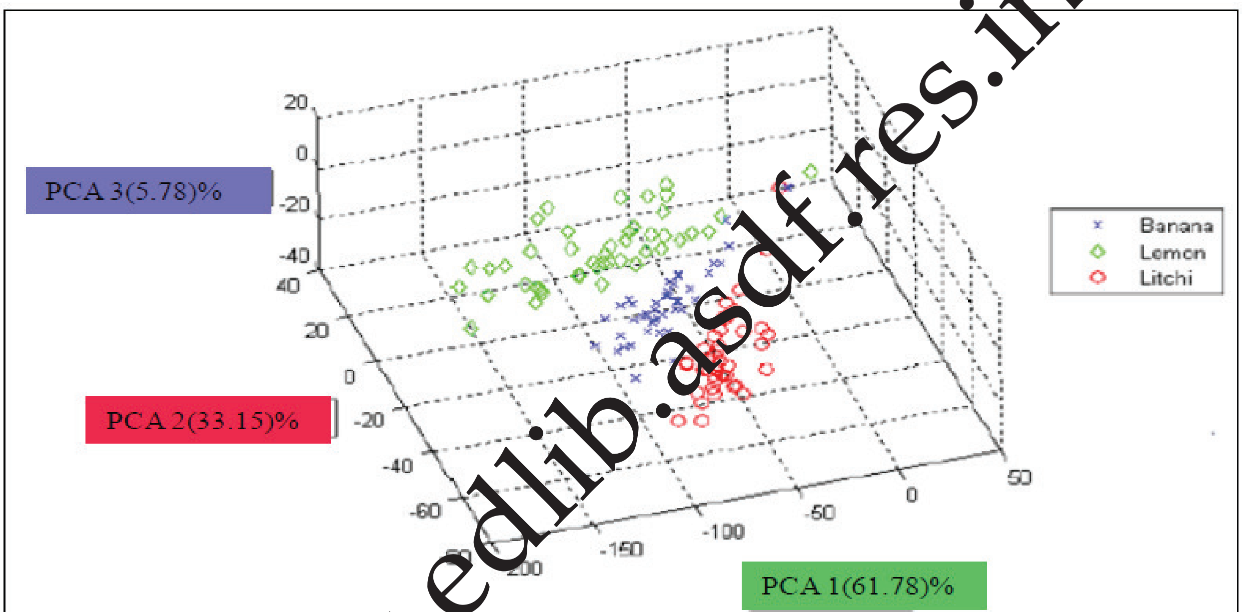

Figure 7: The PCA result of lemon, banana, and litchi.

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V. Conclusion

A universal electronic nose capable of identifying or discriminating any gas sample type with high efficiency and for all possible applications has not as yet been built. This fact is largely due to the selectivity and sensitivity limitations of e-nose sensor arrays for specific analyte gases. Electronic noses are not designed to be universally appropriate sensor systems for every conceivable gassensing application nor are they capable of serving every possible analytical need. Artificial or electronic noses with diverse sensor arrays that are differentially responsive to a wide variety of possible analytes have a number of advantages over traditional analytical instruments. Electronic nose sensors do not require chemical reagents, have good sensitivity and specificity, provide rapid results, and allow non-destructive sampling of odorants or analytes.

The potential for future developments of innovative enose applications is enormous as researchers in many fields of scientific investigation and industrial development become more aware of the capabilities of the electronic nose. The current trend is toward the development of electronic noses for specific purposes or a fairly narrow range of applications.

The prototype has been tested with three complex fruit odors, namely, lemon, banana, and litchi. The prototype of the proposed portable E-Nose system and the verification software achieved classification accuracy in excess of 95%. This E-Nose prototype is highly suitable for implementation as a portable system.

VI. References

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