Classification of Food Types in a Box with Gas Sensors Using a Machine Learning Method. Case Study of Intelligent Electronic Nose

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Abstract. The Active and Assisted Living (AAL) paradigm has helped the expansion of the use of sensors, which is increasingly common in research work related to activity monitoring. However, one of the major disadvantages found in using sensors inside the home or other types of environment to monitor activities is the non-acceptance by users of having sensors around them because they may see their privacy compromised. Therefore, nowadays it is important to search for non-invasive and low-cost sensors that provide the user with the security and accessibility to feel comfortable with them. In this work a case study has been carried out with the design and construction of a Metal Oxide Semiconductors (MOS) sensor array with which it is intended to monitor the type of food used in the kitchen by means of the K-Nearest Neighbours (K-NN) machine learning method. Specifically, the case study presented seeks to differentiate between bananas, lemons, chorizo and prawns in a first approach as an intelligent electronic nose. Gas sensors have been used to take advantage of their non-invasive character for the user, although the disadvantage of not being widely explored in the scientific literature has been found. The results obtained in the case study presented in this paper to classify these four foods have been promising to advance in this research topic.

Keywords: Gas sensors · Metal oxide semiconductors sensors · Classification of food · k-nearest neighbors · Intelligent electronic nose

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1 Introduction

Nowadays, there are paradigms such as Active and Assisted Living (AAL) which looks for the improvement of life's quality of elderly and disabled people with the aim of a more friendly integration into society. In order to achieve this, a variety of technologies are used in the daily life of these people [15].

Due to this trend of using technology to improve human life, paradigms, such as the Internet of Things (IoT) paradigm, have been extending to areas such as home life or life support [6]. IoT in one of its definitions is constituted as a connection of a network of physical objects or devices where these smart objects have the ability to self-manage, share information, data, resources, react and act against situations and changes in the environment [10].

One of these smart objects are sensors, whose use has spread throughout the world and in different applications. Sensors are used to measure different magnitudes and can be of many different types: audio, vision, presence, temperature, etc. There is a wide variety of sensing technologies, some cheaper than others, some with greater accuracy and sensitivity and with different sizes and shapes.

However, it is not all advantages, and the use of some of these sensors in home applications has a major limitation. This major limitation is the lack of privacy, which leads to a discomfort on the part of users to use these devices in their homes.

Therefore this proposal is based on the use of gas sensors to identify different 4 types of food (lemon, banana, prawns and chorizo). Benefiting from a great characteristic of gas sensors, their non-invasiveness. In the process of generating the first tests for a future prototype capable of monitoring human activity in the kitchen.

This work is structured as follows. Section 2 presents a review of the literature related to different gas detection technologies and current applications using gas sensors. Section 3 presents the materials and methods carried out. Then, Sect. 4 continues with the case study. Finally, Sect. 5 gives the conclusions and future lines of work.

2 Related Works

This section, on the one hand, reviews the different existing gas sensing technologies and, on the other hand, the current IoT devices or applications based on gas sensing.

2.1 Gas Sensing Technologies

The differences between the various gas sensing technologies reside in the various methods of gas detection. While some sensor use physical variables such as the speed of propagation of light and sound, others sensors use the reaction of the target gas with the sensing element.

The following is a description of the most popular gas sensors that will be used in our proposal.

- ***Electrochemical***
  This type of sensor consists of a membrane which separates the ambient gases from the electrolyte solution and uses chemical reactions to detect the target gas. Speed of the reaction is proportional to the concentration of the target gas present [13].
- ***Metal Oxide Semiconductors (MOS)***
  This type is generally applied to detect target gases through redox reactions between the target gases and the oxide surface. The process has two stages. A first stage where the redox reaction takes place and results in an electronic variation of the oxide surface and, a second stage where the previous electronic variation results in a variation of the electrical resistance of the sensor [19].
- ***Catalytic***
  In this type of sensor, there is a variation of the internal resistance and an increase in temperature when there is contact between the catalytic element and the combustible gases in the environment, which is how the detection takes place [8].
- ***Polymers***
  These types of gas sensors are more sensitive to inorganic gases, such as ammonia and some volatile organic compounds (VOCs). For this reason, in general, they are most commonly used to detect solvent vapours in gas phase, such as aromatic compounds, alcohols or halogenated compounds and a wide range of VOCs but some studies apply them to the detection of inorganic gases such as CO_2 and H_2O. Their mode of detection is the same as MOS, in this case the polymer layers change upon exposure to the target gas [7].
- ***Carbon Nanotubes***
  This type of sensor with electrical properties is very sensitive to small quantities of gases at ambient temperature without the need for heating and without the need for a pre-concentration phase. Examples of such gases are alcohol, ammonia (NH_3), carbon dioxide (CO_2) and nitrogen oxide (NO_x) [9].
- ***Acoustics***
  This type of sensor uses the different speeds of sound propagation depending on the gases present in the environment to detect them. This can be through signal attenuation, sound velocity, acoustic impedance or a mix of some of them. [14].
- ***Optic***
  This type of sensor is similar in behaviour to acoustic sensors in that it uses waves. But it type of sensor makes use of the different wavelength absorption properties of gases to detect them [4].

2.2 Applicactions Based on Gas Sensing

Gas sensing is very diverse and can be applied to different areas. For instance, in the food sector, Chen et al. [3] design an electronic nose (E-Nose) in combination with a camera to classify the ripening time of bananas into 4 stages: unripe, half ripe, fully ripe and overripe.

Also in the same sector, Ramón Aparicio et al. [1] have developed a work where they detect the rancid defect of virgin olive oil with an E-Nose. To select the sensors which compose the E-Nose, they use a training set from admixtures of virgin olive oil from Portuguese origin with different percentages (0–100%) of a rancid standard oil. Other authors such as Chen, Jun et al. [2] have presented a paper where their aim was to detect and predict the freshness of beef, pork and lamb and classify it into three states: fresh, sub-fresh and putrid. The results were quite good and encouraging with accuracies of 89.5%, 84.2% and 94.7% for pork, beef and lamb, respectively.

In other sectors such as the animal sector, there are some scientific works like the one by Manzoli, Alexandra et al. [11] which present the use of an E-Nose for monitoring volatile compounds as an indicator of the fertile period of bovine females with the aim of providing an improvement in genetics and in the control of genetic or acquired diseases. In addition, Cramp, A. P. et al. [5] have developed an E-Nose to detect cutaneous myiasis in sheep. This disease is debilitating, painful and potentially lethal for sheep and early detection, which is currently difficult, will allow sheep to be treated in time without it spreading through the flock.

In the health sector, there is some work such as the work by Westenbrink, E. et al. [18] where they present the development and application of an E-Nose to detect colorectal cancer (CRC). They used 92 urine samples from CRC patients, irritable bowel syndrome (IBS) patients and controls to detect through the E-Nose. Also, Yu, Kai et al. [20] present an E-Nose dedicated to home healthcare. This E-Nose is able to detect benign lung diseases, such as pneumonia and pneumoconiosis and is able to perform with high accuracy a classification between healthy control or lung cancer patients.

So this literature review shows that the use of this type of E-Nose composed of gas sensors have a wide variety of applications but all of them with good results and with the advantages of being non-invasive. At the same time there are a wide range of gas sensing technologies, some cheaper than others, some more suitable for certain conditions. Taking into account all this, our proposal, based on the collection and subsequent analysis of data derived from the recognition of food in the kitchen, will be carried out thanks to the design of an array of MOS type sensors, whose main advantage is its low cost.

3 Materials and Methods

This section presents the materials used in the proposal and includes the selection of the gas sensors and the architecture of components.

3.1 Gas Sensor Selection to the E-Nose

This subsection details the selection of gas sensors used to the sensor array or E-Nose to monitor the type of food used in the kitchen by means of machine learning methods.

This E-Nose is composed with MOS sensors. However, in the wide range of gas sensor devices, Figaro sensors have been selected because they have provided a prominent performance in scientific and technical field [3,12,16,17].

In this contribution, the selection of devices, which have been integrated to configure E-Nose, are shown in the Table 1.

Table 1. Sensors type used in the sensor array.

Sensor type	Main applications
2600	Hydrogen, Hydrocarbons
2602	Ammonia, Hydrogen Sulfide (high sensitivity to VOC and odorous gases
2610	Alcohols, Butane, Liquid Petroleum Gas, Propane
2611	Natural Gas, Methane
2620	VOC, Alcohols, Organic Solvents Steam

3.2 Architecture of the Intelligent E-Nose

The architecture of the proposed intelligent E-Nose is presented in this section. The general architecture is shown in Fig. 1 which integrates a smart board with the array of gas sensors.

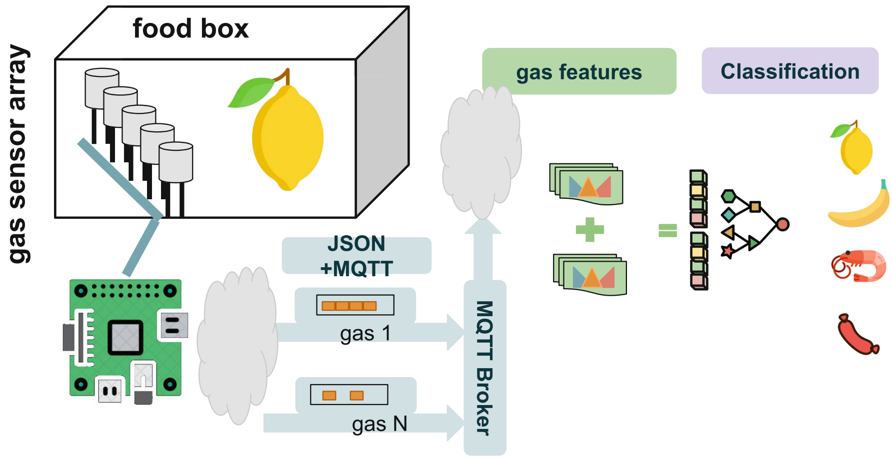


Fig. 1. Arquitecture of components

The components of the architecture are described as follows:

- ***Raspberry Pi 4 Model B.*** This is the development board used to collect the data from the sensor array to send it to the database and display it. In short, it is the one responsible for data flow control.
- ***MCP3008 chip.*** This integrated chip is an analogue to digital converter with 8 channels and 10 bits resolution. Thanks to this integrated chip the Raspberry Pi is able to read the values of the sensor array as it provides it with an analogue/digital converter pin that it does not have by default.
- ***Figaro sensors.*** These sensors make up the array in charge of detecting the different gases. They have all been described in Table 1.
- ***Nipron HPCSA Desktop PC Power Supply.*** The sensor array requires an external power supply for proper operation due to the fact that the voltage pins of the Raspberry Pi are not enough.

  In Fig. 2 is illustrated the schematic diagram of connections of the proposed intelligent E-Nose.

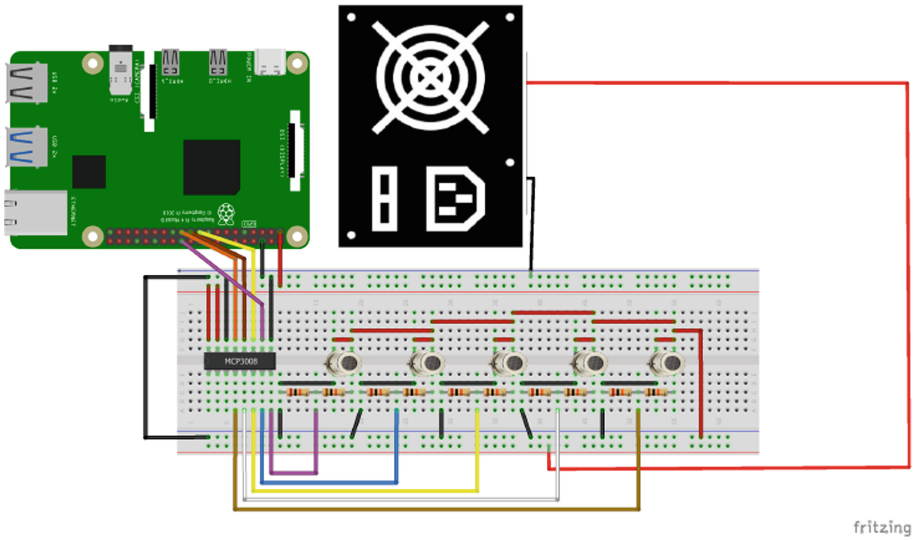


Fig. 2. Schematic diagram of connections.

Furthemore, a controller in Python has been developed for measuring the gas sensors in real-time and distributing under MQTT using JSON format to provide value and timestamp for each sensor which is defined in a given topic. The controller runs within the Raspberry Pi under an edge computing paradigm, providing: persistence, publication in real-time under MQTT and dashboard with the visualization from previous information under ssh. The Raspberry Pi also includes computational capabilities to develop machine learning in streaming for future work proposal.

3.3 Features and Classification with Machine Learning Methods from Gas Sensor Streams

In this section, the machine learning methods for processing the gas sensor streams collected by the E-Nose is presented in order to classify the nearest food box are described.

To do so, a sensor s collects data in real time in the form of a pair $\overline{s_i} = \{s_i, t_i\}$, where s_i represents a given measurement and t_i the timestamp. Thus, the data stream of the sensor source s is defined by $\overline{S_s} = \{\overline{s_0}, \ldots, \overline{s_i}\}$ and a given value in a timestamp t_i by $S_s(t_i) = s_i$.

The opening and closing of the food determine a window size of a time interval $W_w = [W_w^-, W_w^+]$ which enable segmenting the samples of a the sensor streams $\overline{S_s}$, which aggregates the values $\overline{s_i}$ by means of a :

$$\bigcup S_s \cap W_w = \bigcup_{s_i}^{\overline{s_i}} s_i, t_i \in [W_w^-, W_w^+] \tag{1}$$

Next, several aggregation functions $\bigcup$ define the feature vector for describing the sensor stream S_s. In this work, we have determine: *Tbasal*) $\bigcup = t_0$ which determines the basal value of the food box at the beginning of the opening $s_i, t_i = W_w^-$, *Tmax*) $\bigcup = max$ which determines the maximal value of the food box between the opening and closing $max(s_i)t_i \in [W_w^-, W_w^+]$, , *Tmin*) $\bigcup = min$ which determines the minimal value of the food box between the opening and closing $min(s_i)t_i \in [W_w^-, W_w^+]$. and *Tinc*) $\bigcup = \Delta$, which represents the higher interval between basal value and maximal or minimal $max(max - t_0(S_s \cap W_w), t_0 - min(S_s \cap W_w))$.

So, all sensor streams are described by the aggregation functions configuring a feature vector which represents the signals of the food within the box. This feature vector is served as input of classification model which relates to the label which defines the food within the box.

$$(\bigcup_1 S_1, \bigcup_2 S_1 \ldots \bigcup_1 S_2, \bigcup_2 S_2 \ldots \bigcup_N S_s) \cap W_w \to Y_y \tag{2}$$

4 Case Study to Classify 4 Types of Food

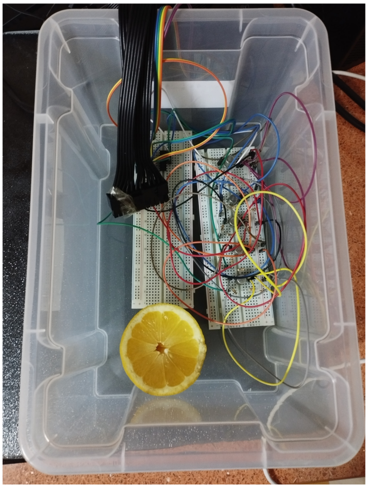
In this section, the case study developed in real time in a real environment are presented to classify 4 types of food.

The feature extraction following the proposal presented in Sect. 3.3 is shown in Table 2.

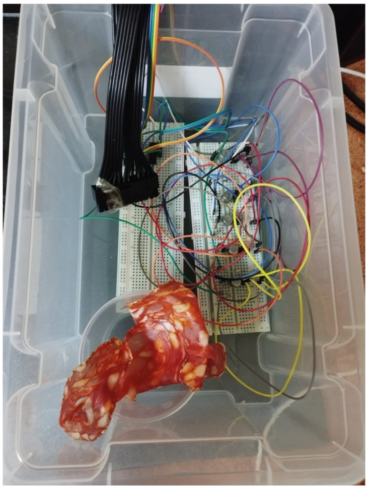
The experimental setup were defined by a case study which includes 5 scenes developed in a kitchen where 4 food items (banana, lemon, chorizo and prawns) where evaluated in the box. Figure 3 shows images of the box where two types of food are introduced. To carry out each scene, an user introduces one of the foods into the intelligent E-Nose where the array of sensors is located and then cover it. The food will remain in the covered box for 5 min. Then the lid will be

Table 2. Feature vector for scene 1 of sensors 2600 and 2602

	2600			
Label	Tbasal	Tmax	Tmin	Tinc
Lemon	720	764	720	44
Banana	712	756	712	44
Chorizo	717	732	717	15
Prawns	716	716	692	-24
	2602			
Label	Tbasal	Tmax	Tmin	Tinc
Lemon	495	834	495	339
Banana	520	718	520	198
Chorizo	500	550	500	50
Prawns	488	576	488	88



(a) Lemon.



(b) Chorizo.

Fig. 3. Photographs of the box where two types of food are introduced.

opened and the food will be taken out. The box will remain open and without food for another 5 min as if it were being cleaned.

Before using this sensor array, the gas sensors were pre-heated for seven days as recommended by the manufacturer. On the day of the test, a simple 30 min pre-heat was performed to check that the measurements collected by the sensor array were stabilised to the environment in which they were being taken.

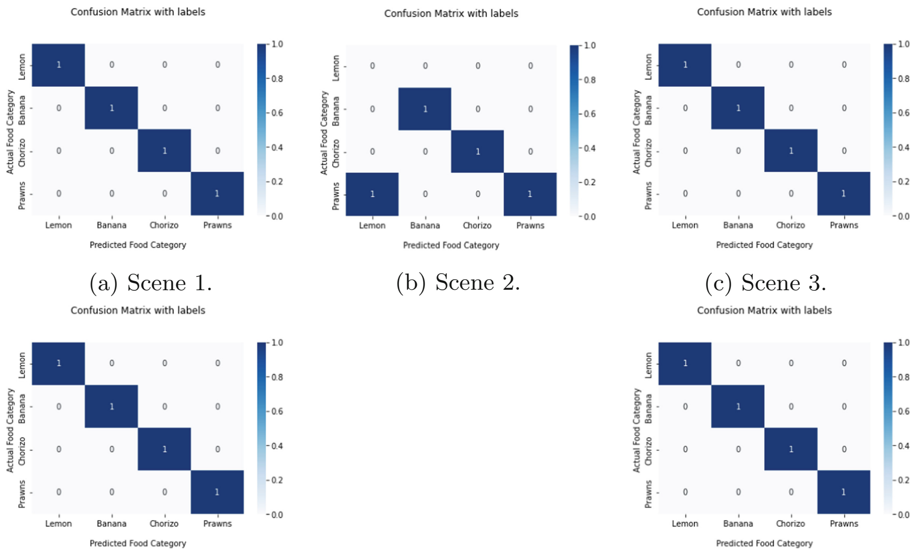
To obtain the results of the measurements collected from the array of sensors, first a preprocessing was performed to have all the measurements collected within a range of 0–1, where 0 is the minimum value and 1 is the maximum value.

Table 3. Results of scene 1, scene 2, scene 3, scene 4 and scene 5.

Scene 1		Scene 2		Scene 3		Scene 4		Scene 5	
Precision	1	*Precision*	0.625	*Precision*	1	*Precision*	1	*Precision*	1
Recall	1	*Recall*	0.75	*Recall*	1	*Recall*	1	*Recall*	1
f1_score	1	*f1_score*	0.6666	*f1_score*	1	*f1_score*	1	*f1_score*	1

For classification purposes, the model of Nearest Neighbours (K-NN) is proposed. It enables a light computing capabilities for learning and evaluation of the data which is compatible with smart and IoT boards. The K-NN integration was developed using the scikit-learn Python library. On the evaluation, we propose a rigorous method based on cross validation: developing the learning from 4 scenes and leaving the other unseen and unknown data of the other scene for testing. In order to evaluate the entire dataset, the learning and testing of scenes are combined under cross-validation approach. In Table 3, we describe the results obtained in the case scene.

And in addition the confusion matrixes are shown in Fig. 4. As can be seen in the results table, which is illustrated in Fig. 3, and in the confusion matrices for the 5 scenes, which is illustrated in Fig. 4, the results obtained were generally good.



(a) Scene 1. (b) Scene 2. (c) Scene 3.

(d) Scene 4. (e) Scene 5.

Fig. 4. Confusion matrixes.

In scenes 1, 3, 4 and 5 the foods being sampled were predicted with complete accuracy. However, in scene 2 all foods were correct except for the lemon which was confused with the spraw, so the accuracy is 62.5°%, the recall is 75% and the f1_score is 66.66%.

5 Conclusions

In conclusion, in this work we have carried out the construction of an array of gas sensors. To do so, Figaro gas sensors have been used for their great advantage of non-invasiveness so that users feel more comfortable and feel that they are not intruding on their privacy.

In this case, this sensor array has been used for a case study in the kitchen. This case study was to identify four foods (banana, lemon, prawns and chorizo) in five different scenes developed by a user.

The results obtained from the measurements collected by the gas sensor array have been very encouraging as only one food in one of the scenes was not accurate. Although this first case study has its limitations, the good results obtained promise a very interesting future line of work.

In addition, some of the improvements that could easily be included would be the following: introducing more gas sensors in the array, which would allow a wider range of foods to be detected, and carrying out a case study involving more types of food and providing new results.

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