

# Artificial neural network-based intelligent sensor-based electronic nose for food applications

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## ABSTRACT

Food commerce, especially for the general public, is greatly impacted by the capacity to identify and recognize chemical samples for food applications. Every chemical sample response has a unique, distinguishing smell. These advancements highlight the method of an artificial neural networks (ANN) to distinguish the distinctive fragrance from the reaction of substances. The categorization of various smell patterns has diminished confidence in ANN technology. Using an ANN technique and a sensor-based e-nose system for food applications, each chemical's identification has been done commercially. The system comprises a 5-gas sensor selection that recognizes chemical talk while allowing for an improvement in permitting while falling gas is planned outside. To build a model of a different signal reaction, individual sensors are equally collected and merged into the innovation -favored sensor array. Demonstrates how it is related to the chemical test. The e-nose categorization has been tested with five different chemical samples and five different sensor classes. The e-nose approach, which comprises five sensors, can classify each chemical reaction model, starting with the results. With more sensors being employed, the classification accuracy of the precise chemical reaction improves. These data demonstrate that the ANN-based e-nose method promises a successful classification system for chemical sample responses for a characteristic odor sample.

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## 1. INTRODUCTION

This study Investigated effect of the All kinds of innovation are possible with motivation. As the sense of display inspires image processing, the electronic nose is also recognized as a smell sensor, odor sensor, artificial nose, and electronic [1] knowledge is motivated by the sense of smell. The electronic nose system easily enables responded to be aware of their environment, if possible, and to identify and classify chemicals in food [2], [3]. In technology, though, automatic identification and classification of chemical samples are demanding since the chemical mixtures intercommunicate in nature [4]. Many more different substances construct a common smell which is more effective than those of entity mechanism. Recompense is the casing, while one section counteracts one more module. Mask is the arrangement of one odor with an unpleasant one.

Even while there is an existing report of cannot be analyzed [5], [6]. They split up into components with elevated correctness awaiting the improvement of the e-nose technology. Mutually with the improvement of E-nose, to understand mixtures of odor communications and the sensor response to these associations [7]. These sensors are implemented in various industries. These sensors' main objective is to signify any changes in the liquid or to detect any air chemical variation. These are significantly implemented in cities because it is essential to look for changes and provide safety. The essential implementation of chemical sensors can be seen in commercial atmospheric observation and process organization, which can either purposely or accidentally evolve chemicals, dangerous, reusable operation in room stations, and many others [8], [9].

The field of electronic nose systems has been developed quickly with explosive chemicals' objective for food production very much the social structure. As mention above, various investigate groups are functioning in this area, and several information have available. However, consistent, immediate, and constant real-time monitor of odors for an exact application has not been successful. Therefore, the reason for this reading is to expand an electronic nose signal processing system that can make absolute those preferred features. This thesis focuses on two functional areas [10]. The perfection of identification and presentation of real-time algorithms to make probable small portable devices with fast response and reduced cost. Second, new signal processing methods are proposed for odor mixture applications [11]. Various electronic nose instruments are used in different fields of farming. With use of various innovations in data analysis and pattern recognition techniques, these electronic noses have resulted in significant advancement in agriculture. Accurate information about soil, weather and nutrient conditions can be obtained using wide variety of sensors [12]. Sensors are mostly used for quality control and monitoring manufacturing. E-nose equipment's continuous-monitoring capability enables manufacture methods and results meet the quality baselines and requirements set by authoritarian agency and the customers for critical salability in the market and assessment of technologies. As mentioned, identifying chemical compounds of significance in the workplace or general environment requires an analytical instrument with excellent selectivity and sensitivity [13]. It is competent of real-time measurement of complex, organic, and inorganic compound mixtures progress in analytical technology. The response of explosive chemical detection and characterization for which a detailed study needs to be carried out and hence the present study has been taken up on hand. A complete investigation of the sensor's description, fabrication of sensor with promoting layers and its application for the detection of dangerous chemicals like carbon tetrachloride (CCL<sub>4</sub>), acetone (CH<sub>3</sub>)<sub>2</sub>CO, ammonia (NH<sub>4</sub>), methanol, ethanol, compound have been taken up. Additionally, a preliminary study on enhancing sensitivity by using a particular type of indication technique, known as explosive chemical vapor, has experimented, and films with nano-material are the deposit. A study on substrates for sensor devices is also designed [14]. Detection and identification of electronic nose, which consisted of an array of five fabricated sensors, selective sensors for the quantitative discrimination of CCL<sub>4</sub>, CH<sub>3</sub>CO, NH<sub>4</sub>, methanol and ethanol, volatile organic compounds and Non-volatile organic compound [15]. Due to the high requirements in food and agricultural application to detect explosives chemicals to monitor air quality, soil quality and food quality for regulation compliance, rapid on-site exposure and characterization of suggestion amount of NH<sub>4</sub>, CH<sub>3</sub>CO, CCL<sub>4</sub>, methanol and ethanol, non-volatile and volatile organic compound in the air become an important research area [16]. Quick detection and characterization of poisonous gas traces require multiple spots, fast analysis, and measure the level of gases [17]. The discovery of organic and inorganic evidence is very challenging for conventional logical methods because target organic and inorganic concentration is low and gases are in mixed state. Needs for onsite monitoring of environmental air quality is difficult to be met by current electronic nose-based techniques due to following problems:

- Long sampling time
- Low sampling frequency
- Limited range

Various applications like detection of chemical traces, explosives, and dangerous chemical gas use gas sensors. Gas sensors work based on the principle of conductivity change in P-type and N-type semiconductors in presence of gases [18]. This conductivity change is measured and gases are detected. Following are some of the advantages of metal oxide-based gas sensors compared to others:

- Quick response
- Low cost

Most of these type gas sensors use five gas sensors to find target organic and inorganic in the air due to explosives chemicals interference. Following problems prevent them from wide adoption:

- High power consumption
- Reduced selectivity
- Low compassion

Therefore, the present is dangerous requires developing real-time, convenient, high-performance sensors to notice organic and inorganic significance at the threshold.

Even though the 1<sup>st</sup> investigation into detecting distinctive aromas begin in [19]-[22] in the 1921s, the thought to observe smells with a substance, e-nose sensor collection is mainly declared in [23] and next in [24], [25] in the early 1980s. Conversely, the e-nose idea might not be realized on that occasion due to restrictions on the sensor's equipment. In the delayed 1990s, then, the expression e-nose was mentioned. Early characterization, an e-nose, is collected from a multisensory array that is answerable for more than a single chemical component. Consequently, equally, technical improvements in sensors the recognition of the possibility that the E-nose hold the guide to a significant expansion of its application.

**2. TYPES OF GAS SENSE METHOD**

Explaining the change in quantity or measures can be defined as a sensor. In universal, sensors are term as the procedure that generates a signal or output signal on the variation in the inputs' level. For example, there are dissimilar types of sensors, which can be measured as a temperature sensor that produces and voltage based on the input temperature change in Figure 1.

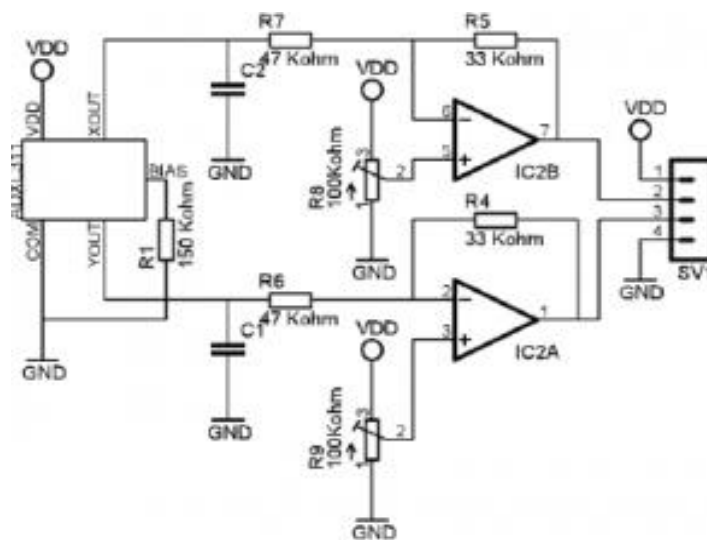


Figure 1. Type of sense method

**2.1. Performance of gas sensor's permanence**

To estimate the presence of the gas sense method, must consider numerous indicators:

- Sensitivity: the smallest value of an objects gases' atmosphere absorption when might detected them.
- Selectivity: the capability of gas sensors to recognize a detailed gas amongst a gas combination.
- Reaction time: the epoch from the occasion when gas absorption reaches detailed importance when the sensor generates a detected indication.
- Power utilization.
- Reversibility: whether the sense of possessions might go back to its exclusive recognition
- Adsorptive (as well as affect compassion and selectivity)
- Manufacture charge.

Additional indicator for dissimilar sense method in Table 1.

Table 1. Sensor specifications

Sensor name	Manufacturer	Model ID/product	Sensitivity (%)
Methanol	Sigma	MFCD00004595	99.8%
Ethanol	Aldrich Micron	MQ3	99.2%
Carbon Tetrachloride	ASAIR	MFCD00000785	99.5%
Acetone	ASAIR	AGSO2MA	99%
Ammonia	K-emit	VT763	99%

## 2.2. Method of an E-nose

An E-nose consists of an equal software and hardware mechanisms as briefly depicted in a chemical categorization in Figure 2. Initially, the chemical air is immersed by the sensor selection. The recognition of the indication occurs according to the modification in the atmosphere, incidence, and parameters depending on the type of chemical apparatus in the sensor collection. Since the separate type of sensors is typically in are employment in sensor arrays, the obtained signal should be preprocessed to understand individuals' substance change and a satisfactory method is to digitalize them to multiplicity a dataset.

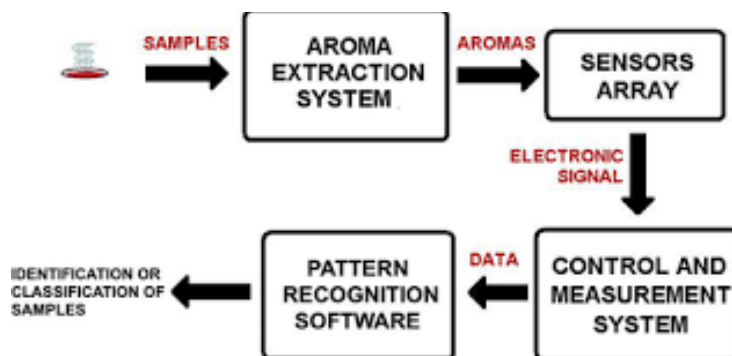


Figure 2. A description of E-nose system

## 2.3. Food/soil samples

This research work sees an improvement in performance. Standard food samples and soil moisture samples at or below 35 °C are both kept at the designated test temperature to hold onto extra chemically mixed samples in Table 2. With particulars on the food samples, E nose instrument preprocessing and characteristic vector and removal, and categorization.

Table 2. Performance and comparison of soil quality

Soil moisture	Percentage	Soil quality	Soil quality level
13.5	0-6 %	Moderate acidity	Suitable for crop
20.5	0-3 %	Normal acidity	Suitable for crop soybean and Pie
5.5	0-0 %	No acidity	Suitable for crop
-	0-9 %	More acidity	Difficult to crop
27.5	0-12 %	Acidity	No use for crop

### 2.3.1. Electronic nose instruments used

Widely available of commercial E-nose. In this instrument, sensors are constructed from a metal oxide semiconductor doped with a copper metal catalyst and operate at high temperatures (up to 450 °C). When the VOCs from the test material are introduced, the sensors' conductivity changes, resulting in a measurable electrical signal on a pair of metal electrodes connected to the sensor. Varying each sensor's selectivity in the array can be achieved by changing the sensor/doping materials and altering the operating temperature.

### 2.3.2. Instrumental technique

The majority commonly used method for the detailed analysis of the composition of elements in substance, in general, uses the chemical mechanism division in a combination, followed by the detection and identification of these mechanisms. In most cases, techniques are used to identify the character's workings. This technique is used to distinguish the chemical compositions of resources and also to recognize sources. The mixture of gas mass spectroscopy and chromatography (MS-GC) is the most accepted method for calculating volatile compounds since the exception. Separation is got by integrated use of gas chromatographic technique with high sensitivity mass spectroscopy and its facility to identify the explosive chemicals based on their separation pattern.

### 3. METHOD

The projected E-nose system is separated into 3 sections. The primary is hardware enlargement. In the hardware improvement, the detector circuit, which consists of the sensors array and analog to digital convertor, is measured and knowledgeable. The next element focuses on the software expansion to expand the pattern-recognition algorithm based on artificial neural network (ANN) using MATLAB software. The ANN is used to categorize the type of chemicals into their individual group. The previous element is to interface the hardware and software with an information method.

#### 3.1. Collection of sensors

An array of 5 chemical gas sensors chemically functionalized using different chemical samples was used. Each sensor is a chip, which has a pair of matching planar. The electrodes are made of polysilicon. The conductive polysilicon is covered with a roughly 20-nm-thick layer of SiO<sub>2</sub>. This layer provides for the good chemical necessary for a different organic composite, which serves as a thin layer to attract targeted chemical response in the surrounding atmosphere to the surface.

#### 3.2. Extract features starting Arduino IDE

Here's a step-by-step tutorial on utilizing the Arduino IDE to extract features from your serialized. It is imperative that the sensor in the Arduino-based serialized copier configuration detects parts per million (PPM) values precisely, which should be eight fewer than the recorded data. Once the sensor has warmed up for more than an hour, this precision needs to be kept. The detected values also need to be inside the critical range that the sensor's datasheet specifies.

#### 3.3. Food sample collection

Unusual rice samples are preferred for this investigation as their process is quick, and soon, it may reason loss to commerce or client. Eight dissimilar rice samples were kept in revolving in the sample assembly room during the experimentation with each type of food. Throughout the process, the foods are conserved at 35 °C. Separate impervious boxes are used to store the food to avoid their odor and, thus, noise instruction.

#### 3.4. Environmental air monitoring

The chemical discharge from industry, automobile, and home into the environment has caused IoT many global environmental and pollution problems. The pollutants have become a most important source of odor contamination. In 1989, toxic leakage from food waste entered into lakes in United Kingdom and poisoned the water making it unsuitable for aquatic and human life.

#### 3.5. Chemical sensor materials

The variety of gas-sensitive materials is complete and can be separated into numerous ways, moreover by substance type or by the character of the communication with the systematic. The dissimilar category of chemical sensor materials has been reported according to the variety of substances used. The first type involves a range of inorganic materials. These contain semiconductors, metal oxides, porous article, and metallic catalysts. These types of resources when they are operating at temperature gathering as catalytic materials in permanent, or chemically immediate, and sensors.

## 4. RESULTS AND DISCUSSION

The chemical oxide catalysts prepared from I preserve have been seen the spectrum of those chemical thin pictures made through immediate makes a series of soft explosive in an NH<sub>4</sub>, CH<sub>3</sub>CO, CCL<sub>4</sub>, methanol, and ethanol from a metallic target (dash line) compared to chemical samples formed by making a series of soft explosive in a CCL<sub>4</sub>, CH<sub>3</sub>CO, NH<sub>4</sub>, methanol, and ethanol target (solid line and liquid line). The important variation across the spectrums is that the samples extracted from explosive targets contain confidence peaks that typically create 360-360.5 above the essential evaluation associated with the copper materials, respectively for copper material, and communicate to unexpected overcome electrons with disposition in Figure 3. The development of the target towards higher necessary energies individual with the existence of the performance peaks suggests that these thin films organized by making a series of soft explosives from explosive chemical targets in the air have mixed volatile chemical states Figure 4.

Thus, chemicals, which are to be the enter data for the method and the E-nose employ equally, are confidential. The regular recognition method cannot be achieved with not a composed collection of detailed aromas in Figure 5. The array of the sensor is responsible for detect besieged chemicals in a go-between. Each targeted smell sees a complete sensor; in other verbal communication, each sensor is dependable for sensing a demanding type of aroma. Chemical sensors are used to detect chemicals in the average. These sensors swap chemicals in order into the organized signal in Figure 6.

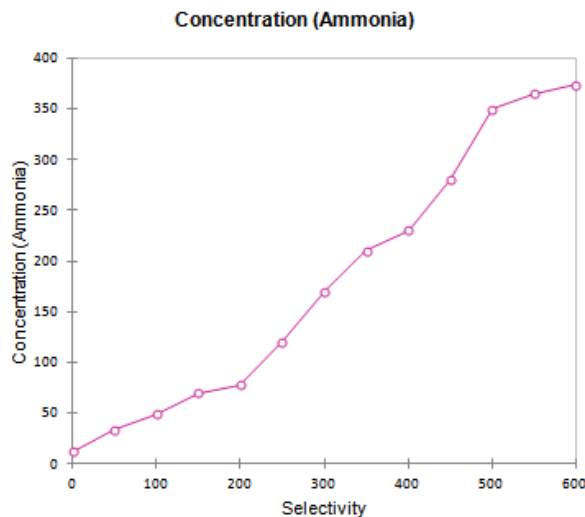


Figure 3. Ammonia gas concentration analysis

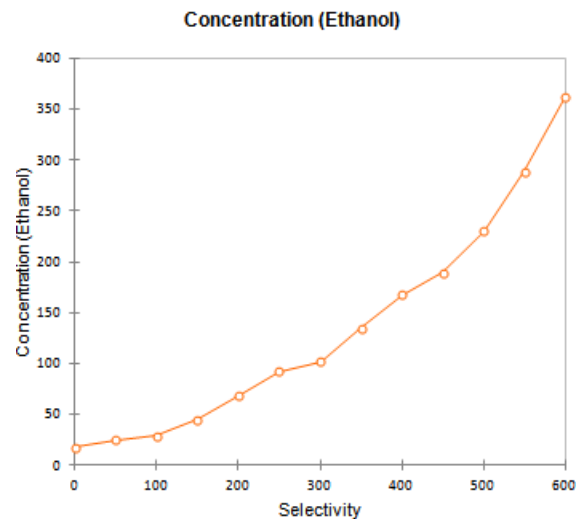


Figure 4. Ethanol gas concentration analysis

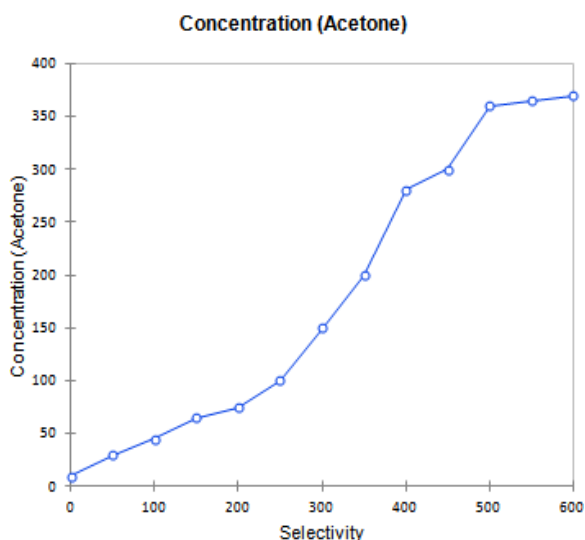


Figure 5. Acetone gas concentration analysis

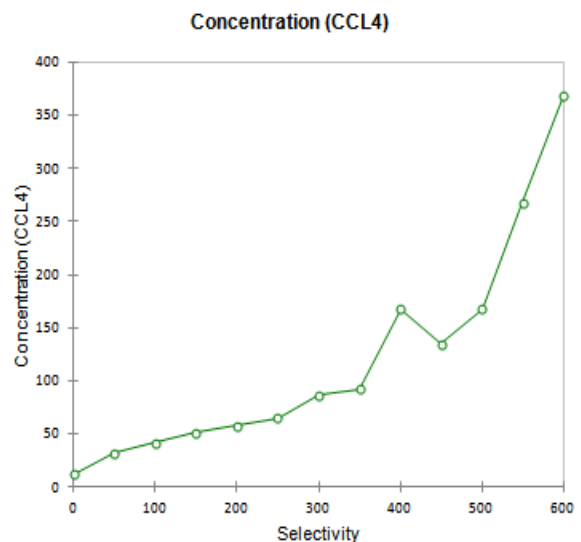


Figure 6. Carbon tetrachloride gas concentration analyses

On the other hand, by gas in air from a performance target, a contracted peak at  $-2.531\%$  was observed Figure 7. No target peaks were present in the series of soft explosive, indicating that the film is mainly collected from CCL<sub>4</sub>, NH<sub>4</sub>, CH<sub>3</sub>CO, methanol, and ethanol. Copper material also equipped thin films from a chemical compound target in a gas. Was an experimental relation to those volatile targets for a thin film, as displayed in Figure 8, this is same as that of results expressed in the literature. In the series of soft explosive for a chemical compound, the core levels were found at  $-2.531\%$  and  $120\%$ , in that order, both of which are in gathering with those values typically experimental in NH<sub>4</sub>, CH<sub>3</sub>CO, CCL<sub>4</sub>, methanol, and ethanol thin films. Testing at the limit, there is no observation of signification irregularities Table 4.

Relation experimentation was conduct to authenticate this finale by using the CCL<sub>4</sub>, NH<sub>4</sub>, CH<sub>3</sub>CO, methanol, and ethanol into the gas stream. As shown in Figure 8, the explosive gas achieves in the low high-temperature range displays the same sign and reaction. The equivalent development high temperature, i.e., from a negative chemical gas consequence to an exact temperature result compared with results in Figure 9. It can be inferred that same catalytic decomposition procedure was an effective. The magnitude of response to higher temperature at lower volume of gas suggests that the NH<sub>4</sub>, CCL<sub>4</sub>, CH<sub>3</sub>CO, methanol, and ethanol consumed much less temperature to preserve temperature. Due to oxidant deficiency, less air is generated.

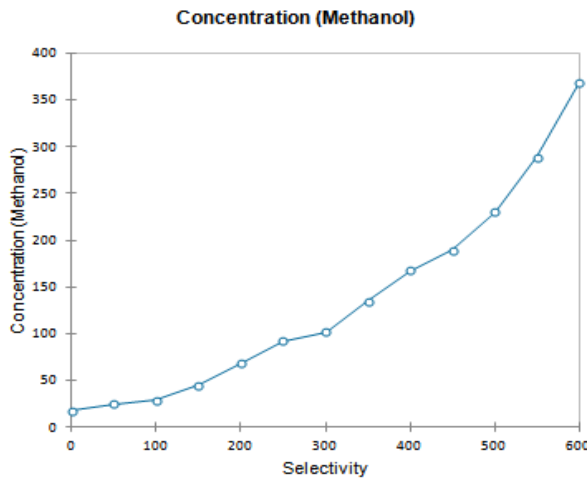


Figure 7. Methanol gas concentration analysis

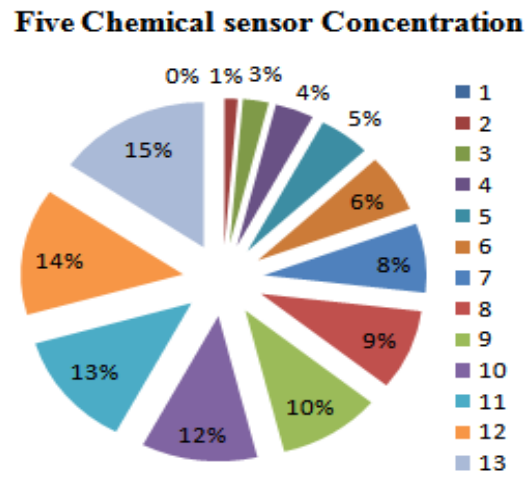


Figure 8. Five chemical concentration analysis

4.1. ANNs

The operational principles of neural networks inspire ANNs. They are normally calculated as completely associated multilayer systems, and an instance agreement is known Tables 3 and 4. The numeral of the hidden layer change depending on the charge to be clever. The input level and weights connecting the input and unknown layers verify hidden layers' activations. Likewise, hidden layers and ideals between them fix the formation of the output level.

Table 3. Chemical gas concentration

Voltage	CCL4	Acetone	Ammonia	Methanol	Ethanol
0	12	10	12	18	18
50	32	30	34	25	25
100	42	45	49	29	29
150	51	65	70	45	45
200	58	75	78	68	68
250	65	100	120	92	92
300	87	150	170	102	102
350	92	200	210	135	135
400	168	281	230	168	168
450	135	300	280	189	189
500	168	360	350	230	230
550	268	365	365	289	289
600	349	370	374	369	363

Table 4. Comparison of target value and ANN error

Sensor	Calls	Total time	Time (%)
1 Sensor	One	2.05135s	84.09%
2 Sensor	One	00.0256s	8.06%
3 Sensor	One	00.0131s	4.04%
4 Sensor	One	00.0049s	1.06%
5 Sensor	One	00.0006s	0.02%
6 Sensor	One	00.0005s	0.02%
7 Sensor	One	00.0004s	0.02%
8 Sensor	One	00.0003s	0.02%
		Total	3.960s=100%

It is important to mention now that the organization's function of personality neurons is the entry of ANNs, and missing them, any system behaves like a linear deterioration representation. Though present linear function, non-linear activations are usually selected to support the method in knowledge difficult data arrangement and complex practical mappings to make dependable calculation Figure 9. Another explanation for selecting non-linear function is that they are extra suitable to be used in back-propagation.

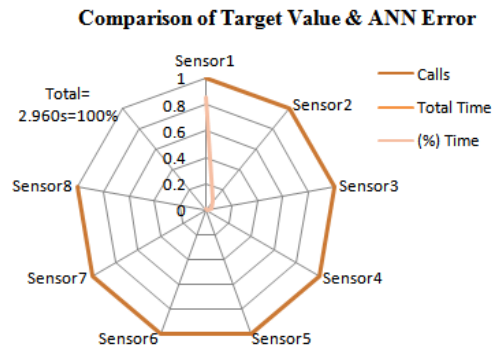


Figure 9. Comparison analysis

**4.2. Foodstuff and potion**

E-nose-connected investigative topics have considerably increased in the previous decade, mainly in the food industry. Infectivity of food lead to dissipate of resources and to recognize infectivity in food products is possible via E-nose system excellence evaluation, hazardous chemicals detection and classification in beverages and food can be achieved through some unique array of sensor Figure 10 and Tables 5 and 6.

Table 5. Accuracy of food quality

Product	Accuracy	Quality
Mango	96	112
Rice	97	110
Jack fruit	96	120
Orange	97	110
Banana	97	112
Leman	96	190
Water melon	97	100

Table 6. Preparation samples

Training	Sample	M.S.E.	Random
Training	0348	01.01165	0.09897
Validation	075	0.00000	0.00
Testing	075	04.073298	0.09647

Final examination presentation = 05.1956

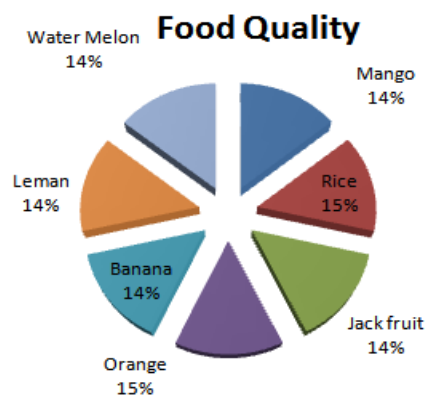


Figure 2. Food samples accuracy

The presence of rust during food manufacturing and storage can lead to corrosion, which diminishes the quality of the food and may result in the formation of harmful chemicals. These chemicals can pose significant food safety risks. Fortunately, the damaged equipment releases chemical gases that can be detected by an electronic nose (E-nose), as illustrated in Figure 11.



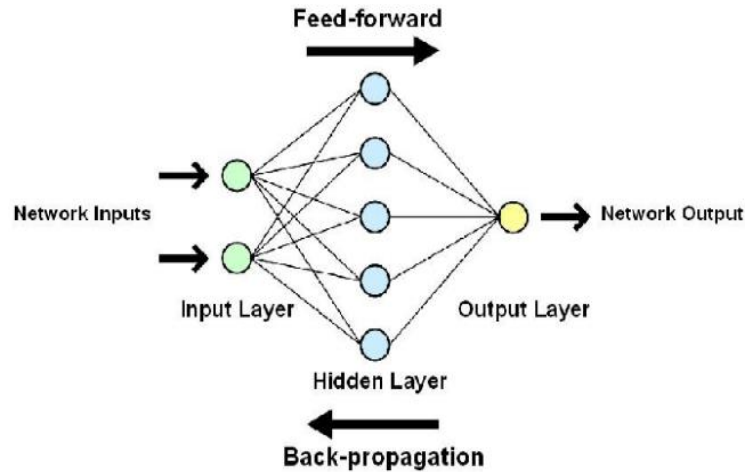


Figure 11. Using ANNs

**4.3. EC gas sensors**

Robustness, power effectiveness, process temperature, and capability to sense varied types of gases are the major reason for select and develop sensors in E-nose submission Figure 12 and Table 7. In these sensors, electrochemical corrosion or reduction occurs on a catalytic electrode outside. The quantity of gas is considered by measure the present current. Safety and engineering monitor application usually develop sensors Figure 13 and Table 7.

Table 7. Chemical analysis progress

Name	No. of iteration	Percentage
Epoch	0258	100%
Time	0:00:02	-
Performance	01.14	0.000
Gradient	0.127	00.0000001
Mu	05.00	00.000000001
Effective	0125	0.000
Sum squared	055.7	0.000

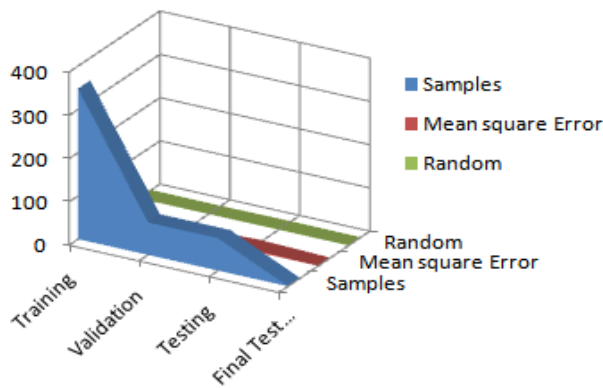


Figure 12. Training sample analysis

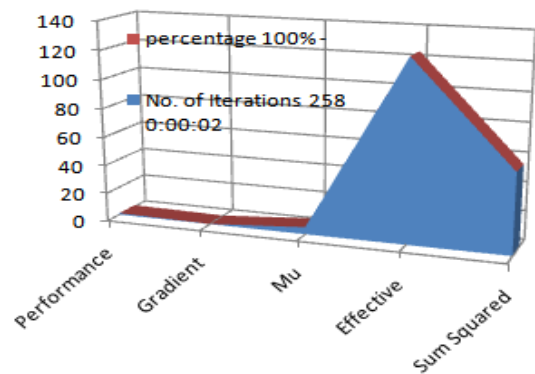


Figure 13. Chemical analysis

**5. CONCLUSION**




Recent observation investigates the E-nose method with an improved categorization module-based on ANN technique for chemical identification of this work. The expected E-nose has been designed to include a simple structure. Thus, simply lacking must do the multipart experimentation compared to the present E-nose arrangement. The future E-nose method is intentionally built with 5 chemical gas sensors to estimate 5 dissimilar chemical reactions. The selected sensor array shows its association with the chemicals' odor

throughout the analysis and explains why present are power changes when the chemical reaction is here. The data signal since the sensors array is scheme according to the 1-feature investigation, three-feature analysis, and 2-feature analysis. The reason for these analyses is to monitor the E-nose's ability to complete the maximum accuracy using a variety of information of sensors to categorize the type of chemicals based on the smell. Also, they can check whether all the sensors are appropriate to be used in this E-nose scheme. In this task, use the type of chemicals since a dissimilar relation. It is easy to categorize only using this feature. The data signals obtained from the sensors array are sent to categorization using the ANN technique for authorization. The ANN can effectively categorize the chemical. Consequences also show that the industrial E-nose method with 5 sensors has the maximum capacity in organized samples. In the end, the presentations of E-nose in classify the right chemical increase with the number of sensors use.




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